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Abstract

The aim of this paper is to analyse to what extent the previous status of children in poverty affects current child poverty, even when we control for observed and unobserved individual heterogeneity and treat the initial condition problem. On the basis of Wooldridge's (2005) methodology, we estimate a dynamic random effects probit model considering three levels due to the hierarchical structure of our data: observations for each year (level 1) of the children (level 2) nested into countries (level 3). We corroborate the relevance of lagged status in poverty and assess the role of context variables in explaining differences across countries in child poverty dynamics. In particular, we highlight the significance of family benefits in reducing child poverty and assess which features of these benefits are more effective to reduce child poverty: means tested vs. non-means tested benefits. This way, some key insights are provided to design more effective public policies to alleviate child poverty.

Keywords: child poverty persistence, state dependence, initial conditions, social transfers, family benefits

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1. Introduction

Reducing child poverty in European countries is one of the goals of the Europe 2020 strategy for inclusive economic growth. According to Eurostat (2016), on average more than one out of every 5 children is living in a situation of poverty in the EU. However, as the poverty experience can be for more than one year, it is important to examine poverty persistence in order to help governments design appropriate and targeted policies. Persistent poverty differs substantially from short-term poverty, as it identifies a group of people who are potentially 'trapped' in this condition. In this sense, we should take into account that children are a group that needs to receive special attention, as poverty persistence of that group may involve serious longer-term consequences, damaging future life opportunities (Corak, 2006; Griggs and Walker, 2008; Esping-Andersen and Myles, 2009, Chzhen, 2014).

During the Great Recession, the rise in poverty was particularly marked for children in the OECD (Organisation for Economic Co-operation and Development) countries (Jenkins *et al*., 2013). According to the OECD (2014), around 76.5 million children live in poverty in the 41 most affluent countries. The number of children entering into poverty during the recession was 2.6 million higher than the number that have been able to escape from it since 2008 (UNICEF, 2014). In this context, the study of poverty dynamics seems essential to understand how the stock of poor people in a given year primarily depends on the previous year's stock (Jenkins and Schluter, 2003). It is crucial to follow the same individuals over several years in order to draw a complete picture of the dynamics of poverty and to design effective anti-poverty policies (see Jenkins, 2000, 2011; Valetta, 2006; Addison *et al*., 2009). Although there are many works that address the dynamics of poverty, the studies focusing on children are scarce. By studying child poverty dynamics, we not only get a better insight into the processes leading to patterns of disadvantage, but can also understand better the influence of different national contexts on the social risks experienced by different types of households. The extent to which different national contexts protect their citizens from poverty persistence, or vary in respect to the factors leading to poverty persistence, tells us a great deal about the workings of their socioeconomic systems and welfare regimes (Layte and Whelan, 2003).

This paper tries to offer a complete picture of the child poverty phenomenon in the European countries in order to provide some insights for policy makers to design more effective social protection policies to fight child poverty. As the redistributive outcomes of a particular system are dependent on the socio-demographic composition of population, the extent of market income inequality and other such factors (Marx *et al.*, 2016), we simultaneously combine demographic and socioeconomic characteristics of households and country-level factors in a multilevel model when analysing child poverty from a dynamic perspective. We specifically: i) analyse whether and to what extent the previous status of children in poverty affects current child poverty, even when we control for observed and unobserved individual heterogeneity and treat the initial condition problem; ii) assess the role of context variables in child poverty dynamics and in explaining differences across countries in child poverty persistence; iii) evaluate the significance of family benefits in reducing child poverty; and iv) examine which features of family benefits are more effective to reduce child poverty: means tested vs. non-means tested family benefits. As can be seen, all these aspects are key in the analysis and design of social policies against child poverty.

In order to control for the usual problems of poverty dynamic studies, our methodology is based on Wooldridge (2005), who proposes a solution to handle the problem of endogeneity of the initial conditions, while controlling for unobserved heterogeneity. We use the longitudinal component of the EU-SILC micro-data for 26European countries and macro data stem from statistics collected by Eurostat for the countries involved in the analysis for the period 2009-2012.

Main findings reveal that past poverty experience plays a crucial role in the probability of experiencing child poverty, even when we control for individual heterogeneity and the initial condition. We find that factors related to household composition, such as lone-parent families, families with more children or with a lower proportion of workers, and some characteristics of the head of the household related to education are closely linked with the risk of poverty. Moreover, we reveal that the most important factors to explain differences across countries in child poverty dynamics are associated to the context level variables. In particular, family benefits have a significantly positive effect in reducing child poverty, and more specifically, means-tested family benefits. In addition, we find that a lower risk of poverty also depends on labour market performance.

The remainder of this paper is as follows. Section 2 reviews the literature and establishes research hypotheses. Section 3 describes the data and explanatory variables used. Section 4 explains the methodology followed in this study. Section 5 discusses the results. And section 6 presents some conclusions.

2. Background and Hypotheses

The recent literature on income distribution underlines the importance of studying the dynamics of poverty (Jenkins and Rigg, 2001; Bárcena-Martín and Cowell, 2003; Layte and Whelan, 2003; Cappellari and Jenkins, 2004; Cantó *et al*., 2007; Jenkins, 2011; Ayllón, 2013; Ayllón, 2015a; Chzhen, 2016).

Empirical studies on poverty dynamics have increased in the last decades due to the increased availability of longitudinal data. They started to appear in the United States during the eighties due to the availability of data from the Panel Survey of Income Dynamics (PSID). Later, in the nineties, studies on poverty dynamics emerged in Europe thanks to the European Community Household Panel (ECHP), a panel survey in which a sample of households and persons was interviewed year after year from 1994 to 2001 and which, after some years, became a basic tool for the analysis of social cohesion dynamics in the EU. Afterwards, it was substituted by the EUSILC database, which in spite of having a shorter duration (individuals are interviewed for a maximum of four years), is suitable for studying short-term poverty transitions (European Commission, 2012).

Studies on poverty dynamics typically refer to a single country (e.g. Jenkins and Rigg, 2001, Cappellari and Jenkins, 2002, Bradshaw and Holmes, 2010, Jenkins, 2011, for the United Kingdom (UK); Cantó and Mercader-Prats, 2002, Gradín and Cantó, 2012, and Ayllón, 2015b, for Spain; Lindquist and Sjögren Lindquist, 2012, for Sweden; McKernan and Ratcliffe, 2005, and Riegg *et al*., 2008, for the United States (US), among others) or a limited number of developed countries (e.g. Duncan *et al*., 1993; Bradbury *et al*., 2001; Oxley *et al*., 2001; Layte and Whelan, 2003; Fouarge and Layte, 2005; McKernan and Ratcliffe, 2005; Valletta, 2006; Riegg *et al.*, 2008; Callens and Croux 2009; Galloway *et al*., 2009; Mendola *et al*., 2009; Damioli, 2010; Andriopoulou and Tsakloglou, 2011; Polin and Raitano, 2014; Chzhen *et al*. 2015; among others).

Most of the studies referring to a single country use probit models to analyse the dynamics of child poverty by means of first-order Markov Chain models. In general, the main conclusions obtained in these papers are that children who experience poverty in the past have more risk of being poor than the others. In addition, all of them conclude that there exist certain characteristics of households and heads of households that make children more vulnerable to experiencing poverty and poverty persistence, such as a large number of children living in the household or high labour instability of the household head (see, e.g., Jenkins and Schluter, 2003; McKernan and Ratcliffe, 2005; Cantó *et al*., 2007; Browne and Paull, 2010; Polin and Raitano, 2014).

