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Measuring Poverty Persistence

Alessio **FUSCO**[1]
Philippe **VAN KERM**[1,2]

www.liser.lu

[1] Luxembourg Institute of Socio-Economic Research (LISER), Luxembourg
[2] University of Luxembourg, Luxembourg

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Alessio Fusco
Luxembourg Institute of Socio-Economic Research (LISER)

Philippe Van Kerm
Luxembourg Institute of Socio-Economic Research (LISER) and University of Luxembourg

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Abstract

This chapter reviews the literature on the measurement of poverty persistence. The review has two parts. We first cover the literature on poverty persistence indicators which develops “principled”, descriptive summary measures. We then review the econometric literature which teases out the determinants of poverty persistence. Finally, we describe the challenges and limitations the literature on poverty persistence face.

Keywords: poverty persistence, chronic poverty, hazard models, Markovian models, state dependence, attrition

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1. Introduction

Poverty is not a static phenomenon, it is a dynamic one (Jenkins, 2011). It is well documented that a large share of the poor only make a transitory poverty experience following potential adverse events such as a job loss or divorce. Others however – the chronic or persistent poor – remain in poverty for long periods of time. And some individuals frequently fall into and climb out of poverty. Snapshots provided by cross-section measures of poverty describe the stock of poor people at a point in time, but are silent about intertemporal patterns.

Poverty persistence is less commonly studied than cross-sectional poverty, and it is much less prominent in official statistics. The more demanding data required – databases containing reliable repeated measurement of poverty status – are indeed less widespread and more difficult to collect.[1] The American Panel Study of Income Dynamics (PSID), the German Socio-Economic Panel (GSOEP) or the UK Understanding Society are examples of the only few surveys on households and individuals consistently capturing poverty status over long periods of time. The European Community Household Panel (ECHP), a harmonized multi-country panel survey has been collected between 1994 and 2001 and has allowed for the first international comparisons across all EU-15 countries based on comparable data. The ECHP has been replaced by the European Union Statistics on Income and Living Conditions (EU-SILC) in 2003. EU-SILC covers all European Union countries but has only a 4-year rotating panel design, aimed for calculation of the commonly agreed EU indicator of persistent poverty (see below). Administrative data extracted from fiscal or social security records have become a rich alternative to such traditional panel surveys for analysis of poverty persistence. Administrative record matching can allow analysts to reconstruct, ex post, long-run income trajectories for large populations – possibly the entire population of a country (e.g., Larrimore et al., 2020). This avoids attrition problems endemic to surveys while offering data on a long window

[1] We focus on income poverty. However, relying on other measures of well-being does not change the essence of poverty persistence measurement (see e.g., Pudney, 2008 or Fusco, 2016 for subjective variables).

of time. Such data sources remain however relatively rarely available and are not free of issues, discussed below.

Measuring poverty persistence is also more complex conceptually. What do we mean by "poverty persistence" and how should we measure it? Having defined the concepts, how can we tease out their determinants? This Chapter reviews the approaches used in recent research. We cover two streams of the literature. The first one aims at measuring the extent of persistent poverty by quantifying and aggregating the poverty experience of individuals over time. This descriptive approach is based on the construction of indicators of poverty persistence which follows a "principled", often axiomatic approach (Section 2). The second stream aims at analyzing the determinants of persistence into poverty by specifying econometric models, notably to capture how much the experience of poverty begets future poverty ('state dependence') and distinguish this from the contribution of individual heterogeneity (Section 3). Both approaches face challenges and limitations which we review next (Section 4).

