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Moving in and out of poverty in Mexico: What can we learn from pseudo-panel methods?

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Non-Technical Summary

The study of poverty dynamics typically requires knowledge about the living conditions of the same individuals at different points in time, also known as longitudinal or panel data. However, because of technical and economic reasons, these surveys are uncommon, especially in developing countries. In contrast, most countries nowadays produce good-quality cross-sectional surveys, collected within well-established projects and over long periods of time. Thus, several authors have proposed econometric (or pseudo-panel) approaches to exploit repeated cross-sections and gain some knowledge about poverty dynamics.

In this paper, we estimate the magnitude of the movements in and out of poverty in Mexico, using available cross-sectional data from 1992 and 2012. We contrast the results of two alternative methods, each of which has previously been validated, but which have rarely been directly compared. This analysis provides useful insights into the differences and similarities of these approaches, such as the conditions to prefer one over the other. Finally, available longitudinal information let us compare our estimates of poverty dynamics to those from a true panel, at the cost of adopting several assumptions to overcome data comparability issues.

Our results suggest that about a third of the Mexican population moves in and out of poverty over short periods of time, highlighting the importance of policies targeted to avoid relapses in this population. A large percentage of the population was identified as persistently poor (i.e., poor in one period and expected to remain poor in the next), but this rate have gradually fallen in the last decade. Substantial contrasts are found between subgroups of the population, showing another facet of inequality in Mexico. The evidence in this paper indicates that both pseudo-panel methods yield similar estimates of trends in mobility, with the discrepancies being mainly associated with the income correlation parameter. The pseudo-panel mobility rates are similar to those calculated with true panel data, although comparability between sources of information requires several assumptions.

Moving in and out of poverty in Mexico: What can we learn from pseudo-panel methods? *

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Abstract

We estimate the magnitude of movements in and out of poverty in Mexico using repeated cross-sections between 1992 and 2012. Using the bootstrap, we explicitly compare results obtained with two pseudo-panel methods. Both pseudo-panel methods produce similar trends of mobility, the differences being mainly associated with the income correlation parameter. Calculations with true panel data show similar levels of mobility, despite data comparability issues. Our results suggest that an important fraction of the Mexican population moves in and out of poverty over short periods of time; and that the rate of poverty persistence seems to have declined considerably in the last decade. Substantial heterogeneity is found for specific groups of the population.

Keywords: Poverty dynamics, Mexico, Pseudo-panel methods

JEL classification: I32

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1. Introduction

The longest series of comparable poverty data in Mexico shows that the percentage of the population living in poverty went from 53.1 in 1992 to 52.3 in 2012 (CONEVAL, 2013).[1] Although the change over this period is modest, the poverty rate reached a maximum of 69.0 percent in 1996 (just after the economic crisis of 1995-1996) and a minimum of 42.9 percent in 2006 (before the financial crisis of 2007-2008). These fluctuations suggest that, despite the high rates of poverty in Mexico, there is an important fraction of the population escaping or falling in poverty throughout the period.

Although high levels of wealth and income inequality provide a partial explanation for the persistence of poverty in Mexico (Campos-Vázquez et al., 2014, Galindo et al., 2009, Londoño & Székely, 2000, Székely, 2005b), there are still large gaps in our understanding of the factors associated with the transitions in and out of poverty in the country. However, these elements can potentially provide key insights to improve the design of social policy, since interventions aimed to alleviate persistent or chronic poverty may be inadequate to prevent or surmount transient events of poverty.

The analysis of poverty dynamics, however, has been usually restricted due to limitations in the sources of information. Although ideally we would use longitudinal or panel data to analyse how the living conditions of the same individuals change over time, many developing countries do not have this kind of information and, when panel surveys do exist, they are usually available for few waves or over short periods of time. [2] In contrast, most countries nowadays periodically produce cross-sectional data, usually within well-established projects that have been collected for long periods of time.

This paper introduces estimates of poverty mobility in Mexico, taking advantage of recent developments by Bourguignon et al. (2004) and Dang et al. (2014), who have proposed two different approaches to study poverty dynamics in the absence of longitudinal information. We use repeated cross-sectional data from 1992 to 2012 to compute the rates of transitions in and out of poverty with both methods. We compute bootstrapped standard errors for all figures, in order to assess the statistical

[1] According to the national income poverty line. The series from 1992 to 2012 is presented in Figure 1. Székely (2005b) provides estimations of the evolution of income poverty in Mexico since 1950.

[2] See Baulch (2011) for a compilation of longitudinal household surveys in developing countries.

significance of their differences.

We find that most of the discrepancies between methods can be associated with the income correlation parameter (or *shocks persistence parameter*, as in Bourguignon et al., 2004), so that when we use a similar value of this parameter in both methods the mobility rates' confidence intervals tend to overlap. However, important gaps can be observed in periods of economic crisis, presumably related to the different treatment of the contemporaneous component of transitory income in each method.

In addition, longitudinal information available since 2002 allows an assessment of how our pseudo-panel transition rates compare with those obtained with a true panel. Most of the previous studies have been focused on either using panel data as cross-sections to validate the relevant methodology, or to the use of cross-sectional data to estimate pseudo-panel mobility rates. However, for countries where cross-sectional data is the only or most frequent source of information, it is relevant to explore how similar are the figures obtained with both kinds of data.

A comparison involving two different surveys entails additional sources of error, so we consider several scenarios to improve the comparability between our data sets. In particular, although both our cross-sectional and longitudinal data sets have the same underlying sampling population, the income data in the panel survey is collected using a different and less detailed questionnaire, resulting in marked differences in the poverty rates. We adjust the income distribution in the panel data to replicate that of the cross-sectional information to compare both sets of estimates. Nonetheless, due to the several assumptions required to make the panel and cross-sectional data comparable, we show this comparison only as a reference. However, in spite of these considerations, our findings suggest that the pseudo-panel estimates provide similar levels of mobility as the adjusted panel. This is an encouraging outcome, so that future research exploring the differences between panel and cross-sectional income information may improve the precision of the pseudo-panel estimations. This may be of particular interest for policy makers, as cross-sectional information is usually available for longer periods of time, with higher frequency and with bigger sample-sizes than typical panel surveys. In this sense, pseudo-panel methods can be used to provide poverty mobility rates readily when cross-sectional data becomes available.

To our knowledge, this is the first analysis of its kind to provide a medium-term perspective on the evolution of poverty persistence and the magnitude of the movements in and out of poverty in Mexico. Our results suggest that an important fraction of the Mexican population moves in and out of poverty over short periods of time, and that there is a high, but declining rate of poverty persistence. We find evidence of considerable variation in the dynamics of poverty experienced by groups of the population typically considered in higher risk of poverty (such as households with low levels of human capital or in rural areas). These results suggest that recognising the specificities and characteristics of the dynamics of poverty for different groups can significantly contribute to define appropriate policies to improve poverty alleviation efforts.

The rest of the paper is organised as follows: Section **2** presents a review of the related literature, focusing on previous results available for the Mexican case. Section **3** briefly introduces the pseudo-panel approaches of Bourguignon et al. (2004) and Dang et al. (2014). In Section **4**, we describe the cross-sectional and panel-data sets we use in our analysis. Section **5** contains the main results from each method and a comparative analysis. Section **6** introduces estimations for different sub-groups of the population and Section **7** the main conclusions.

2. Literature review

Mexico has a long tradition in the study of income dynamics;[3] however, little is known about the dynamics of poverty.[4] One reason for the lack of evidence is the limited availability of information about changes in income or expenditure for the same individuals over time. The longest and most comprehensive panel study in the country, the Mexican Family Life Survey (hereinafter MxFLS), started in 2002 and has already two additional waves: 2005-2006 and 2009-2012. Some studies have already taken advantage of the first two waves of this survey to study poverty dynamics (Garza-Rodríguez et al., 2010, Rascón & Rubalcava, 2009). Rascón & Rubalcava (2009) use the MxFLS to estimate the dynamics of urban poverty in Mexico between 2002 and 2005-2006. These authors find that only 34 percent of the urban poor escaped poverty from

[3]See, for example, the studies by Antman & McKenzie (2007a,b), Esquivel & Cruces (2011), Fields et al. (2007), Gong & Van Soest (2002), Hernández (2006)

[4]For reviews of the recent literature on the measurement of chronic and transient poverty in developing countries see Baulch & McCulloch (2002), McKay & Lawson (2003), and Dercon & Shapiro (2007).

2002 to 2005, while 60 percent of the initially non-poor in 2002 remained in the same condition. Garza-Rodríguez et al. (2010) find that around 70 percent of the overall poverty rates can be considered chronic (i.e., households found to be poor in 2002 and 2005-2006), while 31 percent of the households changed its poverty status (falling in or escaping of poverty).

Some other authors have employed short panels, frequently designed for specific groups of the population, such as Parada & López-Feldman (2013) and Parada & López-Feldman (2013). These authors use data from the Mexican National Rural Household Survey 2002 and 2007, and find that around 60 percent of rural households in Mexico experienced extreme (or food) poverty in at least one of these years, while only 20 percent fall in extreme poverty in both years.