On the other hand, works that simultaneously consider a group of countries in the analysis of child poverty dynamics are scarce. The pioneering comparative analyses were performed by Duncan *et al*. (1993) and later by Bradbury *et al.* (2001). The former examines the flows into and out of poverty in eight nations (Canada, the Lorraine region of France, West Germany, Ireland, Luxembourg, The Netherlands, Sweden, and the US) by comparing pairs of years between 1980 and 1988 using different national data sources. The latter compares child poverty dynamics cross nationally at the beginning of the 1990s in seven nations (the US, Britain, Germany, Ireland, Spain, Hungary and Russia). They examine flows into and out of the poorest fifth of the children's income distribution through multivariate methods. Both studies conclude that despite the very different macroeconomic conditions, demographic structures and degree of income inequality among countries, there exist some common aspects affecting child poverty dynamics in the same manner. They conclude that factors such as income changes and parents' education in families with children affect the probability of child persistence in poverty. Jenkins and Schluter (2003) compare patterns of movements into and out of child poverty through descriptive statistics in Britain and Germany using data from the British Household Panel Survey and the German Socio-Economic Panel for the period 1992-7. They conclude that child poverty is particularly persistent among children in lone parent households and households with a nonworking head. More recently, Chzhen *et al*. (2015) analyse child poverty dynamics in the EU during the recent economic crisis by using the EU-SILC database. They find that there is substantial heterogeneity among the European countries in the rates of child poverty entry and exit. That study is different from ours in that we study child poverty dynamics in the European countries from a macro-to-micro perspective, while they model transitions into and out of poverty in separate models for each European country, without considering initial conditions and unobserved heterogeneity problems.

Other studies of the dynamics of poverty in general usually compare countries according to types of welfare systems (see, for example, Layte and Whelan, 2003; Fouarge and Layte, 2005; Callens and Croux, 2009; and Polin and Raitano, 2014), and conclude that it is difficult to infer clear links between welfare state characteristics and poverty dynamics, as this relationship depends on various interdependent factors that can differ across groups of countries and can be differently affected by the various welfare schemes and the design of each policy.

Different approaches have been applied to study poverty as a dynamic process, depending on the main focus of the research. There are two main types of multivariate models that are usually employed to study poverty dynamics: hazard rate models and first-order Markovian models. In general, hazard rate approaches assume that the consideration of individual unobserved heterogeneity captures the correlation across individual spells and thus identifies various types of individuals in the sample through a joint distribution of individual specific effects with respect to spells of poverty and non-poverty. This assumption requires the estimation of a single exit and re-entry hazard rate for each individual, independently of the number of poverty spells previously experienced, but generally avoids considering any endogenous selection bias due to initial conditions or attrition (Jenkins, 2004). In contrast, the Markovian model stems from the belief that the complete individual poverty history may play a relevant role, in itself, in determining the likelihood of experiencing a new spell of poverty or non-poverty. Furthermore, the Markovian model has the advantage of jointly modelling poverty exits and entries and accounting for unobserved heterogeneity. Therefore, it is sometimes proposed as a complement to the hazard regression approach rather than a substitute. The random-effects probit models proposed by Wooldridge (2005), within the so-called first-order Markovian transition models in which an individual's present poverty status depends on the previous one, enables estimating state dependence through the different explanatory variables, and not only as one estimated parameter of the lagged dependent variable (which is interpreted as genuine state dependence).This model handles the initial condition problem in a dynamic, non-linear, unobserved effect panel data model, therefore incorporating important aspects that the literature on poverty analyses in recent years has stressed as crucial for the adequate measure of persistence in poverty.

Regarding the variables that are found to influence the risk of movements in poverty, the literature differentiates among those related to the household as a whole and those related to the household head. With respect to the former, there is a higher probability to overcome the threshold of child poverty with married parents rather than widowed and divorced parents (Oxley *et al.*, 2001; McKernan and Ratcliffe, 2005). It is shown that children living with older and younger parents are at a greater risk of movements into and out of poverty (Jenkins and Schluter, 2003; McKernan and Ratcliffe, 2005). Likewise, the probability of escaping poverty is higher for those households headed by males (Polin and Raitano, 2014). There exist other factors linked to the household head that affect child poverty dynamics. Among other aspects, there is evidence that the higher the education level of the head, the higher the household's chances to leave poverty in households with children (Cantó and Mercader-Prats, 2002; Cantó *et al*., 2007; Browne and Paull, 2010). The labour market status of the head of the household is also a major factor in the level of household earnings, and consequently it affects the child's probability of being poor (Cantó *et al*., 2007; Browne and Paull, 2010). In the literature on poverty dynamics, it is recognised that experiencing one year in poverty raises the risk of being poor the following year (Heckman, 1991). The clue is to untangle which part of this dependence is attributable to previous experience in poverty (true state dependence) and which part to favourable (observed or unobserved) characteristics of individuals of being in poverty, as this has policy implications. A significant state dependence in poverty requires breaking the vicious poverty circle and trying to help individuals to escape poverty using income-support policies such as social benefits. On the contrary, if individual heterogeneity is what is determinant for the persistence in poverty, anti-poverty policies should focus on other schemes influencing household characteristics such as education, development of personal skills and capacities or other labour market and social policies (Andriopoulou and Tsakloglou, 2011). Consequently, our first research hypothesis regarding the influence of household characteristics (observed or unobserved heterogeneity) on child poverty in a dynamic context, H1: previous experience in poverty determines current child poverty even when we control for observed and unobserved individual heterogeneity and treat the initial condition problem.[4]

Concerning contextual or macro variables, many social scientists have used welfare system theory when explaining the variation in static poverty rates across different system types in Europe. However, less attention has been devoted to studying the relationship between welfare systems and poverty dynamics (Polin and Raitano, 2014), and even less to child poverty dynamics. Using different methodologies and analysing overall poverty, Layte and Whelan (2003), Fouarge and Layte (2005) and Callens and Croux (2009) note that the more-encompassing systems exhibit lower entry rates. The findings of Polin and Raitano (2014) support the theoretical indeterminacy of the relationship between well-known welfare system typologies and poverty exit, especially when they control for

[4] Accounting for initial conditions is important because individuals in poverty at first interview are not a random-sample of the population.

several individual characteristics that can influence the occurrence of economic and demographic events and can, at least partially, explain the gaps between countries. Jenkins also (2011) supports this finding and claims that it is difficult to infer clear links between welfare state characteristics and poverty dynamics, as this relationship depends on various interdependent factors – i.e., population composition, event occurrence, conditional transition rates after the events, total transition rates – that can differ across groups of countries and can be differently affected by the various welfare schemes and the design of each policy. There could be substantial differences concerning the patterns of poverty dynamics within the groups of countries. Consequently, in order to formulate meaningful policy recommendations, we need to know what policies are related to which individual outcomes, preferably controlling for other possible explanations such as differences among countries in terms of labour market. Therefore, it may be essential to incorporate country-specific features into the analysis (Maître *et al*., 2005).

Regarding country-specific features that affect poverty dynamics, we find works that argue that countries that supply more generous social benefits with universal coverage –smoothing individual's income flows through generous and universal unemployment and social assistance benefits (Esping-Andersen 1990)– should be characterised by a smaller number of individuals falling into poverty and shorter poverty duration (Gallie and Paugam, 2000). Moreover, if the welfare system is accompanied by active labour market policies, lower entries into and higher exits out of poverty should be expected (Fouarge and Layte, 2005). Other contextual factors having a particularly strong effect on child poverty are those related to the labour market (Solera, 2001; Brady, 2006; Whiteford and Adema, 2007; Chen and Corak, 2008; Bäckman, 2009). In this context, countries with higher employment rates and lower in-work at-risk-of-poverty rates are expected to show lower rates of child poverty.