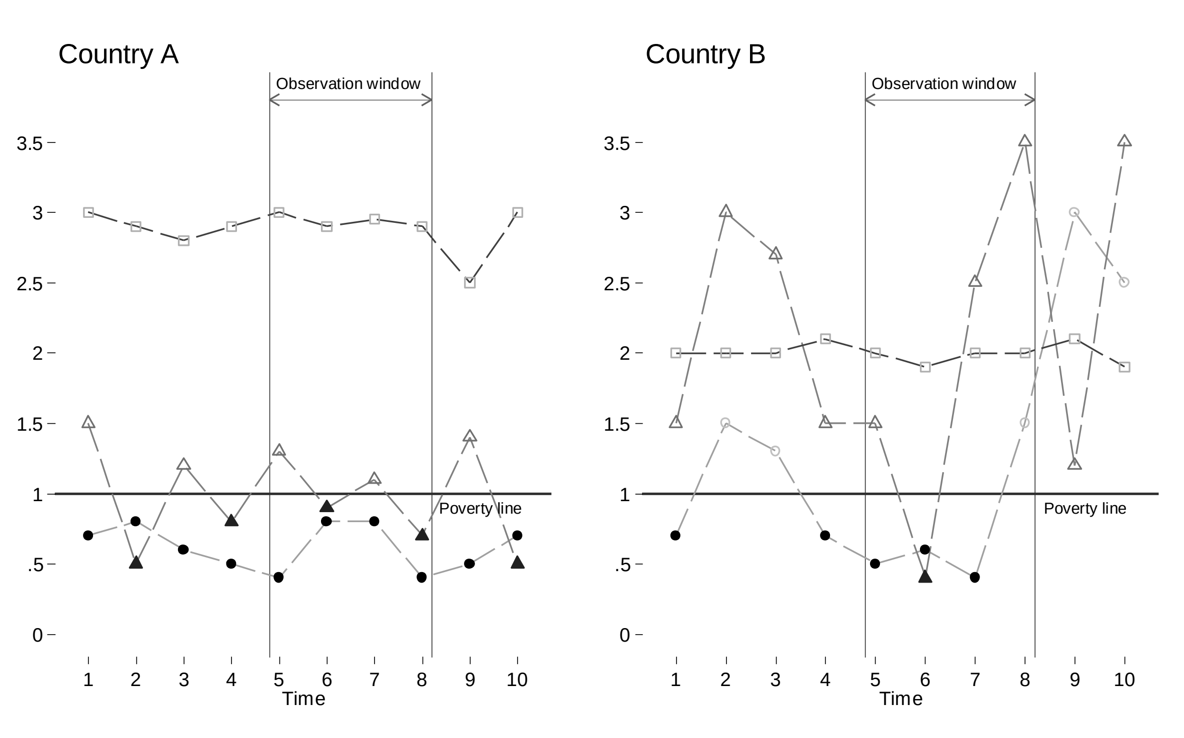
There are a number of topics which we do not cover. The focus on measurement leads us to omit any substantive discussion on the extent and composition of the persistent poor (see Biewen, 2014) or on the determinants of poverty entry and exit (see Gradín et al., 2018). In addition, in the interest of space, we do not cover newly developed methods for analysis of poverty dynamics based on repeated cross-section data which aim to address the absence of long-running panels in many countries, notably in the developing world (see Dang et al., 2014; Hérault & Jenkins, 2019).

2. Indicators of Poverty Persistence

A relatively large stream of the literature has developed summary indices of poverty persistence, which aggregate individuals' poverty experiences over time into indicators of "poverty persistence" in a target population. This approach is "principled" in order to capture the specific meaning of 'persistence' but it is descriptive in essence as its main aim is to portray the level of poverty persistence in a society and to make comparisons over time or across countries.

Figure 1 illustrates the components of the problem. It depicts individual income trajectories in two hypothetical countries: some people have stable income profiles, some have variable profiles but rarely fall below the poverty line, others are persistently in poverty, etc. Given an observation window of, say, four periods (t=5 to $T = t$+3), how can we qualify poverty persistence when aggregating such heterogenous individual profiles and how can we assess which of the two countries exhibit greater poverty persistence?

Figure 1: Intertemporal income patterns in two hypothetical countries



Note: Individual income profiles are expressed as a ratio of the poverty line. The plain horizontal line is the poverty line so that individuals whose income is below that line are considered poor.

The simplest (and perhaps most common) counting approach consists in characterizing individual trajectories by counting the number of times individuals are in poverty within the observation window and, then, fixing a threshold in this dimension to qualify whether a person is persistently poor, to take the share of the population persistently poor as indicator of poverty persistence. Such a basic counting approach ignores the ‘history’ or ‘sequence’ of poverty: for example, an individual exiting and entering poverty every other year will be treated as an individual poor in the first half of the time window and non-poor in the second half.