Given the limitations of available panel-data sets, a growing set of studies have employed pseudo-panel methodologies to study intragenerational changes in poverty status (Ferreira et al., 2012, Franco et al., 2014, Rodríguez-Oreggia, 2014).[5] Ferreira et al. (2012) use a method set out in Lanjouw et al. (2011)[6] to estimate the magnitude of movements in and out of poverty in several Latin American countries. In the case of Mexico, these authors estimate that, between 2000 and 2008, around 75 percent of the Mexican population stayed in the same poverty status, which places Mexico as one of the countries with lower levels of poverty mobility in the region. Franco et al. (2014) use the same method to analyse the magnitude and characteristics of short-term poverty transitions in Mexico over two periods: 2006-2008 and 2008-2010. These authors estimate that, in these periods, between 74 and 90 percent of the population stayed in their initial poverty status.[7]

[5] In a closely related literature, Antman & McKenzie (2007b) find evidence of very low absolute mobility in Mexico (suggesting that the gap between two randomly selected households is reduced very slowly over time), but high and rapid relative convergence (movements around a household's fixed effect). (Antman & McKenzie, 2007a) test the existence of non-linearities in income dynamics and poverty traps in Mexico, not finding evidence of the existence of poverty traps in urban Mexico. These analyses highlight that pseudo-panel approaches have limitations to measure the impact of transitory shocks in income dynamics. Cuesta et al. (2011), within the context of an analysis for several Latin American countries, find that Mexico has high levels of conditional income mobility (i.e., controlling for several socio-demographic variables). Krebs et al. (2013) propose a methodological framework to take into account income dynamics, social mobility and welfare, while controlling for measurement error. The later authors find that much of the observed mobility in Mexico seem to be product of measurement error.

[6] This is a previous version of (Dang et al., 2014), which focuses on the non-parametric bounds (see **3.2**).

[7] In a related study, Rodríguez-Oreggia (2014) uses a matching approach to estimate changes in households with similar time-invariant characteristics. This author estimates that, among the working

3. Pseudo-panel approaches to measure poverty transitions

In contexts where panel data is limited or not available, a number of authors have proposed to exploit the information available in repeated cross-sections (hereinafter RCS) to create synthetic cohorts or pseudo-panels. Deaton (1985) introduced the idea of using aggregate information on groups of individuals with the same observable characteristics to analyse dynamic phenomena. Several authors have extended this approach and proposed conditions for the identification of these models under different assumptions about the composition and number of cohorts, individuals and time periods.[8].

In the case of poverty dynamics, [9] the pseudo-panel approach was initially introduced by Bourguignon et al. (2004) (hereinafter BGK) to analyse individual-level of vulnerability to poverty (viewed as the probability of being poor in one period, conditional on previous earnings). In a recent contribution, Dang et al. (2014) (hereinafter DLLM) take an alternative route, using linear projections of income to *predict* the consumption or income levels of an individual, given various assumptions about the correlation of the stochastic component of income over time (Bourguignon et al., 2004).

Although both pseudo-panel methods focus on using the information of RCS, BGK follow the pseudo-panel tradition closely, highlighting the use of pseudo-cohorts to obtain the income-generating process parameters through a second order moments approach. [10] In contrast, DLLM propose a *forecasting* method that does not rely on cohort-level aggregate information and can be estimated with two or more rounds of information.[11]

population, 36 percent remained poor from 2005 to 2010, this rate being significantly higher among the population with primary education (47 percent) or in rural areas (48 percent).

[8] Ridder & Moffitt (2007) and Verbeek (2008) provide reviews of the conditions for identification in different contexts.

[9] In this paper, we focus exclusively on what Fields & Viollaz (2013) denominates *dispersion-based* approaches, which build individual-level pseudo-panels instead of the *mean-based* approaches, such as Antman & McKenzie (2007a,b).

[10] Due to the dynamic nature of this model, the BGK's method requires at least three periods of data to be estimated. However, as noted by the authors, three points of information may be insufficient to provide accurate estimates of the key parameters.

[11] Moffitt (1993) and Verbeek (2008) highlight that the variables used to construct synthetic cohorts in pseudo-panel models function as instruments and should satisfy the appropriate conditions for consistency.

The DLLM's method has been validated in several countries,[12] but, to our knowledge, only one validation exercise has compared directly the BGK's and DLLM's methods (Fields & Viollaz, 2013).[13] In addition, most of these exercises have used primarily panel data treating them as cross-sections, which allows the comparison of the observed mobility rates with those calculated using pseudo-panel methods. Although this approach is useful for validation exercises, in many applications the main source of information would be exclusively the RCS, thus the relevance of exploring if the pseudo-panel estimates obtained *only with RCS* can produce mobility estimates similar to those calculated with a true panel.[14] In the following sections, we first present a summary of these methods, before introducing the data sets and our results.

3.1 Bourguignon et al. (2004)

BGK propose a procedure to predict the probability of an individual being poor in period $t+1$, given that she is observed only in period t. To do so, each individual i is assigned to a cohort j based on observable characteristics (e.g., year of birth), so that in each period her earnings may be represented as:

$$y_{it}^{j} = x_{it}^{j\prime}\beta_t^j + \xi_{it}^j, \tag{1}$$

where x_{it}^j is a set of individual characteristics (including cohort-specific fixed effects) and ξ_{it}^j includes both the unobserved determinants of permanent income and the transitory shocks to earnings. If we assume that ξ_{it}^j follows an autoregressive process of first order, then:

$$\xi_{it}^j = \rho^j \xi_{it-1}^j + \epsilon_{it}^j, \tag{2}$$

[12]In their paper, DLLM perform validation exercises using panel data for Indonesia and Vietnam as cross-sections, while Cruces et al. (2014) do a similar analysis for Chile, Nicaragua and Peru. These authors find that the levels of mobility calculated with true panel data were within the bounds defined by the DLLM's method; although the width of this range seems to depend on the precision of the income models (see Section **3.2**).

[13] Fields & Viollaz (2013) find that these methods provide a poor approximation to the dynamics of income, and limited estimation of movements in and out of poverty. However, the characteristics of their exercise differ substantially from the assumptions required by these methods, so that it is unclear if this is due to the methods or to the specificities of the data used in their exercise.

[14]In their exercise, BGK provide estimates using both panel and RCS data, but they do not recommend the comparison of panel and pseudo-panel point estimates due to differences in the sample and the parameters of the income equation.

where ϵ_{it}^{j}, the transitory element of earnings, has variance $\sigma^2_{\epsilon jt}$. Although equation 2 cannot be estimated using RCS, BGK suggest that it is possible to learn some information about ρ^j and $\sigma^2_{\epsilon jt}$ using cohort-level variation. If the RCS have the same underlying population over time, and movements in and out of each cohort are random between periods, then, for each cohort j:[15]

$$\sigma^2_{\xi t} = \rho^2 \sigma^2_{\xi t-1} + \sigma^2_{\epsilon t}. \tag{3}$$

Using the previous results, we require to have some estimation of x_{it+1} and β_{t+1} to predict the probability of being poor in $t+1$, ,[16] named $\hat{x}_{it+1}$ and $\hat{\beta}_{t+1}$. Using $\hat{x}_{it+1}$ and $\hat{\beta}_{t+1}$, and assuming that $\epsilon_{it} \sim N(0, \hat{\sigma}^2_{\epsilon t})$, then $\hat{v}_{it+1}$, the probability of individual i observed in time t of being poor in $t+1$, is given by:

$$\hat{v}_{it+1} = Pr(\hat{y}_{it+1} < z | x_{it}, \hat{x}_{it+1}, \hat{\beta}_{t+1}, \hat{\sigma}^2_{\epsilon t+1}) = \Phi\left(\frac{z - \hat{x}'_{it+1}\hat{\beta}_{t+1} - \hat{\rho}\xi_{it} - \epsilon_{it}}{\hat{\sigma}^2_{\epsilon t+1}}\right) \tag{4}$$

where $\Phi(\cdot)$ denotes the cumulative density of the standard normal distribution and z is the value of the poverty line.[17]

BGK propose to derive $\hat{v}_{it+1}$ in 2 steps. First, to estimate equation 1 for each cohort and period to obtain $\hat{\sigma}^2_{\xi t}$. In a second step, we use these results to calculate $\hat{\rho}$ from equation 3.

This procedure is feasible when at least three rounds of RCS are available, but a consistent estimation of $\hat{\rho}$ would typically require a larger number of periods (Ridder & Moffitt, 2007, Verbeek, 2008). In addition, estimation of equation 3 using OLS can potentially produce estimates outside of the expected values for $\hat{\rho} \in [0,1]$ and $\hat{\sigma}^2_{\epsilon t} > 0$, as OLS do not guarantee that these restrictions are satisfied.

In that case, it may be feasible to obtain non-negative values of $\hat{\sigma}^2_{\xi t}$ and estimates of $\hat{\rho} \in [0,1]$ using a half-normal distribution model to impose both restrictions simultaneously (Battese & Coelli, 1988, Stevenson, 1980). In this model, the density function

[15]For the sake of clarity, in the rest of the discussion we drop the superscript j, since the estimation process is the same for every cohort.

[16]For example, using time invariant variables whose values can be assumed fixed, or time-variant variables for which retrospective information is available or whose value could be easily predicted. In the case of $\hat{\beta}_{t+1}$, they may be assumed fixed or adjusted to consider the average income growth between surveys (assuming the income distribution is fixed).