Previous analyses have most often focused on macro relationships between policies and outcomes, underlining the crucial role of family policy transfers in alleviating child poverty (see Kangas and Palme, 2000; Matsaganis *et al.* 2006; Tárki, 2010). However, most of these studies have neglected the links between country-level factors and micro-level characteristics of children, despite the fact that redistributive outcomes of a particular system are dependent on the characteristics of the underlying population (see Marx *et al*., 2016). Therefore, there is a need for a micro-to-macro analysis of child poverty. Moreover, only a static analysis would have to assume that a point in time represents a long-run equilibrium or steady state, although this is unlikely to be the case as cash transfers and taxation policy evolves under different governments and in response to the economic cycle (McKnight, 2015). Therefore, it makes much more sense to approach the topic by comparing the evolution of trends in contextual variables and the relationships between these variables within and between countries. In addition, cross-country poverty comparisons can provide unique insights into the role of economic and institutional influences on poverty outcomes (see Valletta, 2006). Consequently, a cross-national analysis from a longitudinal perspective is required. Therefore, based on the evidence of the relevance of country specific features on static poverty, we formulate our second research hypothesis regarding child poverty dynamics, H2: Context variables influence child poverty and help to explain differences across countries in child poverty and child poverty persistence once we control for the sociodemographic composition of countries.

Furthermore, regarding contextual variables, Moene and Wallerstein (2001, 2003) claim that the analyses of redistribution need to be done at a more disaggregated level. In this paper, we answer this call by analysing specific indicators of the welfare state and partitioning benefits into separate components, in line with Kzyma and Williams (2016), to better capture possible different roles of the benefits in child poverty dynamics. With these considerations in mind, the third research hypothesis is H3: Family benefits are more relevant in reducing child poverty than more general benefit functions.

It is also important to know the effect of the 'selectivity' of the benefits, i.e. knowing the effect of transfers depending on whether transfers are limited to children with scant economic resources or not. Some schemes may rest heavily on the insurance principle, while others may put more weight on the need principle (Marx *et al.*, 2016). Thus, universality and selectivity can coexist within one system. Furthermore, it is known that the selectivity may either involve direct means-testing or be applied by other measures intended to target the benefit to deprived groups. A recent review of the international evidence concludes that despite a considerable volume of research, the universal versus means-tested debate is far from resolved (Gugushvili and Hirsch, 2014). We also try to answer this question by disaggregating significant benefits into means-tested and non-means-tested benefits.[5] Therefore, our last hypothesis is H4: Means tested rather than non-mean tested family benefits are more effective in the fight against child poverty.

[5] Means-tested benefit is a type of selective benefit, access to which requires checking applicants' resources, and non-means-tested benefits are the contrary.

In summary, we have proposed four hypotheses:

- H1: previous experience in poverty determines current child poverty even when we control for observed and unobserved individual heterogeneity and treat the initial condition problem.
- H2: Context variables influence child poverty and help to explain differences across countries in child poverty and child poverty persistence once we control for the sociodemographic composition of countries.
- H3: Family benefits are more relevant in reducing child poverty than more general benefit functions.
- H4: Means tested rather than non-mean tested family benefits are more effective in the fight against child poverty.

The answer to all these hypotheses is particularly important for the analysis and design of child poverty alleviating policies.

3. Data and Explanatory variables

3.1. Data

Poverty is not a fixed condition, but a complex phenomenon that develops over time. In order to study the dynamics of child poverty in Europe during the period 2009-2012, we use the 2012 longitudinal component of the EU-SILC micro-data wave for 26 European countries and macro data that stem from statistics collected by Eurostat for the countries involved in the analysis.

EU-SILC dataset has numerous advantages: it comprises annual waves for nearly all EU countries; it is based on a homogeneous conceptualisation of income, for both household disposable income (i.e., the sum of all incomes from any source earned by all family members, net of personal taxes and gross of welfare cash benefits) and various sources (e.g., employment, self-employment, pensions, welfare benefits); it provides information on several individual and household features. However, EU-SILC characteristics can limit the study of poverty dynamics, since the EU-SILC is a rotating panel in which individuals are interviewed for a maximum of four years; our analysis of poverty dynamics is thus limited by this fact. Therefore, this brief observation period does not allow the use of modelling frameworks, such as hazard rate models, appropriate for studying the duration and recurrence of poverty spells.

Despite the drawbacks of this database pointed out by some authors[6], the EU-SILC has been used by several authors in the study of poverty dynamics (Van Kerm and Pi Alperin, 2013; Jenkins and Van Kerm 2011, 2014; Polin and Raitano, 2014; Chzhen, 2016).

In our study, children are defined as those under the age of 18 living in the household unit (see Chen and Corak, 2008; Chzhen and Bradshaw, 2012; Gornick and Jäntti, 2012; among others). Following Eurostat, our poverty measure is based on annual disposable household income[7]. The analysis pools the data from the 26 countries into one merged file that contains 53,841 observations. The unit of analysis is the child and the unit of measurement is the household, as an individual is classified as poor if he/she lives in a household with disposable household equivalent income below 60 per cent of the contemporary median equivalent income of the country where the household is located. To adjust household income according to its size, we use the modified OECD equivalence scale[8].

In order to measure the change in living standards since the crisis, the baseline poverty line is held constant by using the poverty line anchored in 2008. We chose this year for the anchored poverty line because Eurostat uses 2008 as the reference time for the EU-2020 strategy and because it coincides with the onset of the economic crisis period. The poverty line is adjusted for price inflation but not for changes in median incomes, so that "individuals may compare their material circumstances not only with those of the average person in the society in which they live, but also with their own in a previous period" (Matsaganis, 2013). Moreover, during economic crises, the anchored poverty rate is more sensitive to the deteriorating living conditions of the poor (Social Protection Committee, 2013).

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[6] For a review of the advantages and disadvantages of EU-SILC for comparing poverty dynamics across countries, see. e.g., Wolff *et al.* (2010), Jenkins and Van Kerm (2011), Iacovou *et al.* (2012) and Iacovou and Lynn (2013).

[7] Disposable household income is defined as the sum, for all household members, of gross personal income components plus gross income components at the household level minus regular taxes on wealth and income, social insurance contributions and regular inter-household transfers paid. Income data correspond to the year prior to the survey for all countries except the UK (income reference periods refer to the period around the interview with income total converted to annual equivalents) and Ireland (income data refer to 12 months prior to the interview). As argued by Böheim and Jenkins (2006), the differences in income reference periods are unlikely to be a major source of non-comparability across countries.

[8] A value of 1 to the first adult in the household, 0.5 to each remaining adult, and 0.3 to each member younger than 14.

3.2. Explanatory variables

We employ four different groups of determinants of child poverty. The main descriptive statistics are reported in Table 1.

Table 1. Descriptive statistics

VARIABLES	Mean	Standard Deviation
Micro determinants		
Household's characteristics		
oneadult	0.059	0.235
nchildren	1.933	0.983
prop_workers	0.812	0.291
prop_self_employed	0.125	0.281
Household's head characteristics		
young_head	0.156	0.363
women_head	0.313	0.464
secondary_head	0.622	0.485
tertiary_head	0.304	0.460
Macro determinants		
Country's living standard and labour market		
lnGDP	0.745	0.710
employ_rate	70.080	6.658
working_poor	7.628	3.001
Generosity of social benefits functions		
sickness_disability	8.297	2.206
oldage_survivor	9.625	2.662
unemployment	1.174	0.809
housing_soc_exclusion	0.757	0.560
family_children	2.069	0.832
family_children_no_means	1.706	0.948
family_children_means	0.355	0.380

Note 1: Generosity variables refer to the level of spending of each social protection function measured as a share of the GDP.
Note 2: The reference categories are: households with more than one adult, for *oneadult*, households headed by individual older than 30, for *young_head*, households headed by men, for *women_head*, households headed by individual with education lower than secondary, for *secondary_head*and *tertiary_head*).

First, we include the lagged poverty status, y_{ict-1}, which takes a value 1 if the child was poor in the previous interview and 0 otherwise, to capture true estate dependence,

Second, we consider the following explanatory variables related to the household as a whole. The binary variable one_adult, reflecting lone parenthood. We also take into account the number of children in the household (*nchildren*), the proportion of potential active worked full-time hours (including employees and self-employed) and the proportion of potential active hours worked as self-employed through variables *prop_workers* and *prop_self_employed*, respectively.