The official EU indicator of "at risk of persistent poverty" follows a similar logic: an individual is considered persistently poor if she is poor at the end of the observation window and has been poor in at least two of the preceding three years. The indicator is built-in the 4-year rotating design of EU-SILC. Jenkins and Van Kerm (2014) showed that the relationship between this indicator and cross-sectional poverty is near-linear, which questions the usefulness of indicators of poverty persistence based on short panels. Note the subtle distinction in perspective from the basic counting approach: the EU indicator aims to capture how much poverty at time T is persistent, whereas the previous approach measures poverty persistence over a window from t to T.

While such simple counting approaches allow to examine how patterns have changed over time, possibly by population subgroups (Jenkins and Van Kerm, 2011), the literature has developed more sophisticated axiomatic approaches to account for additional features of poverty histories, notably duration, intensity, recurrence, lifecycle and intertemporal transfers. Some axioms are natural extensions to the intertemporal case of the standard cross-sectional poverty axioms of continuity, focus, monotonicity and transfer. However, the temporal dimension has the implication that each axiom can be formulated in several ways – see Hoy and Zheng (2018). Other axioms are specific to the intertemporal case. For example, the chronic poverty axiom specifically focuses on the poverty spells patterns and specifies that living in poverty for a prolonged period of time is worse than having separate experiences of poverty. This axiom is however debated and not endorsed by all authors.[2]

Several alternative axiomatic indicators have been proposed. Foster (2009)'s measure of chronic poverty requires the definition of a poverty line in each period and of a poverty duration threshold. An individual is considered in chronic poverty if she lives long enough in this situation. For each individual, the measure of poverty is then the average over time of the normalized gaps in each period, while the aggregate value is the

[2] Other axioms have been proposed in the literature such as the decomposition axioms which requires that the inter-temporal poverty be a weighted average of poverty over different time periods.

average poverty measured among the persistent poor. This index does not satisfy the chronic poverty axiom presented earlier as it is indifferent to the sequence of poverty periods.

Bossert et al. (2012) take a different approach and consider that a measure of poverty persistence should be sensitive to this sequence. Their measure takes into account the length of poverty spells (the longer the spells, the higher intertemporal poverty) but also the lengths of the breaks between spells (the longer the breaks between spells, the lower intertemporal poverty). In their case, the individual measure is a weighted average of the Foster Greer Thorbecke indices for each period, where each spell of poverty is weighted by its length – and therefore, no duration cut-off is needed. The weights play an important role as they make the measure sensitive to temporal pattern. Dutta et al. (2013) note that non poverty spells do not play a role (because their weight is null) and extend the framework. Their extension is sensitive to whether non poverty periods are grouped or separate and whether poverty is followed or preceded by affluence.

Hoy and Zheng (2011) give a high weight to the chronic poverty axiom so that poverty duration is key. They also take a life course perspective in introducing an early poverty axiom which states that poverty occurring early in life is more detrimental due to its longer term impact. Their index gives a higher weight to longer poverty spells and to poverty spells occurring at the beginning of life. There is therefore a trade-off between persistence of poverty and its timing (Hoy et al., 2012).

Other indicators have been proposed.[3] Gradín et al. (2012) aim at reconciling static and dynamic poverty measurement. Their index consider poverty duration and social preference for well-being equality as it accounts for the extent of inequality between poverty profiles. Mendola et al. (2011) and Mendola & Busetta (2012) put emphasis on the sequence of spells of poverty. Their indicator is sensitive to the patterns of poverty and non-poverty spells along the life course. The lower the distance between two consecutive spells, the higher their contribution to poverty persistence.

[3] Yet another strand of the literature –not detailed here in the interest of space-- builds upon decompositions of income trajectories into a permanent and a transitory component and develops measures of chronic versus transitory poverty accordingly (see Jalan and Ravallion, 1998).

3. Econometric Modelling

The literature just reviewed aims to depict the extent of persistent poverty in a society as a whole and to make comparisons of poverty persistence across societies. The modelling approach, in turns, aims to explore the micro-level determinants of poverty dynamics, and aims to help understanding the mechanisms leading to persistence in poverty. What individual factors shape poverty histories? What helps poverty exits and what drives poverty entries? This literature is, in particular, interested in determining how much the experience of poverty today increases the risk of experiencing poverty in the future, that is, how much "state dependence" there is in poverty (Heckman, 2001).[4] According to Biewen (2009), the reasons leading to state dependence can include bad networking, health problems, household dissolution, human capital depreciation or demoralisation that can result from experiencing poverty. The higher the extent of state dependence, the stronger one can expect poverty to be persistent (and the more difficult policy responses are).