[17]In this discussion, we assume that all incomes are expressed in constant prices, so that a unique poverty line is required.

for $\sigma^2_{\epsilon t}$ is given by:

$$f\left(\sigma^2_{\epsilon t}\right) = \frac{1}{\omega\sqrt{2\pi}\left(1-\Phi\left(-\mu/\omega\right)\right)} e^{-\left(\sigma^2_{\epsilon t}-\mu\right)^2/2\omega^2}, \tag{5}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal and μ and ω denote the mode and variance of $f(\sigma^2_{\epsilon t})$. Estimation of equation 5 can be achieved using a maximum likelihood approach to estimate $\hat{\rho}$.[18]

BGK do not provide estimates of the transitions in and out of poverty, so we propose taking m random draws of $\epsilon_{it} \sim N(0, \hat{\sigma}^2_{\epsilon t})$, $\tilde{\epsilon}_{it+1}$,to compute:

$$\hat{y}^B_{t+1} = \hat{x}'_{it+1}\hat{\beta}_{t+1} + \hat{\rho}\hat{\zeta}_{it} + \tilde{\epsilon}_{it+1}, \tag{6}$$

which can be used to obtain the elements of the poverty transition matrix, M^B,[19] defined as:

$$M^B = \begin{pmatrix} Pr(\hat{y}^B_{t+1} < z \text{ and } y_{it} < z) & Pr(\hat{y}^B_{t+1} < \text{ and } y_{it} > z) \\ Pr(\hat{y}^B_{t+1} > z \text{ and } y_{it} < z) & Pr(\hat{y}^B_{t+1} > \text{ and } y_{it} > z) \end{pmatrix},$$

so that the overall mobility estimates can be calculated using the average over the m replications.[20].

3.2 Dang et al. (2014)

The DLLM's method, instead of adopting the standard pseudo-cohorts approach, defines a *forecasting* framework to estimate y_{it+1} for a sample observed in t, but not in $t+1$.[21] Although this method can be used under very flexible conditions and with only 2 rounds of RCS, the cost is that no explicit estimate of ρ is obtained. Instead,

[18] In the context of the pseudo-panel tradition, the model defined by BGK can be seen as a linear dynamic model where $y_{it} = \varrho y_{it-1} + x'_{it}\psi_t + \epsilon_{it}$ (assuming x_{it} includes only time-invariant variables, so that $\psi = \beta(1-\varrho)$). However, a consistent estimation of ϱ would require $x_{it} \perp \epsilon_{it}$, which may not be true for most applications (Moffitt, 1993, Verbeek & Vella, 2005). Moffitt (1993) and Verbeek & Vella (2005) propose different options to achieve a consistent estimation of $\hat{\rho}$; however, most cross-sectional surveys rarely collect the required data to implement these alternatives.

[19] For comparability, we define a transition matrix analogous to that used by Dang et al. (2014), as shown in the next section.

[20] Alternatively, if we assume that ζ^j_{it} and ζ^j_{it+1} follow a bi-normal distribution, we may use our previous estimates to compute the joint probability using a version of equation 11, as will be explained in the following section.

[21] Alternatively, we can define the problem in terms of estimating the expected income in t for the sample observed in $t+1$, but the procedure is analogous (Dang et al., 2014).

these authors adopt a series of conditions to provide structure to the underlying autocorrelation of the income generating process (Dang et al., 2014, Fields & Viollaz, 2013). In consequence, this method does no produce point estimates unless an external estimate of ρ is available.

The main goal of the DLLM's method is to estimate the matrix M^D (analogous to M^B), defined as:

$$M^D = \begin{pmatrix} Pr(y_{it+1} < z \text{ and } y_{it} < z) & Pr(y_{it+1} < z \text{ and } y_{it} > z) \\ Pr(y_{it+1} > z \text{ and } y_{it} < z) & Pr(y_{it+1} > z \text{ and } y_{it} > z) \end{pmatrix},$$

where all the elements are defined as before. To do so, these authors use a version of equation 1 to distinguish the systematic and transitory components of y_{it}; however, instead of pursuing a correct specification of the income-generating process, their goal is to obtain an informative linear projection of y_{it} on x_{it} (a vector of time-invariant characteristics), defined as:

$$y_{it} = x'_{it}\beta_t + e_{it}, \tag{7}$$

where e_{it} is the residual term.

The basic idea of this method is to estimate $\hat{y}_{it+1}$ using a combination of the systematic component of expected income, $x'_{it+1}\hat{\beta}_{t+1}$, plus an estimation of e_{it+1}. Since x_{it} includes only time-invariant variables, it can be assumed as fixed between t and $t+1$. However, as $\hat{e}_{it}$ and $\hat{e}_{it+1}$ cannot be estimated for the same individuals, the problem addressed by this method is how to obtain an appropriate estimate of $\hat{e}_{it+1}$ for households observed only in period t.

As a first step, we can rewrite the elements of M^D using equation 7, so that, for example, the first element of this matrix would be:

$$Pr(e_{it+1} < z - x'_{it+1}\beta_{t+1} \text{ and } e_{it} < z - x'_{it}\beta_t). \tag{8}$$

In this expression, it is evident that, to estimate M^D, we require further assumptions about the correlation between e_{it+1} and e_{it}, i.e., ρ.

If we assume that the underlying sampling population for the RCS is the same in t and $t+1$, and that ρ is non-negative (Dang et al., 2014), then $\rho \in [0,1]$. Hence, the maximum mobility would be observed when $Corr(e_{it+1}, e_{it}) = 0$, i.e., when the transitory components of income are unrelated over time; and the minimum mobility when $Corr(e_{it+1}, e_{it}) = 1$, i.e., when $e_{it+1} = e_{it}$. However, the true value of ρ will most likely lie somewhere in between these bounds.

In the absence of panel data, the authors propose to sidestep the estimation of ρ and construct non-parametric and parametric bounds of mobility. In the case of non-parametric bounds, they focus on building estimates of $\hat{e}_{it+1}$ associated with the extreme theoretical values of ρ. In the parametric case, assuming that e_{it+1} and e_{it} have a bivariate normal distribution with an exogenously determined ρ, it is possible to directly evaluate the value of each element in M^D.

The non-parametric upper bound of mobility (i.e., when $\rho = 0$) is constructed assigning to each i a random draw with replacement of $\hat{e}^{t+1}$ (the residuals of equation 7 in $t+1$). Defining this new residual as $\tilde{e}_{it}^{t+1}$, the expected income is constructed as:

$$\tilde{y}_{it}^{t+1UB} = x_{it}'\hat{\beta}_{t+1} + \tilde{e}_{it}^{t+1}, \tag{9}$$

which can be used to obtain the elements of M^D. The overall mobility estimates correspond to the average of k replications of this process (the authors suggest $k = 500$).

In the case of the lower bound, ρ is assumed to take a value of 1, so that $\hat{e}_{it+1} = \hat{e}_{it}$. Thus, the expected income is:

$$\tilde{y}_{it}^{t+1LB} = x_{it}'\hat{\beta}_{t+1} + \gamma\hat{e}_{it}, \tag{10}$$

where $\gamma = \sqrt{\frac{Vare_{it+1}}{Vare_{it}}}$ is an adjusting factor to rescale the residuals for the change in β. Similarly to the upper bound, we can use $\tilde{y}_{it}^{t+1LB}$ to obtain the elements of M^D.

Despite the flexibility of the non-parametric bounds, their width may be considerable (Dang et al., 2014, Fields & Viollaz, 2013), reducing their attractiveness for policy analysis. In order to refine this estimation, DLLM propose to improve the precision of their estimator, at the cost of assuming that e_{it+1} and e_{it} follow a joint bivariate normal distribution with non-negative correlation ρ and standard deviations $\sigma_{e_{it}}$ and $\sigma_{e_{it+1}}$, respectively. This assumption is useful only with previous knowledge about the value of ρ (e.g., from a true panel), but even in contexts where no such estimates exist, it may be possible to define smallest and highest hypothesised values for ρ, such that $\rho \in [\rho_S, \rho_H]$ and $0 < \rho_S < \rho_H < 1$. These values can be defined considering the available panel information for other periods in the same country or in similar contexts.

Given $\tilde{\rho}$, an exogenously determined estimate of ρ, we can use the estimates of equation 7 to construct each element of the M^D matrix. In particular, we can estimate the probability of being poor in both t and $t+1$ as:

$$Pr(y_{it+1} < z \text{ and } y_{it} < z) = \Phi_2\left(\frac{z - x'_{it+1}\hat{\beta}_{t+1}}{\hat{\sigma}_{e_{it+1}}}, \frac{z - x'_{it}\hat{\beta}_t}{\hat{\sigma}_{e_{it}}}, \tilde{\rho}\right), \tag{11}$$

where $\Phi_2(\cdot)$ refers to the bivariate normal cumulative distribution function. When no estimate of ρ is available, then suitable values of ρ_S and ρ_H may be used instead of $\tilde{\rho}$.

In the following sections, we use both the BGK's and the DLLM's methods to estimate the magnitude of movements in and out of poverty with Mexican data. First, we introduce the sources of information for our estimations and briefly describe the variables that we use.