Third, apart from household variables, we include other factors linked to the household head that affect the dynamics of child poverty. We classify children as living with a *young_head* (younger than 30). Likewise, we take into account the binary variable *women_head*, which captures children living in households headed by a woman, and the variables *secondary_head* and *tertiary_head* that capture the effect of education of the head of household on child poverty movements.

Fourth, we also include a set of country-level variables with potential influence in the dynamics of child poverty according to the literature. Thus, we control for differences in the economic situation of countries by introducing the variable *lnGDP*, which is the logarithm of real GDP per capita[9] expressed in euros per inhabitant with reference year 2005.Other potential significant factors are those related to labour market. Given that parental employment is one of the main determinants of child poverty, higher employment rates within countries are also likely to contribute to low persistence in child poverty. For this purpose, we use the employment rate (*employ_rate*) which refers to the proportion of the working age population that is employed, and the share of individuals who are classified as employed and are poor (*working_poor*), since along with the employment rate, the rate of in-work poverty in a country reflects the institutional country-level setting of the labour market and welfare state-related polices. With regard to public policy, we introduce the level of generosity of each social protection function[10]. We consider family/children benefits (*family_children*) which are primarily targeted at the group we are interested in, children. We take into account other benefits that form part of the anti-poverty package, but are not paid solely to families with children, namely

[9] GDP per capita is transformed on the log scale because increases in income at lower income levels are expected to have greater effects on poverty than at higher levels of income.

[10] Each social protection function consists of transfers, in cash or in kind, by social protection schemes to households and individuals to relieve them of the burden of a defined set of risks or needs.

housing benefits and social exclusion (*housing_soc_exclusion*); unemployment benefits (*unemployment*) old age/survivors benefits (*oldage_survivor*); and sickness/healthcare and disability benefits (*sickness_disability*). We consider the five aggregated functions mentioned above, measured as a share of the GDP.

We also analyse in detail family/children benefits in order to know whether the use of means-tested transfers targeted at children are the most effective to reduce child poverty. Thus, we alternatively disaggregate family benefits into means-tested benefit (*family_children_means*) and non-means-tested benefit (*family_children_no-means*).

4. Methodology

Previous cross-national comparisons in the overall poverty dynamics literature has mainly followed two different approaches. The first one consists in running a regression in which all countries are pooled together and cross-country heterogeneity is captured by a country-specific intercept (fixed or random), assuming equal effects of characteristics on poverty across countries (e.g. Fouarge and Layte, 2005, and Callens and Croux, 2009; Bárcena-Martín and Moro-Egido, 2013). A second approach is to estimate separate equations for each country and base the cross-national analysis on the comparison of the coefficients of those models (e.g. Valletta, 2006).

Our model belongs to the former approach. We take into account the hierarchical structure of data involving three levels: observations for each year (level 1) of the children (level 2) nested into countries (level 3). Thus, the model captures the effect of explanatory variables that vary both within children and across children over time, and across countries and within countries over time. Because of the idea that children may be influenced by their social and political context, we might expect that two randomly selected children from the same country will tend to be more highly correlated than two children selected from different countries; therefore, it is important to account for such unobserved country-level effects. The same reasoning applies to two periods of the same children.

Given our interest in the effects of both individual- and country-level predictors, we run a multilevel model for a set of countries. One of the main advantages when we use mixed or multilevel models is that we gain precision as compared to using aggregate (country-level) data only. In addition, it permits controlling for individual and country-level influences simultaneously. In a multilevel framework, statistical models that employ repeated observations of nations have shown how comparative longitudinal survey data can be used to test hypotheses about the consequences of both time-varying and time invariant macro-social conditions (Fairbrother, 2014).

Moreover, in the dynamic study of poverty it should be taken into account that an individual who has experienced poverty in the past is more likely to be poor in the future than an individual who has not experienced poverty. According to Heckman (1981a), there are two explanations for this phenomenon. The first one is the presence of "true state dependence", in the sense that the lagged state enters the model in a structural way as an explanatory variable, i.e. the experience of poverty raises per se the risk of being poor the following year. The second explanation, called "spurious state dependence", is that heterogeneity makes the individuals differ in their propensity to experience poverty in all periods. This would mean that part of the observed poverty persistence is due to heterogeneity either in observable or in unobservable characteristics.

Literature on poverty dynamics has also shown the importance of taking into account the initial poverty status. In terms of transitions analysis, this issue is called the initial condition problem. This problem, developed by Heckman (1981b), can be summarised by 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 because individuals with a higher tendency to remain permanently poor may be over-represented in the sample (Cappellari and Jenkins, 2004). Therefore, in the case of state dependence, controlling for the observed and unobserved determinants of initial poverty status is important.

In order to control for crucial aspects that the literature on poverty dynamics suggests taking into account, such as longitudinal dependence due to unobserved heterogeneity and initial conditions problem, we follow the Wooldridge (2005) approach described in the literature review section and apply a dynamic random11 intercept and slope probit model. This model allows modelling persistence variation across countries[12].

The latent poverty propensity y^{*}_{ict} of children *i* at any country c and year t is specified as:

[11] Regarding the exchange ability assumption required when treating cluster effects as random, we can assume it is satisfied as we include country-specific covariates.

[12] According to Bryan and Jenkins (2015), around 30 countries would be necessary for non-linear multilevel models in order to obtain reliable results in relation to the contribution of the country effect. We are close to fulfilling this requirement (26 countries).

$$y^*_{ict} = \gamma_1 y_{ict-1} + \beta_1 x_{ictM} + \delta_1 Z_{ct} + T_m + \theta_{0c} + \theta_{1c} y_{ict-1} + \varepsilon_{ic} + u_{ict} \qquad (1)$$

The observed binary poverty status of the individual is defined as:

$$y_{ict} = \begin{Bmatrix} 1\ if\ y^*_{ict} > 0 \\ 0\ else \end{Bmatrix}$$

where y_{ict-1} denotes the individual's poverty status in the previous year (t-1), since latent poverty propensity depends on what the poverty outcome was in the previous period. x_{ictM} are the micro variables centred in the mean[13], Z_{ct} are the contextual variables, T_m are the time dummy variables[14], θ_{0c} is the random intercept, which represents the differences between countries in child poverty risk, θ_{1c} designates the random slope, which represents the difference persistence across countries, since children in different countries are expected to have different degree of persistence; $\varepsilon_{ic} \sim N(0, \sigma^2_\varepsilon)$ are individual-country specific effects independent of x_{ictM} and u_{ict} for all i, c, t; and $u_{ict} \sim N(0,1)$. All residuals are assumed to be independent and to follow normal distributions with zero mean.

In order to avoid the violation of the orthogonality condition in random effects models, correlation of these individual-specific terms with the observed characteristics is treated by assuming a relationship of the form[15]:

$$\varepsilon_{ic} = a\overline{x_{ic}} + \alpha_{ic}$$

where $\overline{x_{ic}}$ is a vector with the time means of explanatory variables for each individual, with the exception of intrinsically time-varying variables such as age and secondary and tertiary education, and $\alpha_{ic} \sim N(0, \sigma^2_\alpha)$ are the individual-specific effects which are independent of x_{ictM} and u_{ict} for all i, c, t. Equation (1) can then be rewritten as:

$$y^*_{ict} = \gamma_1 y_{ict-1} + \beta_1 x_{ictM} + a\overline{x_{ic}} + \delta_1 Z_{ct} + T_m + \theta_{0c} + \theta_{1c} y_{ict-1} + \alpha_{ic} + u_{ict} \qquad (2)$$

[13] They are centred in the mean, as we do with macro variables later.

[14] We use time dummy variables in order to capture the increasing effect of state dependence year by year.