The empirical difficulty is to disentangle state dependence from unobserved individual heterogeneity. Observing that individuals who experience poverty today are more likely to be found in poverty tomorrow is no proof of the existence of state dependence. Such a pattern can be observed if some individual characteristics make people systematically more likely to experience poverty (such as ill health or low skills), even when the experience of poverty itself does not affect the odds of future poverty. In such a case, the persistence of poverty is driven by persistent factors that affect poverty risks in all time periods and the apparent state dependence said to be "spurious".

Since Bane and Ellwood (1986), several models have been used to study the determinants of poverty dynamics and distinguish state or duration dependence from heterogeneity based on various multivariate regression models – see for example Jenkins (2000, 2011) for reviews. Two broad types of models can be distinguished: hazard

[4] Balboni et al. (2021) analyse the reasons why people stay poor – difference in abilities vs. difference in opportunities arising from access to wealth.

regression models and transition models. The classification is not sharp and both types of models bear much similarity.

Hazard regression models focus on modelling poverty spell durations. The objective is to predict the (expected) duration of a spell of poverty starting at time t as a function of the characteristics of a person. Given the discrete-time nature of poverty data – where poverty status is typically measured annually – such models are usually specified as discrete-time hazard regressions, that is as models specifying the probability that a poor person exits poverty as a function of the number of years she has already spent in poverty in her current spell and of individual characteristics. Early hazard models were based on separate single spell models of exits and of re-entry (e.g., Jenkins & Rigg, 2001). More complex duration models have later been developed to allow for modelling repeated spells, jointly modelling exits and re-entries, and integrating unobserved individual heterogeneity components to distinguish genuine from spurious state dependences in the so-called mixture hazard models (see, e.g., Stevens, 1999; Biewen, 2006; Devicienti, 2011). Identification and estimation of these more complex hazard regression models however requires access to long running panels and can be practically difficult.

The more recent literature relies on simpler Markovian-type transition models. Instead of attempting to specify a model for the whole duration of poverty spells, transition models focus on transition probabilities between t-1 and t where the process is only allowed to have "short memory". They make simpler assumptions about the nature of the dynamic process. Typically, poverty is assumed to follow a first order Markov process. This (strong) assumption implies that transition probabilities depend only on the previous poverty status and not on the entire duration of poverty before that. This simplification however comes with significant advantages in that identification of the model does not require access to long-running panel data, allows disentangling unobserved heterogeneity from genuine state dependence, and is easy to estimate.

Two types of Markovian models are currently in widespread use: non-linear dynamic panel data models and endogenous switching models. Endogenous switching models are based on the idea that past poverty has a "slope effect", which means that individual characteristics have a differentiated impact on current poverty conditional on the previous year poverty status (Thomas & Gaspart, 2014). Non-linear dynamic panel data specifications assume that past poverty has an "intercept-only effect" on current poverty. Such models are based on random effect dynamic probit models where poverty in a given year is modelled as a function of lagged poverty and a set of individual or household characteristics. Initial conditions are usually treated by following Wooldridge (2005) and conditioning on the initial poverty and strictly exogenous covariates. Other key aspects are the possibility to measure average partial effects (APE) and to model household permanent characteristics by contrast with time varying characteristics in the so-called correlated random effect models. In these models, state dependence is measured as the APE of the lagged poverty status. Recent applications include Fabrizi and Mussida (2021) who assess the extent of genuine state dependence by estimating a correlated random effects probit model with endogenous initial conditions (see also Fusco & Islam, 2020). The approach has been extended in several ways. Biewen (2009) shows how to incorporate feedback effects in this type of analysis (see also Ayllón, 2015 or Ayllón & Fusco, 2017). Prieto (2021) uses a random effect dynamic ordered probit to model jointly poverty persistence and affluence persistence.