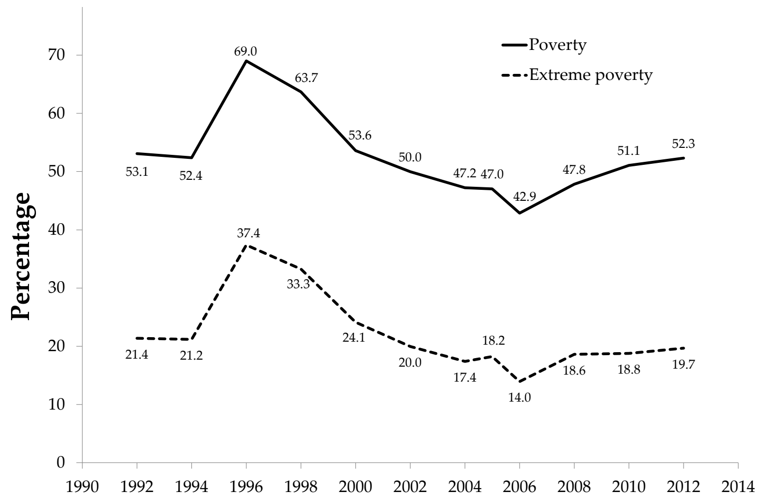
4. Data

4.1 Poverty data

In 2009, Mexico introduced a new multidimensional poverty measure that combines information of income and six other social deprivations (such as health, education and social security) to identify the population living in poverty (CONEVAL, 2010). Due to technical and legal requirements, a novel source of information was developed to produce the official poverty figures to provide the information required to identify the population living in poverty with this approach. Although the new data provides a richer set of characteristics of the households, it is not possible to estimate the poverty incidence before 2008, limiting its use for the analysis of poverty dynamics. For this reason, in this work we use a definition of poverty based on the (absolute) poverty line approach, which was used by the Mexican government until 2009 (CONEVAL, 2010, Székely, 2005a). [22]

[22] Franco et al. (2014) use the Lanjouw et al. (2011) approach to provide estimates of the multidimensional poverty transitions matrix for 2006-2008 and 2008-2010. However, these authors assume as fixed

Figure 1: *Income poverty headcount rates. Mexico 1992-2014.*



Notes: The official denomination for the income poverty headcount is "pobreza de patrimonio" (patrimonial poverty), while that of the extreme poverty headcount is "pobreza alimentaria" (food poverty). Source: CONEVAL (2013).

According to the income poverty definition used in Mexico, a household is considered poor if its current per capita income is inferior to the poverty line (or *pobreza de patrimonio* in Spanish) (Székely, 2005a). [23] The monthly value of the poverty line for urban areas in August 2012 was $2,403 Mexican pesos (about $188 USD or £120 GBP) per person, while in rural areas it was $1,627 pesos (about $127 USD or £81 GBP) per person. [24] Figure 1 shows the evolution of the poverty headcount rate from 1992 to 2012. This Figure presents the most common features of the dynamics of poverty in Mexico: a large rise after the economic crisis of 1994-1995, followed by a gradual recovery ending with the global economic crisis of 2008-2010.

4.2 Cross-sectional information

The cross-sectional data we use comes from the Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH), which was introduced in 1984 and has been carried out in 1989, 1992 and every other year thereafter. The ENIGH is the traditional source of

the social deprivations to produce their estimates, so that the only source of variation is income.

[23] The official definition included two other poverty lines for targeting purposes: an extreme poverty line (*pobreza alimentaria*), and an intermediate poverty line (or *pobreza de capacidades*) (Székely, 2005a). In this paper we focus exclusively on the general poverty line. Refer to Appendix **A.1** for the definition of the income variable.

[24] The value of the poverty line refers to the minimum income a person needs to acquire essential goods and services, including food, education, health, clothing, housing and transport.

information for the measurement of poverty and inequality in Mexico, although since 2008 the Módulo de Condiciones Socioeconómicas (a boost sample of the ENIGH) has been used to calculate the official poverty estimates (CONEVAL, 2010).

In this paper, we use data from the last ten rounds of the ENIGH, covering the period starting in 1992 to 2012. We do not use the previous surveys (1984 and 1989) since–due to changes in the sampling and questionnaire design–these rounds have traditionally not been used to produce poverty figures. Although our data comprises only 10 rounds of RCS data, this number is significantly higher than that used in (Fields & Viollaz, 2013), which used only 3 rounds of data to apply the BGK's method.

The ENIGH includes detailed information about labour and non-labour income, expenditure, socio-economic characteristics of the household and its members, assets and characteristics of the dwelling. Although this survey provides a rich set of variables for analysis, due to changes in questionnaire only a subset of these is comparable over the period (a crucial aspect in this analysis). Although the sample sizes vary over time, usually each round contains information of around 10,000 households and 50,000 individuals, which allows for disaggregation of urban and rural areas (INEGI, 2014).

4.3 Longitudinal information

We use available panel data to assess how our pseudo-panel transition rates compare to those obtained with a true panel. To this end, we use data from the MxFLS, the longest and most comprehensive panel study in Mexico. This survey started in 2002 and has already two additional rounds: 2005-2006 and 2009-2012. This survey provides information about socio-economic, demographic, health and migration. The original sample of the MxFLS included about 8,400 households and 35,000 individuals, and in both follow-ups the re-contact rate was close to 90% of the original households (Rubalcava & Teruel, 2006, 2013). We use all available rounds, using the households that can be followed along the three waves (i.e., excluding households formed from the original sample). In order to correct for attrition and changes in the composition of the sample, we use the follow-up longitudinal expansion factors for each year.

4.4 Selection of variables

One of the key elements in the DLLM's and the BGK's methods is that the covariates in equations 1 and 7 should be easily predicted for the next period or based on retrospective information (if available). This includes time-invariant characteristics (e.g., sex and education), as well as those unlikely to change over short periods of time (e.g., marital status). As our cross-sectional data sets do no include retrospective questions, we restricted the variables to those included in all rounds of the RCS. To test the robustness of our results, we define three models or specifications.[25] The variables in each model are:

Model 1: a basic set of variables including age, sex, marital status, educational level, and labour force participation, as well as variables identifying self-employees and households in rural areas to control for larger variability of income in these groups.

Model 2: the variables in Model 1, plus an identifier for household heads working in the informal sector or who are illiterate, as well as number of children in the household.

Model 3: the variables in Model 2, plus characteristics of the dwelling (dirt floors, access to drinking water, number of rooms) and assets of the household (vehicles, fridge and computer).

The descriptive statistics of the variables used in the estimation of equations 1 and 7 are shown in Table A.1, while Appendix **A.1** contains their definitions.

Table A.1 shows descriptive statistics of the variables used in the estimation of the cross-sectional models (due to space constraints, some years were omitted, but the whole set is available upon request). A key element in this table is the magnitude of the changes over the period in many characteristics of the household heads, such as the proportion who is female (that increased from 12 to 24 percent over the period) or the percentage of heads with less than primary school (which dropped from 43 to 23 percent). These changes suggest that the population sampled in each round of the RCS is continuously changing, so that the assumption of stability in the underlying

[25] Additional tests included a wider set of variables; however, as recommended by DLLM, we decided to keep a parsimonious set that maximised the explanatory power of the model (i.e., the adjusted and unadjusted R^2).

population may hold only over short periods of time. Under this consideration, the pseudo-panel analysis in this study focuses on transitions over pairs of consecutive rounds of the RCS, to minimise the possibility of significant changes over the period.[26]

5. Results

5.1 Bourguignon et al. (2004)

In the BGK's method, equation 1 is estimated for cohorts of households with heads born during the same period of time. We test three different cohorts definitions: using the sample as a whole, with 10-year intervals (e.g., households whose head was born between 1930 and 1939, 1940 and 1949, and so on) and with 5-year intervals (households whose head was born between 1930 and 1934, 1935 and 1939, and so on). [27] Then, we estimate equation 1 through ordinary least squares (OLS), using as dependent variable the log of the per capita current income in constant prices of 2012. We estimate this model for each cohort and year, using the three specifications described in Section **4**. Regression estimates of the income equations for each year, sample and model are available upon request to the authors.

Using the residuals from equation 1, we proceeded to estimate equation 3. OLS estimation, however, produced $\hat{\rho}$ and $\hat{\sigma}^2_{\xi t}$ estimates outside the expected bounds for several cohorts (i.e., values of $\hat{\rho}$ outside the $[0, 1]$ interval or values of $\hat{\sigma}^2_{\xi t}$ below zero). As an alternative, we follow the suggestion by BGK and use a half-normal distribution model to impose both restrictions simultaneously (Battese & Coelli, 1988, Stevenson, 1980). We estimate a model similar to that presented in equation 5 using a maximum likelihood approach to estimate simultaneously $\hat{\rho}$ for all cohorts (see Section **3.1** for further details).

Table 1 contains the estimates of $\hat{\rho}$ for each cohort definition and specification of the income equation.[28] Even when the number of available periods may reduce the levels of precision of $\hat{\rho}$ (as seen by the magnitude of the standard errors), it is possible

[26] A similar approach was used by Franco et al. (2014), although the changes over the period they analyse were relatively small. In contrast, Ferreira et al. (2012) compare the period 2000 to 2008, for which important differences can be observed in several variables demographic variables (see Table A.1).

[27] We tested cohorts with a 3-year interval as well, but the results were qualitatively similar to the other cohort definitions.

[28] For all the estimates we report bootstrapped standard errors. See Appendix **A.2** for details.