[15] See Mundlak (1978) and Chamberlain (1984).

The fact that the beginning of the observation period may not necessarily be the same as the beginning of the outcome experience (see Skrondal and Rabe-Hesketh, 2014) causes the initial response (at t = 0) to be affected by the random intercept at child level and by the responses that would have taken place before the survey. A solution to the initial conditions problem is the conditional maximum likelihood estimator proposed by Wooldridge (2005), which suggested an auxiliary model for the conditional random-intercept distribution in which the mean depends on the initial response:

$$y_{ict}^{*} = \gamma_1 y_{ict-1} + \gamma_2 y_{ic0} + \beta_1 x_{ictM} + a\overline{x_{\iota c}} + \delta_1 Z_{ct} + T_m + \theta_{0c} + \theta_{1c} y_{ict-1} + \alpha_{ic} + u_{ict} \quad (3)$$

According to Akay (2012), the Wooldridge method tends to produce biased estimation of the estate dependence for short panels. Rabe-Hesketh and Skrondal (2013) propose to include x_{ic0} as additional covariates to reduce the substantial finite sample bias. Akay (2012) found that this solution makes the bias in the estate dependence negligible. Therefore, the model can then be rewritten as:

$$y_{ict}^{*} = \gamma_1 y_{ict-1} + \gamma_2 y_{ic0} + \beta_1 x_{ictM} + \beta_2 x_{ic0} + a\overline{x_{\iota c}} + \delta_1 Z_{ct} + T_m + \theta_{0c} + \theta_{1c} y_{ict-1} + \alpha_{ic} + u_{ict} \quad (4)$$

Moreover, according to Fairbrother (2014), separate longitudinal and cross-sectional associations between Z_{ct} and y_{ict}^{*} can be identified by calculating the mean of Z_{ct} across all relevant years for each country. The coefficient on the country mean $\bar{Z}_c$ captures the effect on y_{ict}^{*} of enduring cross-national differences in Z_{ct}. To capture the effect on y_{ict}^{*} of variation of Z_{ct} over time within each country, $\bar{Z}_c$ can then be subtracted from Z_{ct}. The resulting longitudinal component Z_{ctM} (a country-year level variable) is group-mean centered, and is orthogonal to Z_{ct}, such that the two coefficients can be estimated separately. Therefore, the model is the following:

$$y_{ict}^{*} = \gamma_1 y_{ict-1} + \gamma_2 y_{ic0} + \beta_1 x_{ictM} + \beta_2 x_{ic0} + a\overline{x_{\iota c}} + \delta_1 Z_{ctM} + \delta_2 \bar{Z}_c + T_m + \theta_{0c} + \theta_{1c} y_{ict-1} + \alpha_{ic} + u_{ict} \quad (5)$$

As is usual in the literature, we use the variance partition coefficient (VPC) to evaluate the proportion of variance accounted for by higher-level units. For this three-level nested model, we have two VPC. The first is the level-3 that sets the proportion of the total variance due to differences between countries. The second is the level-2 that sets the proportion of the total variance due to differences between individuals within countries. We focus on the level-3 interclass correlation at the country level in order to explain the differences between European countries regarding the risk of child poverty.

$$VPC_{level-3} = \frac{\sigma^2_{\theta_0} + 2 \cdot y_{ict-1} \cdot Cov(\theta_0, \theta_1) + y^2_{ict-1} \cdot \sigma^2_{\theta_1}}{\sigma^2_{\theta_0} + 2 \cdot y_{ict-1} \cdot Cov(\theta_0, \theta_1) + y^2_{ict-1} \cdot \sigma^2_{\theta_1} + \sigma^2_{\alpha} + \sigma^2_{u}}$$

where $\sigma^2_{\theta_0}$ is the variance between countries, $\sigma^2_{\vartheta_0}$is the variance between children within a country, $\sigma^2_{\theta_1}$ is the variance between countries in respect to poverty persistence and σ^2_{u} is the variance between periods of time within children within countries.

Since the interclass correlation given in this paper is conditional on zero values of random-effects covariates, the reduced form of VPC is the following:

$$VPC_{level-3} = \frac{\sigma^2_{\theta_0}}{\sigma^2_{\theta_0} + \sigma^2_{\alpha} + \sigma^2_{u}}$$

We estimate the dynamic random intercept and slope probit model in a sequential way. We first fit Model 1 with only household-level variables. In Model 2 we then add the macro variables in order to check how much of the unexplained variation is due to differences in their levels. With this estimation, we want to unravel the importance of each of the five aggregated benefits functions mentioned above on child poverty and the impact of the labour market, simultaneously controlling for the country's standard of living. Finally, in order to examine which benefits are better to combat poverty, targeted benefits or universal benefits, we estimate family transfers distinguishing means-tested and non-means-tested benefits (Model 3).

5. Results

We present the results of the estimations for the dynamic random intercept and slope probit model of child poverty in Table 2.

Table 2. Dynamic Multilevel Probit Model of child poverty. Micro determinants

	Model (1)	Model (2)	Model (3)
Constant	1.324	1.033	1.164
Household's characteristics			
oneadult	0.291*	0.298*	0.307*
nchildren	0.426***	0.419***	0.424***
prop_workers	-0.410***	-0.381***	-0.377***
prop_self_employed	0.192	0.165	0.153
Household'shead characteristics			
young_head	0.071	0.065	0.063
women_head	0.404**	0.426***	0.424***
secondary_head	-0.066	-0.086	-0.087
tertiary_head	-0.619***	-0.643***	-0.636***
Unobserved heterogeneity (child mean values)			
oneadult	0.534**	0.551**	0.550**
nchildren	-0.005	0.008	0.006
prop_workers	-1.974***	-2.037***	-2.037***
prop_self_employed	0.751***	0.779***	0.781***
women_head	-0.046	-0.047	-0.046
True state dependence: y_{ict-1}	0.723***	0.717***	0.734***
Initial conditions: y_{ic0}	1.299***	1.347***	1.344***
$x_{ic0}^{\#}$	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Observations	53,841	53,841	53,841
N. of countries	26	26	26

#Initial response for covariates included to correct for finite sample bias in short panels (Akay, 2012). Results are available upon request from the authors.

We start with the comments on child-level variables. We have observable characteristics affecting the risk of child poverty and, at the same time, we have time-averaged variables introduced in the model in order to control for potential correlation with the unobserved individual specific error term. The variables entered in the estimation with their particular value in any given year indicate the immediate effect of having a particular characteristic. Regarding these variables, we detect that the effects of household characteristics are robust across the four estimated models and they are in line with the literature. That is, a child living with only one parent is more likely to be poor than one living with two parents, a higher number of children in the household increases the child's likelihood of being poor, and children living in households with more proportion of full-time hours worked by household members are at lower risk of child poverty. Concerning head of the household's characteristics, our results are also aligned with previous results. We find that children living with a lower-educated household head or in households headed by a woman are more likely to be poor.

Regarding time-averaged variables, we observe that the sign of the coefficient associated with each time-averaged variable is the same as the sign of the coefficient associated with the corresponding year-specific variable, implying that what helps children avoid poverty does a similar job in a particular year. The effect of time-averaged variables is the same across models. Children living with only one parent during a three-year period are more likely to be poor, and the effect of this averaged variable is even higher than the effect of this variable in a given year. Children living in households with a generally good performance in the labour market (higher proportion of full-time hours worked by household members during a three-year period) are at lower risk of child poverty and the immediate effect of this variable is also negatively correlated with the risk of poverty, although its structural effect is higher than that of the same characteristic in a given year. Finally, the higher the proportion of self-employment hours worked by household members during a three-year period, the higher the risk of poverty, while the immediate effect of self-employment does not exert a significant effect on the risk of being poor.