The main limitation of the non-linear dynamic panel data specification is that the coefficient of the covariates are the same for both poor and non poor individuals. The differential impact of explanatory variable according to lagged poverty is however usually relevant. For example, it is well know that exclusion of the poor from the credit market is an important element of their situation. Endogenous switching models address this concern. Cappellari and Jenkins (2004) specify an endogenous switching model simultaneously modelling poverty transitions for all the pooled transitions, the poverty status in the previous year to account for the initial conditions problem but also sample retention to handle potential non random attrition in a Heckman style procedure. This is done by assuming joint multivariate normality across equations for exit, entry, initial conditions and retention in a multivariate probit set up. The correlations between each equation are allowed to be freely estimated. See also Ayllón (2013) for application to Spain and Fusco & Islam (2012) to Luxembourg. The model allows to analyse the determinants of poverty entry and persistence at the same time. State dependence can be tested by looking at the difference in the coefficient of the explanatory variables between poverty entry and persistence. The development of such models based on multivariate probit specifications benefited from recent advances in simulated likelihood estimation.

4. Challenges and Limitations

We conclude this short review by describing three challenges the literature on poverty persistence face – the lack of long panels, attrition and measurement error.

As mentioned in the introduction, poverty persistence is somewhat less commonly studied than cross-sectional poverty because of the lack of long panels. The main drawback of most axiomatic indicators of poverty is that they often assume that entire (lifetime) income trajectories are observed, or at least, that entire spells of poverty are observed from their beginning to their end. Unfortunately, typical survey data provide income data over a fixed time window, as Figure 1 illustrates. This means that many spells are only partially observed and can be left and right censored. Ignoring the fact that spells of poverty started before and ended after the observation window prevent from inferring correctly the poverty spell distributions and jeopardizes the usefulness of several axiomatic indices. This issue is of course especially problematic in short panels, such as the EU-SILC which is based on a 4 year rotating design. In some countries like the US, Germany or the UK, long term panel surveys exist but the longer the window, the more the panels are exposed to a second problem, namely attrition.

Attrition is the loss to follow-up in longitudinal surveys over time. Selective (non-random) attrition is particularly problematic if the loss to follow-up is correlated with the phenomenon of interest – here poverty entry or exit (Alderman et al., 2001). Biases due to selective attrition have not received much attention in descriptive indicators of poverty persistence (Jenkins & Van Kerm, 2017), but econometric approaches have been developed to model attrition jointly with the process of interest using endogenous sample selection specifications. The challenge is however to find suitable instruments that are correlated with attrition but uncorrelated with the outcome variable. Variables related to the design of survey (such as the change of interviewer) have been found to perform well. A simpler inverse probability weighting strategy requires variables characterizing attrition probabilities but can only control for attrition based on observable characteristics. It is therefore desirable to minimize attrition at the data collection phase. Attrition is closely related to methods of tracking and follow-up in household surveys, notably in case of household dissolution or residential mobility – events which are likely correlated with poverty dynamics.

Measurement error is another challenge as it can create artificial movements into and out of poverty. While it has been widely documented in survey data analysis, the issue of measurement error biases in transition matrices has often been ignored in poverty dynamics (Breen and Moisio, 2004). Practice has often been to apply ad hoc adjustments, such as considering only large jumps across the poverty line (say at least 10%) to be a transition. Lee et al. (2017) however develop a method to deal with measurement error in the calculation of transition matrices and show that time-varying measurement error induces spurious mobility in transition into and out of poverty, so that the risk of remaining poor and the number of years spent poor are downward biased. Millimet et al. (2019) propose a non-parametric partial identification approach to bound transition probabilities under various assumptions on the measurement error process.

Exploiting administrative data sources to reconstruct income trajectories by matching histories of administrative record should mitigate many of the concerns about lack of long panels, selective attrition and measurement error (and small samples). The prospect of having access to more and internationally comparable administrative data sources will likely stimulate new research on poverty persistence in the future. Administrative sources raise other issues however. Most notably, it is often difficult to combine information about individuals living together in a household and to collect comprehensive information on multiple income sources in order to construct comprehensive measures of monetary welfare. As Jenkins and Rios-Avila (2021) show, administrative record are also not free from measurement error. Future research will therefore likely see more complementary use of administrative and survey sources.

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LUXEMBOURG INSTITUTE OF
SOCIO-ECONOMIC RESEARCH

11, Porte des Sciences
Campus Belval
L-4366 Esch-sur-Alzette

T +352 58 58 55-1
F +352 58 58 55-700

www.liser.lu