Table 1: *Estimates of $\hat{\rho^j}$ based on Bourguignon et al. (2004), using different specifications of the income equation and definitions of cohorts.*

	Model 1	Model 2	Model 3
Whole sample	0.509	0.134	0.430
	(0.217)	(0.176)	(0.197)
Year of birth cohorts			
10-year intervals			
1930-1939	0.359	0.418	0.556
	(0.087)	(0.066)	(0.101)
1940-1949	0.289	0.367	0.555
	(0.082)	(0.063)	(0.096)
1950-1959	0.259	0.360	0.560
	(0.086)	(0.064)	(0.094)
1960-1969	0.217	0.270	0.517
	(0.097)	(0.078)	(0.109)
1970-1979	0.000	0.000	0.459
	(0.141)	(0.140)	(0.162)
5-year intervals			
1930-1934	0.275	0.402	0.524
	(0.142)	(0.111)	(0.098)
1935-1939	0.398	0.455	0.572
	(0.071)	(0.065)	(0.064)
1940-1944	0.362	0.436	0.589
	(0.062)	(0.057)	(0.056)
1945-1949	0.257	0.354	0.536
	(0.081)	(0.065)	(0.061)
1950-1954	0.271	0.383	0.559
	(0.075)	(0.063)	(0.060)
1955-1959	0.264	0.373	0.564
	(0.072)	(0.061)	(0.055)
1960-1964	0.236	0.332	0.539
	(0.079)	(0.068)	(0.061)
1965-1969	0.207	0.235	0.495
	(0.096)	(0.093)	(0.073)
1970-1974	0.000	0.139	0.485
	(0.127)	(0.130)	(0.080)
1975-1979	0.083	0.000	0.468
	(0.132)	(0.153)	(0.091)

Notes: Maximum likelihood estimates using a half-normal distribution (Battese & Coelli, 1988). Bootstrapped standard errors (399 replications). Sample restricted to households with heads aged between 25 and 64 years old in cohorts with at least 100 observations in each period. See Section **4.4** for a description of the variables included in the estimation of the income equation. Source: author's calculations using ENIGH data.

to observe some interesting patterns. For example, in practically all cohorts the values of $\hat{\rho}$ are higher for Model 3, which also has the highest R^2's. Analogously, $\hat{\rho}$ estimates with Model 2 are higher than those obtained with Model 1 (with a few exceptions).

Although the confidence intervals of the different $\hat{\rho}$ estimates intersect, the changes in magnitude suggest that its value is highly sensitive to the proportion of the unexplained variance. In addition, for the 10-year and 5-year cohorts estimations, older cohorts seem to have higher values of $\hat{\rho}$, which is consistent with life cycle models where younger individuals face higher levels of uncertainty that diminishes over time. In the case of the whole sample, the estimates are highly imprecise, thus the cohort estimates would be preferred.

Figure A.1 (in Appendix **A.3**), shows the estimates of $\hat{\sigma}^2_{\xi t}$ for each round, cohort and model. In the case of $\hat{\sigma}^2_{\xi t}$, the largest values correspond to Model 1 (for which $\hat{\rho}$ has the lowest values) and the lowest to Model 3 (with the highest $\hat{\rho}$'s). Although in the beginnings of the period the estimates of $\hat{\sigma}^2_{\xi t}$ have higher variability, in recent years they seem to be converging and increasing in magnitude. The rise over time of $\hat{\sigma}^2_{\xi t}$ suggests that income heterogeneity may be increasing over time for all cohorts. This is consistent with previous evidence suggesting that, although income inequality has decreased modestly in Mexico since mid-1990's, the returns to education have fallen for all groups since then, suggesting that the relative importance of the systematic components of income has decreased over time (Campos-Vázquez et al., 2014, Esquivel & Cruces, 2011).

Using the estimates of equations 1 and 3, we take $m = 400$ random draws from $\epsilon_{it} \sim N(0, \hat{\sigma}^2_{\epsilon t})$ to derive $\hat{y}^B_{t+1}$. Then, we compute the elements of M^B in each replication and use their average as the overall estimate of mobility.

Although there is no standard nomenclature for the elements of M^B, in this document we will refer to the proportion of households identified as poor in t and predicted to be poor in $t+1$ as **poverty persistence**. Likewise, we call **upward mobility** to the proportion of poor households in t predicted to escape poverty in $t+1$, and **downward mobility** to non-poor households in t predicted to become poor in $t+1$. The proportion of non-poor households in t, predicted to remain non-poor in $t+1$, would be defined as **non-poverty persistence**. Finally, the sum of the movements in and out of poverty is referred as **total mobility**.

Table 2: *Estimates of poverty mobility based on (Bourguignon et al., 2004)'s approach. Year of birth cohorts (10-year intervals). Model 3. (Percentages)*

Period	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]
1994-1996	39.4	4.6	18.8	37.2	23.4
	(1.012)	(0.826)	(0.744)	(0.901)	(1.436)
1996-1998	46.2	13.9	7.9	32.0	21.8
	(1.102)	(0.985)	(0.770)	(0.929)	(1.685)
1998-2000	39.3	15.7	6.7	38.3	22.4
	(1.235)	(1.036)	(0.848)	(1.003)	(1.762)
2000-2002	35.3	10.1	10.7	43.9	20.8
	(1.335)	(1.085)	(0.972)	(1.174)	(1.905)
2002-2004	31.9	10.6	10.5	47.0	21.1
	(1.271)	(1.124)	(1.042)	(1.234)	(1.976)
2004-2006	27.6	12.1	9.9	50.3	22.0
	(1.069)	(1.020)	(0.917)	(1.157)	(1.887)
2006-2008	25.0	10.1	12.1	52.8	22.2
	(1.076)	(1.059)	(0.956)	(1.113)	(1.969)
2008-2010	29.9	10.6	13.1	46.4	23.7
	(1.217)	(1.181)	(1.136)	(1.210)	(2.188)
2010-2012	27.8	14.5	8.4	49.3	22.9
	(1.193)	(1.157)	(1.306)	(1.389)	(2.274)
2012-2014	25.5	17.4	7.2	49.8	24.7
	(1.292)	(1.232)	(1.273)	(1.485)	(2.041)

Notes: Bootstrapped standard errors in parenthesis (399 replications). Sample restricted to households with heads aged 25 to 64 years, in cohorts with at least 100 observations in each period. See Section **4.4** for a description of the variables included in the estimation of the income equation. Description of columns is the same presented in Table A.3. Source: author's calculations using ENIGH data.

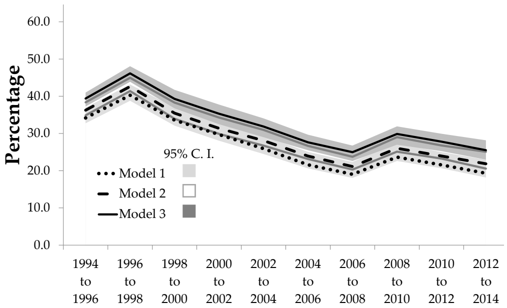
Table 2 presents the mobility estimates for the specification of Model 3.[29] As mentioned above, we analyse movements between consecutive rounds of the cross-sectional survey (i.e., changes over two-year periods). We show only the estimates for the 10-year cohorts, but the full results are available upon request.

Figure 2 contains a graphical comparison of the differences between specifications of the income equation and cohort length. Regarding differences between models, Figure 2a shows that, although all models produce similar figures of mobility, in about half of the periods the differences between Model 1 and 3 are statistically significant (i.e., their bootstrapped 95% confidence intervals do not intersect, see Appendix **A.2**). This suggests that, even when the differences between estimates of $\hat{\rho}$ are not statistically significant (see Table 1), the estimates of mobility can be sensitive to changes in the income equation. However, the magnitude of the differences between Models 1 and 3 is about six percentage points, and with respect to Model 2 even smaller. In contrast, Figure 2b shows the rates of poverty persistence with different definitions of cohorts. In this case, no statistically significant difference can be observed, suggesting

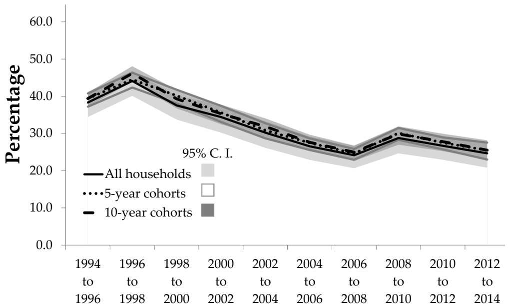
[29] The results for Models 1 and 2 are shown in Tables A.3 and A.4, in Appendix **A.3**.

Figure 2: *Poverty persistence estimates based on Bourguignon et al. (2004)'s approach. Comparison between different specifications and selection of cohort's interval.*

(a) *Differences among specifications (10-year interval cohorts as reference).*



(b) *Differences among cohort definitions (Model 3 used as reference).*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details). Poverty persistence refers to proportion of households identified as poor in period t, that are expected to be in poverty in $t+1$. Sample restricted to households with heads aged between 25 and 64 years old in cohorts with at least 100 observations in each period. See Table 1 for details of cohorts construction and the specification of the income equation models. Source: author's calculations using ENIGH data.

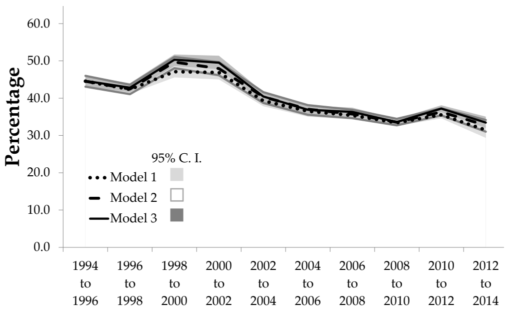
that, at least for this population, the definition of cohort length is less relevant to the mobility estimates than the specification of the income equation.

The first key finding of this study is that, for all models and cohort definitions, the poverty persistence rate depict a declining trend over the period. In spite of important increments around 1996 and 2008 (consistent with the aftershocks of severe economic crises), the percentage of the households identified as persistently poor with this method declined around 20 percentage points between 1996 and 2006. However, in all cases, by the end of the period more than 20 percent of the population was still predicted to be poor in 2012 and expected to remain poor by 2014. In addition, in all periods approximately 1 out of every 4 individuals were moving in or out of poverty, which is consistent with high levels of short-term mobility found by Antman & McKenzie (2007a,b).