Furthermore, the Wald test of parameter's joint significance for all time individual mean variables verifies that without them, estimators would be inconsistent because of significant correlation between the individual-specific random effects and the explanatory variables. For this reason, not controlling for child unobserved heterogeneity would bias the estimation.

We find no evidence to reject our first hypothesis, H1: previous experience in poverty determines current child poverty even when we control for observed and unobserved individual heterogeneity and treat the initial condition problem. Our results confirm the results found in the literature, which establish that the lagged poverty status (y_{ict-1}) is significant to explain current poverty, and we corroborate this finding when we control for unobserved heterogeneity and initial conditions (model 1), and even when we control for country level variables (model 2 to 3).

These findings, as mentioned before, have policy implications, given that true state dependence requires policies to bring individuals out of poverty using income-support policies such as social benefits. Moreover, as child heterogeneity is also crucial for explaining the risk of poverty, these policies should be combined with additional anti-poverty policies that focus on other schemes such as education, development of personal skills, etc.

We additionally find that being poor at the base period (t=0, initial conditions) is significantly more important than being poor at the previous interview (t-1, true state dependence) in order to explain child poverty ($\chi_1^2 = 6.25$; p-value=0.012). This result is in line with other authors (see, for example, Andriopoulou and Tsakloglou, 2011, and Gradín and Cantó, 2012).

Table 3. Dynamic Multilevel Probit Model of child poverty. Macro determinants

	Model (1)	Model (2)	Model (3)
Micro determinants	Yes	Yes	Yes
Country's living standard and labour market			
lnGDP		-1.430	-1.071
employ_rate		-0.079***	-0.074***
working_poor		0.027	0.031
Generosity of social benefits functions			
sickness_disability		0.109	0.129
oldage_survivor		0.242	0.204
unemployment		0.164	0.297
housing_soc_exclusion		-0.443	-0.384
family_children		-0.434*	
family_children_no_means			-0.088
family_children_means			-1.296***
Unobserved heterogeneity (country mean values)			
sickness_disability		0.011	0.025
oldage_survivor		-0.010	0.005
unemployment		-0.003	-0.026
housing_soc_exclusion		0.073	0.059
family_children		0.010	
family_children no_means			-0.030
family_children_means			-0.208
employ_rate		-0.029**	-0.029**
working_poor		0.019	0.020
lnGDP		-0.184	-0.215*
Year dummies	Yes	Yes	Yes
$\sigma^2_{\theta_0}$	0.119	0.020	0.017
σ^2_{α}	0.509	0.558	0.554
$\sigma^2_{\theta_1}$	0.088	0.093	0.100
VPC-level3a	0.073	0.013	0.011
VPC-level3b	0.121	0.068	0.070
LR test $\sigma^2_{\theta_1} = 0$ p-value	0.000	0.000	0.000
Wald test for unobserved heterogeneity at child level p-value	0.000	0.000	0.000
Wald test for unobserved heterogeneity at country level p-value	-	0.000	0.000
Observations	53,841	53,841	53,841
Number of countries	26	26	26

a. VPC-level3 is conditional on zero values of random-effects covariates.
b. VPC-level3 is conditional on one value of random-effects covariates.

Focusing on the different effects of contextual factors in Table 3, Model 2 introduces real GDP per capita, the labour market features and each social benefit function. With regard to the labour market, our results indicate that the employment rate plays a crucial role in explaining child poverty and that there are statistically significant cross-sectional and longitudinal associations between the employment rate and a child's probability of being poor, while the proportion of working poor exerts no significant influence on the child's risk of poverty.

Regarding social transfers, we find a statistically significant relationship between the level of family/children benefits and a child's probability of being poor, whereas other social benefit functions do not have a significant effect on child poverty. Therefore, the part of social protection expenditure specifically targeted at covering risks or needs of children, which includes support (except healthcare) in connection with the costs of pregnancy, childbirth, childbearing and caring for other family members, significantly reduces child poverty risk and is the key social benefit function in reducing child poverty. Consequently, we find evidence to state that family benefits are more relevant in reducing child poverty than more general benefit functions, that is, our third hypothesis, H3.

Model 3 investigates whether a universal or targeted approach is more effective in reducing child poverty through the classification of family/children benefits into means-tested benefits or non-means-tested benefits. Results highlight that means-tested family benefits are more effective than non means-tested ones for reducing child poverty. This finding is in line with Marx *et al.* (2013), who argue that the better targeted the social transfers are, the better the results achieved in order to avoid child poverty. Nevertheless, Marx *et al.* (2016) point out that universality and selectivity can coexist within one system, arguing that some schemes may rest heavily on the insurance principle. In this direction, our results are also consistent with targeting within universal systems in so far as they suggest combining generous family benefits and means-tested schemes to reduce child poverty persistence. From the results in model 3 our fourth hypothesis, H4: Means tested rather than non-mean tested family benefits are more effective in the fight against child poverty, is confirmed.

In the same way as for child heterogeneity, we find that the Wald test of parameter's joint significance for all time country mean variables indicates that not controlling for country unobserved heterogeneity would seriously harm the fit of the model. Therefore, it is necessary to control for unobserved child and country heterogeneity.

Based on the result of the likelihood ratio test, we conclude that the proportion of the total variance contributed by the country-level variance component in dynamic random effects models, VPC-level3, is significantly different from cero for model 1. In this respect, about 7.3 percent of the total variance in model 1 is due to the country-level variance. However, this result does not hold for models 2 to 3; that is, differences between countries in child poverty risk vanish when we introduce social transfer and other context variables. In fact, unobserved country characteristics account for between 1.30 and 1.10 percent (model 2 and 3 VPC-level3) of the total variation in the child risk of poverty; in other words, social transfer and other context variables reduce the share of variance between countries in the total variation of child risk of poverty by more than 80 percent (from 7.3 to less than 1.3).

We also test whether the country variation in poverty persistence ($\sigma^2_{\theta_1}$) is significantly different from zero. We conclude that the effect of experiencing poverty persistence varies across countries. Moreover, we note that context variables reduce the variation between European countries in respect to differences in child poverty risk by more than 80% (from 0.073 to 0.013) as well as in child poverty persistence, but to a lesser degree (43.8%, from 0.121 to 0.068).

Therefore, we can confirm our second hypothesis: context variables influence child poverty, and once we control for the sociodemographic composition of countries, they help to explain differences across countries in child poverty and in child poverty persistence.

6. Conclusion

This paper documents the crucial role of past poverty experience in child risk of poverty, even after controlling for individual heterogeneity (observed or unobserved) and initial conditions. We also reveal the importance of the level of education of the head of the household in determining child risk of poverty, and the particular socioeconomic vulnerability of lone-parent families and households with more children or with a lower proportion of workers. Therefore, beyond their adverse circumstances, our methodological approach highlights that children are also persistent in poverty because of the impact of having previously experienced poverty.

At the country level, we corroborate the effect of context variables on child poverty, explaining child poverty differences across countries from a dynamic perspective. Apart from the significance of labour market performance in the reduction of child poverty, our results clearly reveal that family benefits is the most important social benefit function in reducing child poverty persistence, contrarily to some studies on child poverty that found that a large share of child poverty reduction occurs through benefits that are not directly targeted at children (see, for example, Corak *et al*. 2005). In addition, this paper upholds that the generosity of means-tested family benefits is an effective way to reduce child poverty in European countries, as means-tested instruments are an efficient way of targeting support to the most needed (Whiteford and Adema, 2007). This way, family benefits explicitly or implicitly conditional on the beneficiary's income and/or wealth falling below a specified level are an efficient way of targeting public resources to families in need.

Hence, given these results and in line with Finnie (2000), it should be underlined that an early intervention may offer maximum benefits to the poor children and to society, because there are greater chances for an early rather than a late intervention in order to have long-lasting effects, given the state dependence results. Moreover, this early intervention must be combined with policies that focus on specific aspects of children that have been proven to increase child chances of poverty. Finally, according to our findings, it is important to emphasize the relevance of a universal family benefits system that integrates means-tested programmes in order to mitigate child poverty.

This is an important time to reflect on the commitments to children in Europe based on the European Strategy 2020. The reduction of child poverty should be a priority for European countries. We need to make sure that we do not repeat the mistakes of the past and put in place supports to meet the needs of children who have suffered from poverty for a long time.

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REFERENCES

Addison T., Hulme D. and R. Kanbur (2009): “Poverty Dynamics: Measurement and Understanding from an Interdisciplinary Perspective”, in Addison T., Hulme D. and R. Kanbur (eds), Poverty Dynamics. Interdisciplinary Perspectives, Oxford University Press, 3-28.

Akay, A. (2012): “Finite-sample comparison of alternative methods for estimating dynamic panel data models”, *Journal Applied Econometric*, 27: 1189–1204.

Andriopoulou, E. and Tsakloglou, P. (2011): “The Determinants of Poverty Transitions in Europe and the Role of Duration Dependence”, *IZA Discussion Papers*, 5692, Bonn: Institute for the Study of Labor (IZA).

Ayllón, S. (2013): “Understanding poverty persistence in Spain”, SERIES - *Journal of the Spanish Economic Association*, 42(2): 201-233.

Ayllón, S. (2015a): “Youth poverty, employment and leaving the parental home in Europe”, *Review of Income and Wealth*. 61(4): 651-676.

Ayllón, S. (2015b).: “Childhood, poverty and economic crisis”, Barcelona: “La Caixa” Foundation.

Bäckman, O. (2009): “Institutions, structures and poverty - A comparative study of 16 countries, 1980-2000”, *European Sociological Review*, 25(2): 251-264.

Bárcena-Martín, E. and Moro-Egido, A. I. (2013): “Gender and Poverty Risk in Europe” *Feminist Economics*, 19(2): 69-99.

Böheim, R. and Jenkins, S (2006): “A comparison of current and annual measures of income in the British Household Panel Survey”, *Journal of Official Statistics*, 22(4): 733-758.

Bradbury, B., Jenkins, S.P. and Micklewright, J. (2001): “The dynamics of child poverty in seven industrialised nations”, in: Bradbury, B., Jenkins, S.P and Micklewright, J. (eds.), *The Dynamics of Child Poverty in Industrialised Countries*, Cambridge: Cambridge University Press.

Bradshaw, J. and Holmes, J. (2010): “Child poverty in the first five years of life”, in J. Hansen, H. Joshi, & S. Dex (Eds.), Children of the 21st century: the first five years. The UK Millennium Cohort Series, 2: 13–31. Bristol: The Policy Press.

Brady, D. (2006): “Structural theory and relative poverty in rich Western democracies, 1969–2000”, *Research in Social Stratification and Mobility*, 24(2): 153-175.

Browne, J. and Paull, G. (2010): “Parents’ work entry, progression and retention, and child poverty”, Department for Work & Pensions, Research Report, 626, London.

Bryan, M.L. and Jenkins, S.P. (2013): “Regression analysis of country effects using multilevel data: a cautionary tale”, *IZA Discussion Paper*, 7583, Bonn: Institute for the Study of Labor (IZA).

Callens, M. and Croux, C. (2009): “Poverty dynamics in Europe: a multilevel recurrent discrete time hazard analysis”, *International Sociology*, 24(3): 368-96.

Cantó, O. and Mercader-Prats, M. (2002): “Child poverty in Spain from the 70's to the 90's: a static and dynamic approach”, *Journal of Applied Social Sciences Studies*, 121(4): 543-578.

Cantó, O., Del Río, C. and Gradín, C. (2007): “What helps households with children in leaving poverty? Evidence from Spain”, *Research on Economic Inequality*, 14: 1-29.

Cappellari, L. and Jenkins, S. (2002): “Who stays poor? Who becomes poor? Evidence from the British Household Panel Survey”, *The Economic Journal*, 112: 60-67.

Cappellari, L. and Jenkins, S. (2004): “Modelling low income transitions”, *Journal of Applied Econometrics*, 19: 593-610.

Chamberlain, G. (1984): Panel data, in Handbook of Econometrics, Griliches Z, Intrilligator M (eds). North-Holland: Amsterdam.

Chen, W.H. and Corak, M. (2008): "Child poverty and changes in child poverty", *Demography*, 45(3): 537-553.

Chzhen, Y. (2014): "Child poverty and material deprivation in the European Union during the Great Recession", *Innocenti Working Paper*, 2014-06, Florence: UNICEF Office of Research.

Chzhen, Y. (2016): "Perceptions of the economic crisis in Europe: do adults in households with children feel a greater impact?", *Social Indicators Research*, 127:341-360.

Chzhen, Y. and Bradshaw, J. (2012): "Lone parents, poverty, and policy in the European Union", *Journal of European Social Policy*, 22(5): 487-506.

Chzhen, Y., Toczydlowska, E. and Handa, S. (2015): "Child poverty dynamics and income mobility in Europe", *Innocenti Working Paper*, 2016-16, Florence: UNICEF Office of Research.

Corak, M. (2006): "Do Poor Children Become Poor Adults? Lessons from a Cross-Country comparison of generational earnings mobility", *Research on Economic Inequality*, 13: 143-188.

Corak, M., Lietz, C. and Sutherland, H. (2005): "The Impact of Tax and Transfer Systems on Children in the European Union", IZA Discussion Paper 1589. Bonn: Institute for the Study of Labor.

Damioli, G. (2010): "How and why the dynamics of poverty differ across European countries", paper presented at the 31st IARIW General Conference, St. Gallen, Switzerland, 22–28 August.

Duncan, G.J., Gustafsson, B., Hauser, R., Schmauss, G., Messinger, H., Muffels, R., Nolan, B. and Ray, J.C. (1993): "Poverty Dynamics in Eight Countries", *Journal of Population Economics*, 6(3) 215-234.

Esping-Andersen, G. (1990): *The Three Worlds of Welfare Capitalism*, Cambridge: Polity Press.

Esping-Andersen, G. and Myles, J. (2009): “The welfare state and redistribution”, in W. Salverda, B. Nolan and T. Smeeding (eds.), *The Oxford Handbook of Economic Inequality,* Oxford: Oxford University Press.

European Commission (2012): “Social Developments Employment in Europe 2012”, Brussels: European Commission.

Eurostat, European Commission Eurostat database: Available from <http://ec.europa.eu/eurostat/data/database> (accessed April 2016).

Fairbrother, M. (2014): "Two multilevel techniques for analyzing comparative longitudinal survey datasets". *Political Science Research and Methods,* 2(1), 119-140.

Fouarge, D. and Layte, R. (2005): “Welfare regimes and poverty dynamics: the duration and recurrence of poverty spells in Europe”, *Journal of Social Policy*, 34(3), 407-26.

Gallie, D. and Paugam, S. E. (2000): “Welfare Regimes and the Experience of Unemployment in Europe”, Oxford: Oxford University Press.

Galloway, T.A., Gustafsson, B., Pedersen, P.J. and Österberg, T. (2009): “Immigrant child poverty in Scandinavia: A panel data study”, *IZA Discussion Paper*, 4232, Bonn: Institute for the Study of Labor (IZA).

Gornick, J.C. and Jäntti, M. (2012): “Child poverty in cross-national perspective: Lessons from the Luxembourg Income Study”, *Children and Youth Services Review*, 34(3): 558-568.

Gradín, C. and Cantó, O. (2012): “Why are child poverty rates so persistently high in Spain?”, The Manchester School, 80(1): 117-143.

Griggs, J. and Walker, R. (2008): “*The costs of child poverty for individuals and society: A literature review*”, York: Joseph Rowntree Foundation (JRF).

Gugushvili, D. and Hirsch, D. (2014): “Means-tested and universal approaches to poverty: international evidence and how the UK compares”, Centre for Research in Social Policy. Working paper 640.