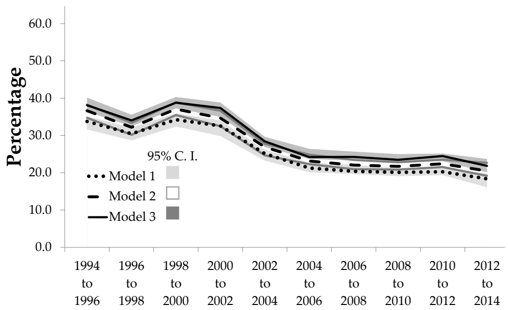
In the next section, we estimate the predicted rates of mobility using the method proposed by DLLM. Although the BGK's and the DLLM's methods share some assumptions (e.g., that the different rounds of the cross-sectional data use the same underlying population), DLLM propose a more flexible approach that does not rely on several rounds of cross-sectional data, so that it can be implemented in a wider range of situations and countries where the cross-sectional information is collected

Figure 3: *Poverty persistence estimates based on Dang et al. (2014)'s approach. Comparison between estimates obtained with different specifications of the income equation.*

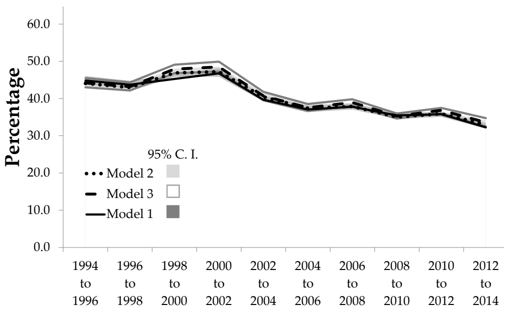
(a) *Non-parametric, Lower Bound ($\rho = 1$)*



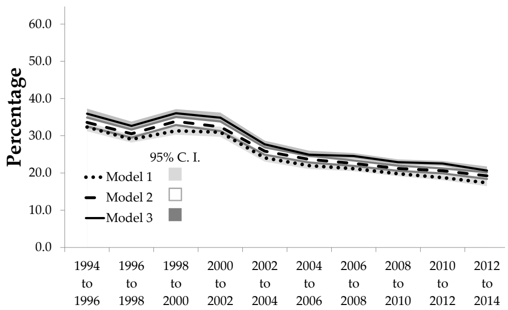
(b) *Non-parametric, Upper Bound ($\rho = 0$)*



(c) *Parametric, $\rho = 1$*



(d) *Parametric, $\rho = 0$*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details). Poverty persistence refers to proportion of households identified as poor in period t, that are expected to be in poverty in $t+1$. The non-parametric upper bound estimates use 500 random draws of $\tilde{e}_{it}^{t+1}$ (see Section **3** for details). For comparative purposes, the sample is the same used to obtain BGK estimates. See Table 1 for details of the sample and the specification of the income equation models. Source: author's calculations using ENIGH data.

less frequently.

5.2 Dang et al. (2014)

The estimation of equation 7 uses the same sample and specifications used to obtain the BGK's estimates. We calculate both the parametric and non-parametric estimates (described in Section **3**). In the case of the non-parametric estimates, $\tilde{e}_{it+1}^{t}$ was estimated using $k = 500$ random draws form the residuals observed in $t+1$. For the parametric estimates, we use three different scenarios: 1) when $\rho_S = 0$ and $\rho_H = 1$; 2) when $\rho_S = 0.2$ and $\rho_H = 0.8$; and 3) when $\rho_S = 0.3$ and $\rho_H = 0.7$.

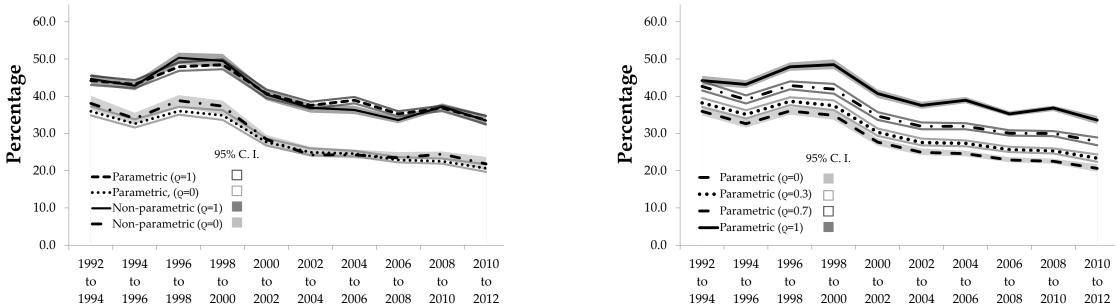
Figure 3 compares the poverty persistence rates for different specifications of the income equation.[30] As seen in Figures 3a and 3c, the non-parametric and parametric

[30] We report, for all the estimates, bootstrapped standard errors or 95% confidence intervals (as detailed in Appendix **A.2**). In the case of the upper and lower bounds of mobility, although they already define

Figure 4: *Poverty persistence estimates based on Dang et al. (2014)'s approach. Comparison between non-parametric and parametric estimates using hypothetical values of ρ. Model 3.*

(a) *Comparison of the non-parametric and parametric estimates when $\rho = 1$ and $\rho = 0$.*

(b) *Comparison of the parametric estimates with different values of ρ.*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details). Poverty persistence refers to proportion of households identified as poor in period t, that are expected to be in poverty in $t+1$. The non-parametric upper bound estimates use 500 random draws of $\tilde{\varepsilon}_{it}^{t+1}$ (see Section **3** for details). For comparative purposes, the sample is the same used to obtain BGK estimates. See Table 1 for details of the sample and the specification of the income equation models. Source: author's calculations using ENIGH data.

lower bounds, the estimation of the three models falls within the confidence interval of the other models. However, in the case of the upper bounds of mobility, the estimation of Model 2 lies within the confidence interval of the other models, but the intervals for Models 1 and 3 do not intersect. In contrast to the BGK's results, where this happened only for a few years, now we can observe significant differences for all years. However, in all cases this difference is inferior to 5 percentage points.

Following DLLM's suggestions, we use for our analysis the model explaining the highest proportion of the variance in the income equation model, i.e., Model 3. However, we should keep in mind that, as in the BGK's results, Model 3 is associated with lower levels of mobility.

Tables 3 to 5 show the non-parametric and parametric mobility estimates for the extreme theoretical values of ρ ($\rho \in [0,1]$), using Model 3. The rates of mobility in both cases are very similar, since both adopt similar assumptions about ρ ($\rho = 1$ for the non-parametric lower bound and $\rho = 0$ for the non-parametric upper bound). Figure 4a shows this graphically.

Although in 1996-1998 and 2004-2006 there are significant differences between the parametric and non-parametric lower bounds, in most cases we cannot reject that the

an interval, they are as well subject to sampling error. Thus, we report as well the bootstrapped 95% confidence intervals for these estimates.

Table 3: *Estimates of poverty mobility based on (Dang et al., 2014)'s approach. Non-parametric estimates. Model 3. (Percentages)*

Period	Lower Bound of Mobility					Upper Bound of Mobility				
	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]
1992-1994	44.6	0.7	16.8	37.8	17.6	38.1	7.3	23.1	31.5	30.4
	(0.770)	(0.138)	(0.648)	(0.785)	(0.637)	(0.907)	(0.547)	(0.860)	(1.001)	(1.006)
1994-1996	42.8	1.2	13.2	42.8	14.4	34.0	10.0	19.7	36.3	29.7
	(0.626)	(0.349)	(0.157)	(0.591)	(0.385)	(0.812)	(0.662)	(0.476)	(0.710)	(0.763)
1996-1998	50.3	9.7	0.2	39.8	9.9	38.8	21.2	9.1	30.9	30.3
	(0.717)	(0.418)	(0.105)	(0.680)	(0.440)	(0.784)	(0.665)	(0.542)	(0.777)	(0.834)
1998-2000	49.5	5.4	1.3	43.7	6.8	37.4	17.6	11.6	33.5	29.2
	(0.931)	(0.326)	(0.535)	(0.937)	(0.667)	(0.990)	(0.740)	(0.783)	(1.144)	(1.065)
2000-2002	40.5	4.9	3.0	51.6	7.9	28.4	17.0	12.7	41.9	29.7
	(0.680)	(0.299)	(0.416)	(0.765)	(0.554)	(0.753)	(0.597)	(0.639)	(0.943)	(0.864)
2002-2004	36.9	5.5	2.3	55.3	7.8	24.2	18.2	12.4	45.2	30.6
	(0.618)	(0.298)	(0.328)	(0.636)	(0.483)	(0.693)	(0.527)	(0.624)	(0.836)	(0.800)
2004-2006	36.3	3.4	4.6	55.6	8.1	24.3	15.5	15.1	45.2	30.5
	(0.564)	(0.224)	(0.329)	(0.614)	(0.392)	(0.620)	(0.481)	(0.588)	(0.779)	(0.726)
2006-2008	33.6	1.5	12.1	52.9	13.5	23.5	11.6	20.3	44.6	31.9
	(0.456)	(0.173)	(0.229)	(0.501)	(0.301)	(0.526)	(0.373)	(0.460)	(0.587)	(0.574)
2008-2010	37.2	3.2	3.8	55.7	7.0	24.5	16.0	15.3	44.2	31.3
	(0.468)	(0.278)	(0.127)	(0.497)	(0.318)	(0.510)	(0.452)	(0.473)	(0.681)	(0.661)
2010-2012	33.5	8.9	0.4	57.2	9.3	21.8	20.5	11.4	46.3	31.9
	(0.799)	(0.549)	(0.085)	(0.838)	(0.564)	(0.896)	(0.804)	(0.664)	(1.005)	(1.012)

Notes: Bootstrapped standard errors in parenthesis (399 replications). Sample restricted to households with heads aged 25 to 64 years, in cohorts with at least 100 observations in each period. See Section **4.4** for a description of the variables included in the estimation of the income equation. The non-parametric upper bound estimates use 500 random draws of $\tilde{e}_{it}^{t+1}$ (see Section **3** for details). [a] Proportion of households identified as poor in period t, expected to be poor in $t+1$. [b] Proportion of households identified as poor in period t, expected to be not poor in $t+1$. [c] Proportion of households identified as non-poor in period t, expected to be poor in $t+1$. [d] Proportion of households identified as non-poor in period t, expected to be not poor in $t+1$. [e] Proportion of households with either upward or downward mobility.
Source: author's calculations using ENIGH data.