Heckman, J. (1991): "Identifying the hand of the past: distinguishing state dependence from heterogeneity", American Economic Review, 81(2): 75-79.

Heckman, J.J. (1981a): Heterogeneity and state dependence. In: Rosen S (ed) *Studies in labor markets*. Chicago Press, Chicago, Illinois.

Heckman, J.J. (1981b): The incidental parameters problem and the problem of initial conditions in estimating a discrete time - discrete data stochastic process. In: Manski C, McFadden D (eds) *Structural analysis of discrete data with econometric applications*. MIT Press, Cambridge, Massachusetts.

Iacovou, M. and Lynn, P. (2013): "Implications of the EU-SILC following rules, and their implementation, for longitudinal analysis", ISER Working paper, 17, Institute of Social and Economic Research.

Iacovou, M., Kaminska, O. and Levy, H. (2012): "Using EU-SILC data for cross-national analysis: strengths, problems and recommendations", *ISER Working paper,* 3, Essex: Institute of Social and Economic Research (ISER).

Immervoll, H., Sutherland, H. and Den Vos, K. (2001): "Reducing child poverty in the European Union: the role of child benefits", *In Child well-being, child poverty, and child policy in modern nations*, ed. K. Vleminckx and T. Smeeding, 407-32. Bristol, England: The Policy Press.

Jenkins S. (2000): "Modelling Household Income Dynamics", *Journal of Population Economics*, 13(4): 529–567.

Jenkins, S. (2011): Changing fortunes: income mobility and poverty dynamics in Britain, Oxford: Oxford University Press.

Jenkins, S. and Rigg, A. (2001): "The dynamics of poverty in Britain", *Department for Work & Pensions,* Research Report, 157, London.

Jenkins, S. and Schluter, C. (2003): "Why are child poverty rates higher in Britain than in Germany? A longitudinal perspective", *Journal of Human Resources,* 38(2): 441-465.

Jenkins, S. and Van Kerm, P. (2011): "Patterns of persistent poverty: evidence from EU-SILC", *ISER Working paper*, 30, Essex: Institute of Social and Economic Research (ISER).

Jenkins, S. and Van Kerm, P. (2014): "The relationship between EU indicators of persistent and current poverty", *Social Indicators Research*,116: 611-638.

Jenkins, S., Brandolini, A., Micklewright, J. and Nolan, B. (2013): *The Great Recession and the distribution of household income*, Oxford: Oxford University Press.

Kangas, O. and Palme, J. (2000): "Does social policy matter? Poverty cycles in OECD countries", *International Journal of Health Services* 30(2): 335-52.

Kyzyma, I. and Williams, D. R. (2016): "Public cash transfers and poverty dynamics in Europe", *Empirical Economics*, 1-40.

Layte, R. and Whelan, C. T. (2003): "Moving in and out of poverty: the impact of welfare regimes on poverty dynamics in the EU", *European Societies*, 5(2): 167-91.

Lindquist, M.J. and Sjögren Lindquist, G. (2012): "The Dynamics of Child Poverty in Sweden", *Population Economics*, 25(4): 1423-1450.

Marx, I., Salanauskaite, L. and Verbist, G. (2013): "The Paradox of Redistribution Revisited: And That It May Rest in Peace?", *IZA Discussion Paper,* 7414, Bonn: Institute for the Study of Labor (IZA).

Marx, I., Salanauskaite, L. and Verbist, G. (2016): "For the Poor, but Not Only the Poor: On Optimal Pro-Poorness in Redistributive Policies", *Social Forces*, 95(1): 1-24.

Matsaganis, M. (2013): *The Greek Crisis: Social impact and policy responses*, Berlin: Friedrich Ebert Stiftung.

Matsaganis, M., O Donoghue, C., Levy, H., Coromaldi, M., Mercader-Prats, M., Rodrigues, C.F., and Tsakloglou, P. (2006) 'Reforming family transfers in southern Europe: is there a role for universal child benefits?', *Social Policy and Society*, 5(2): 189.

McKernan, S.M. and Ratcliffe, C. (2005): "Events that Trigger Poverty Entries and Exits", *Social Science Quartely*, 86 Supp., 1146-1169.

McKnight, A. (2015): "A fresh look at an old question: is pro-poor targeting of cash transfers more effective than universal systems at reducing inequality and poverty?", Working paper 640. Luxembourg: Luxembourg Income Study.

Mendola, D., Buseta, A. and Aassve, A. (2009): "What keeps young adults in permanent poverty? A comparative analysis using ECHP", *Social Science Research*, 38(4): 840-57.

Moene, K. O. and Wallerstein; M. (2003): "Earnings inequality and welfare spending. A disaggregate analysis", *World Politics*, 55: 485-516.

Moene, K., and M. Wallerstein. 2001. "Inequality, Social Insurance and Redistribution" *American Political Science Review*, 95(4): 859–74.

Mundlak, Y. (1978): "On the pooling of time series and cross section data", *Econometrica* 46: 69–85.

OECD (2014): "Society at a Glance 2014: The crisis and its aftermath", Paris: OECD.

Oxley, H., Dang, T., Förster, M. and Pellizzari, M. (2001): "Income inequalities and poverty among children and households with children in selected OECD Countries" in *Child wellbeing, child poverty, and child policy in modern nations*, ed. K. Vleminckx and T. Smeeding, 371-406, Bristol: The Policy Press.

Polin, V. and Raitano, M. (2014): "Poverty transitions and Trigger Events across EU Groups of Countries: Evidences from EUSILC", *Journal of Social Policy*, 43(4): 745-772.

Rabe-Hesketh, S. and Skrondal, A. (2013): "Avoiding biased versions of Wooldridge's simple solution to the initial conditions problem", *Economics Letters*, 120: 346–349.

Riegg, S., McKernan, S. and Ratcliffe, C. (2008): "The dynamics of poverty in the United States: a review of data, methods, and findings", *Journal of Policy Analysis and Management*, 27(3): 577-605.

Skrondal, A. and Rabe-Hesketh, S. (2014): Handling initial conditions and endogenous covariates in dynamic/transition models for binary data with unobserved heterogeneity", Applied Statistics, 63(2): 211-237.

Social Protection Committee (2013): Social Policy Reforms for Growth and Cohesion: Review of recent Structural Reforms, Luxembourg: European Commission.

Solera, C. (2001): "Income transfers and support for mothers' employment: The link to family poverty risks", *In Child well-being, child poverty, and child policy in modern nations,* ed. K. Vleminckx and T. Smeeding, 459-84. Bristol: The Policy Press.

Tárki (2010): "Child Poverty and Child Well-being in the European Union". Budapest: Tárki Social Research Institute.

UNICEF (2014): "Children of the Recession: The impact of the economic crisis of child well-being in rich countries", *Innocenti Report Card,* 12, Florence: UNICEF Office of Research.

Valletta, R. (2006): "The ins and outs of poverty in advanced economies: poverty dynamics in Canada, Germany, Great Britain, and the United States", *Review of Income and Wealth*, 52(2): 261-84.

Van Kerm, P. and Pi Alperin, M. (2013): "Inequality, growth and mobility: the intertemporal distribution of income in European countries 2003–2007", *Economic Modelling*, 35: 931-939.

Whiteford, P. and Adema, W. (2007): "What works best in reducing child poverty: A benefit or work strategy?", OECD Social, Employment and Migration Working Papers 51. Paris: OECD Publishing.

Wolff, P., Montaigne, F. and Rojas González, G. (2010): "Investing in statistics: EU-SILC" in A.B. Atkinson and E. Marlier (eds.), *Income and Living Conditions in Europe*, Luxembourg: Eurostat Statistical Books.

Wooldridge, J. M. (2005) "Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity", Journal of Applied Econometrics, 20: 39–54.