Table 4: *Estimates of poverty mobility based on (Dang et al., 2014)'s approach. Parametric estimates with $\rho_S = 0$ and $\rho_H = 1$. Model 3. (Percentages)*

Period	Lower Bound of Mobility					Upper Bound of Mobility				
	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]
1992-1994	44.2	15.8	0.0	40.0	15.8	35.9	24.0	8.2	31.8	32.3
	(0.647)	(0.295)	(0.158)	(0.739)	(0.427)	(0.652)	(0.204)	(0.000)	(0.693)	(0.204)
1994-1996	43.2	9.8	0.1	46.9	9.9	32.6	20.4	10.6	36.4	31.0
	(0.519)	(0.172)	(0.198)	(0.545)	(0.360)	(0.548)	(0.000)	(0.091)	(0.518)	(0.091)
1996-1998	47.9	0.0	7.2	44.9	7.2	36.0	11.9	19.0	33.0	30.9
	(0.552)	(0.169)	(0.221)	(0.619)	(0.376)	(0.548)	(0.000)	(0.116)	(0.562)	(0.116)
1998-2000	48.5	0.3	2.9	48.3	3.3	34.9	13.9	16.6	34.6	30.5
	(0.719)	(0.254)	(0.229)	(0.846)	(0.469)	(0.681)	(0.123)	(0.076)	(0.752)	(0.167)
2000-2002	40.7	0.3	4.3	54.7	4.6	27.7	13.3	17.3	41.6	30.7
	(0.588)	(0.225)	(0.242)	(0.745)	(0.451)	(0.500)	(0.013)	(0.118)	(0.603)	(0.114)
2002-2004	37.5	0.1	6.1	56.3	6.2	24.9	12.7	18.7	43.7	31.4
	(0.519)	(0.177)	(0.203)	(0.603)	(0.365)	(0.481)	(0.001)	(0.110)	(0.514)	(0.110)
2004-2006	38.9	0.5	2.5	58.1	2.9	24.6	14.8	16.8	43.8	31.7
	(0.449)	(0.195)	(0.154)	(0.557)	(0.328)	(0.395)	(0.099)	(0.045)	(0.464)	(0.089)
2006-2008	35.2	8.2	0.1	56.5	8.3	22.9	20.6	12.4	44.1	33.0
	(0.345)	(0.164)	(0.127)	(0.428)	(0.276)	(0.338)	(0.097)	(0.007)	(0.380)	(0.093)
2008-2010	36.8	2.6	1.1	59.5	3.7	22.5	16.9	15.4	45.2	32.3
	(0.362)	(0.133)	(0.154)	(0.439)	(0.268)	(0.342)	(0.003)	(0.104)	(0.384)	(0.103)
2010-2012	33.6	0.0	6.1	60.3	6.2	20.6	13.0	19.1	47.3	32.0
	(0.597)	(0.235)	(0.283)	(0.756)	(0.497)	(0.508)	(0.000)	(0.157)	(0.602)	(0.157)

Notes: Bootstrapped standard errors in parenthesis (399 replications). Sample restricted to households with heads aged 25 to 64 years, in cohorts with at least 100 observations in each period. See Section **4.4** for a description of the variables included in the estimation of the income equation. Description of columns is the same presented in Table 3. Source: author's calculations using ENIGH data.

Table 5: *Estimates of poverty mobility based on (Dang et al., 2014)'s approach. Parametric estimates with $\rho_S = 0.3$ and $\rho_H = 0.7$. Model 3. (Percentages)*

Period	Lower Bound of Mobility					Upper Bound of Mobility				
	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]
1992-1994	42.7	17.3	1.5	38.5	18.8	38.2	21.8	6.0	34.1	27.7
	(0.646)	(0.214)	(0.061)	(0.701)	(0.240)	(0.647)	(0.259)	(0.119)	(0.721)	(0.347)
1994-1996	39.1	13.9	4.2	42.8	18.1	35.1	17.9	8.1	38.8	26.1
	(0.525)	(0.085)	(0.113)	(0.523)	(0.178)	(0.537)	(0.137)	(0.163)	(0.535)	(0.287)
1996-1998	42.9	5.1	12.2	39.8	17.3	38.6	9.3	16.5	35.6	25.8
	(0.544)	(0.079)	(0.137)	(0.580)	(0.192)	(0.545)	(0.133)	(0.186)	(0.602)	(0.302)
1998-2000	41.9	6.9	9.5	41.7	16.4	37.5	11.3	13.9	37.3	25.2
	(0.696)	(0.144)	(0.119)	(0.783)	(0.237)	(0.685)	(0.209)	(0.185)	(0.820)	(0.377)
2000-2002	34.7	6.4	10.4	48.6	16.7	30.3	10.7	14.7	44.3	25.4
	(0.536)	(0.119)	(0.138)	(0.664)	(0.226)	(0.511)	(0.182)	(0.200)	(0.712)	(0.362)
2002-2004	31.9	5.7	11.7	50.7	17.4	27.6	10.1	16.0	46.3	26.1
	(0.491)	(0.086)	(0.120)	(0.550)	(0.178)	(0.483)	(0.141)	(0.168)	(0.580)	(0.290)
2004-2006	31.9	7.5	9.5	51.1	17.0	27.3	12.1	14.1	46.5	26.2
	(0.418)	(0.119)	(0.083)	(0.501)	(0.162)	(0.402)	(0.163)	(0.124)	(0.534)	(0.261)
2006-2008	30.1	13.4	5.2	51.3	18.6	25.6	17.8	9.7	46.8	27.5
	(0.341)	(0.100)	(0.065)	(0.389)	(0.135)	(0.338)	(0.137)	(0.101)	(0.411)	(0.219)
2008-2010	30.0	9.5	7.9	52.6	17.4	25.3	14.1	12.6	48.0	26.7
	(0.349)	(0.073)	(0.095)	(0.401)	(0.132)	(0.343)	(0.108)	(0.129)	(0.423)	(0.213)
2010-2012	27.8	5.8	11.9	54.5	17.6	23.4	10.2	16.3	50.0	26.6
	(0.541)	(0.119)	(0.172)	(0.667)	(0.250)	(0.519)	(0.188)	(0.237)	(0.719)	(0.398)

Notes: Bootstrapped standard errors in parenthesis (399 replications). Sample restricted to households with heads aged 25 to 64 years, in cohorts with at least 100 observations in each period. See Section **4.4** for a description of the variables included in the estimation of the income equation. Description of columns is the same presented in Table 3. Source: author's calculations using ENIGH data.

differences are zero. For the upper bounds, only in one period (1996-1998) we can observe a significant difference; however, the largest differences are observed around periods of economic crisis, where the parametric estimates seem to be less sensitive to shocks than those obtained with the BGK's method.

In Figure 4, we compare the parametric estimates for the extreme theoretical values of $\rho \in [0,1]$ with those obtained with more realistic values ρ, i.e., when $\rho_S = 0.3$ and $\rho_H = 0.7$. As we can see, the interval between the lower (ρ_H) and upper bound (ρ_S) diminishes drastically, from around 10 percentage points when $\rho \in [0,1]$ (Figure 4a), to less than 5 percentage points when $\rho \in [0.3, 0.7]$ (Figure 4b). This suggests that, if the real value of ρ is within the interval $[0.3, 0.7]$ (which is the case in many countries surveyed in Cruces et al., 2014, Dang et al., 2014), we would expect that the observed mobility rates would be in a very narrow interval.

5.3 Contrasting methods

The results of Sections **5.1** and **5.2** let us address the first of our research questions, i.e., how different are the estimates obtained with the BGK's and the DLLM's methods. [31] For simplicity, in this section we will focus on the analysis of Model 3 (i.e., the specification explaining the higher proportion of the total income variation, as recommended by DLLM), and 10-year cohorts for the BGK's estimates (for which $\hat{\rho}$ do not result in extreme values for all cohorts). In addition, we use the same sample of households in all years, so that the only source of differences in these results is the estimation method.

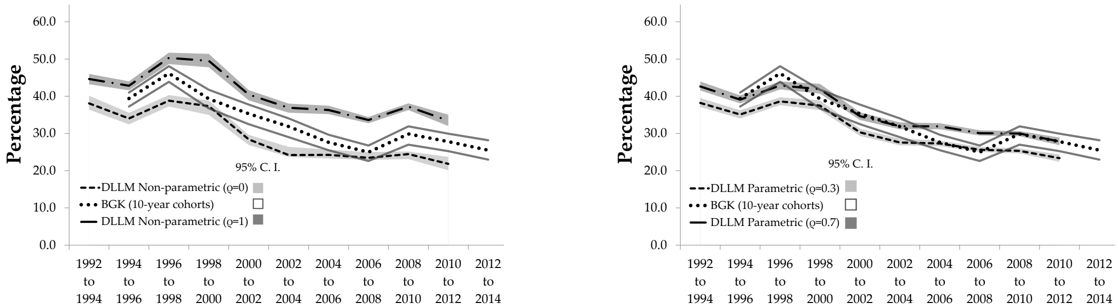
In Figure 5 we can see the BGK's method estimates of mobility, as compared with the non-parametric and parametric estimates using the DLLM's method. Figure 5 shows that all the BGK's method point-estimates are contained within the interval defined by the upper and lower non-parametric bounds of DLLM's approach. This indicates that, despite the different assumptions and procedures adopted by each method, both pseudo-panel approaches yield similar conclusions.

[31] It is important to note that the time scale of both estimates is different. In the BGK's approach, the calculation of $\hat{\rho}$ and $\hat{\sigma}^2_{\epsilon t}$ requires at least one lag of the residuals from equation 3. Thus, we cannot produce estimates for the first transition (1992-1994) using the BGK's method; however, it is possible to *forecast* the first transition *outside* the sample (e.g., 2012 to 2014). In contrast, the DLLM's approach uses pairs of RCS, so that we can obtain estimates for the first transition (1992 to 1994), but cannot generate estimates beyond the period covered by the RCS (i.e., we cannot calculate figures for 2012-2014).

Figure 5: *Comparison of the poverty persistence estimates using Dang et al. (2014) and Bourguignon et al. (2004)'s approaches. Model 3.*

(a) *DLLM's non-parametric bounds and BGK's 10-year cohorts estimates.*

(b) *DLLM's parametric bounds $\rho \in [0.3, 0.7]$ and BGK's 10-year cohorts estimates.*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details). Poverty persistence refers to proportion of households identified as poor in period t, that are expected to be in poverty in $t+1$. The non-parametric upper bound estimates use 500 random draws of $\tilde{e}_{it}^{t+1}$ (see Section **3** for details). For comparative purposes, the sample is the same used to obtain BGK estimates. See Table 1 for details of the sample and the specification of the income equation models. Source: author's calculations using ENIGH data.

In the case of the DLLM's parametric approach, Figure 5b exhibit the poverty persistence estimates when $\rho \in [0.3, 0.7]$ and those of the BGK's method. In this case, the BGK's method estimates are situated within the range defined by the DLLM's method (with the exception of 1996-1998). In fact, the BGK's method estimates are closer in magnitude to those obtained with the DLLM's method when $\rho = 0.7$; while a low value of ρ (e.g., $\rho = 0.3$) is associated to marked differences between methods (specially at the beginning and the end of the period). These results not only confirm the relevance of the correlation parameter to assess the differences between methods, but also confirm that both methods provide similar levels of mobility. Indeed, in most periods the confidence intervals intersect, the significant differences being associated with periods of economic crisis (when the BGK's method usually produces higher levels of immobility).

The last refinement of the DLLM's method consists in estimating the parametric transition rates using a value of ρ obtained from panel data, either available for panel data from other period or from other countries. Hence we use the MxFLS to approximate the value of the correlation parameter for our RCS data. Furthermore, the longitudinal information can be used to directly compare the pseudo-panel estimates with those from a true panel. In the following section we provide this analysis, calling attention upon the several problems that arise in the comparison of two different sources of information.

5.4 Comparing the panel and pseudo-panel estimates

5.4.1 The value of ρ

The information available in the MxFLS can be used to estimate $\hat{\rho}$ and assess the pseudo-panel poverty mobility estimates. However, as mentioned before, a comparison involving two different sources of information entails adopting several assumptions to harmonise their discrepancies. In particular, although both our cross-sectional and longitudinal data have the same underlying population, income data in the panel survey was collected collected using a different and less detailed questionnaire, which results in poverty headcount rates substantially different to those of the RCS (see Table A.5).[32]

On one hand, the gap between rounds of the MxFLS is uneven and different to that used in the ENIGH, which could affect the calculation of ρ (which we would expect to be higher over shorter periods of time). As a first step, given our information constraints, we propose to compare the MxFLS information with that of the closer round of the cross-sectional data, specifically the one closest to the year where MxFLS's income data was collected, so we compare the MxFLS 2005-2006 with the ENIGH 2006 and the MxFLS 2009-2010 with the ENIGH 2010 (since 61 percent of the MxFLS's income data was collected in 2009 and 32 percent in 2010).

On the other hand, income information in the panel is considerably different to that of the cross-sections. Although the construction of the income variable in the panel followed closely the income definition used for the RCS, the income distribution in the MxFLS has lower means and higher variances than those observed in the ENIGH. Hence, we transform the MxFLS's income data, so as to have the same first and second order distribution moments in the "comparable" rounds of both data sets, without modifying the household's order.

Using the adjusted income, $\tilde{y}_{it}$, it is possible to estimate $\hat{\rho}^L$, the longitudinal estimate of ρ. To do so, we first estimate by OLS income equations for each year analogous

[32] This discussion is closely related to problems arising from measurement error, to which longitudinal information is particularly susceptible (Antman & McKenzie, 2007a,b, Deaton, 1985); although this is a relevant area of research, in this document we do not focus our attention to corrections of these issues.

Table 6: *Observed correlations in the MxFLS data from 2002 to 2005-2006 and from 2005-2006 to 2009-2012.*

Period	2002 to 2005-2006		2005-2006 to 2009-2012	
Income[a]	0.466		0.432	
	(0.443	0.489)	(0.408	0.456)
Residuals				
I. Unadjusted data				
Model 1	0.271		0.291	
	(0.243	0.298)	(0.264	0.318)
Model 2	0.207		0.238	
	(0.179	0.235)	(0.210	0.266)
Model 3	0.164		0.209	
	(0.135	0.192)	(0.180	0.237)
II. Adjusted[b]				
Model 1	0.278		0.262	
	(0.246	0.309)	(0.230	0.294)
Model 2	0.226		0.218	
	(0.193	0.258)	(0.185	0.251)
Model 3	0.184		0.195	
	(0.151	0.217)	(0.162	0.228)
III. Two-year intervals[c]				
Model 1	0.426		0.512	
	(0.393	0.457)	(0.479	0.542)
Model 2	0.371		0.467	
	(0.334	0.406)	(0.430	0.501)
Model 3	0.324		0.442	
	(0.284	0.361)	(0.402	0.478)

Notes: 95% confidence intervals in parenthesis calculated by using Fisher's z-transform. Sample restricted to households with heads aged between 25 and 64 years old in 2002 with observations in the three rounds (balanced panel, N=4,453). Longitudinal sampling weights used to correct for attrition bias. a. Refers to monthly current per capita income in 2012 prices. b. MxFLS income adjusted to have the same mean and variance as that observed in ENIGH 2002 for MxFLS 1, ENIGH 2006 for MxFLS 2 and ENIGH 2012 for MxFLS 3. c. Calculated using the formula $\hat{\rho}^a = \hat{\rho}^{1/T}$ and adjusting to a two-year period as $\hat{\rho}^{a2}$ (see Section **5.4** for further details). Source: author's calculations using ENIGH and MxFLS data.

to those in equations 1 or 7.[33] Using the estimates of these equations, we use their residuals, $\tilde{e}_{it+1}$ to calculate ρ from both $\tilde{y}_{it}$ and $\tilde{e}_{it}$ as $Corr(\tilde{y}_{it}, \tilde{y}_{it+1})$ (the income correlation parameter) or $Corr(\tilde{e}_{it}, \tilde{e}_{it+1})$ (the persistence of shocks parameter). Table 6 shows these two correlations for the three specifications of the income equation defined in Section **4**, and for the two periods for which panel data is available: 2002 to 2005-2006 and 2009-2012.

The correlations in Table 6 correspond to different periods of time, so that we can

[33] Table A.2 provides descriptive statistics of the variables used to estimate these models, which are essentially the same used for the cross-sectional data. It is relevant to note that, although most variables have similar patterns in both the cross-sectional and longitudinal data sets, there are marked differences in at least two variables: the proportion of households living in rural areas and the proportion of informal workers. See Appendix **A.1** for definitions of the variables.

use them as a lower bound of the correlations that would be expected if panel data were available with higher frequencies.[34] Alternatively, if we assume a first order autoregressive model, as in equation 2, we can estimate the value of ρ for annual data as $\hat{\rho}^a = \hat{\rho}^{1/T}$, where $\hat{\rho}^a$ is the income correlation over consecutive years and T is the number of years between surveys. Panel III of Table 6 shows the correlations adjusted for periods of two years.

As shown in Table 6, the confidence interval of the BGK's approach $\hat{\rho}$ (see Table 1) overlaps with that observed in the panel data, once adjusting for the differences in time intervals. In spite of the high inaccuracy of the BGK's method $\hat{\rho}$, it is relevant to note that they can provide a general indication about the magnitude of this parameter, which is particularly relevant in contexts where no panel data exists at all.

5.4.2 Poverty transitions rates

The adjusted income described in the last section, $\tilde{y}_{it}$, can be used to estimate the poverty transitions matrix from 2002 to 2005-2006 and from 2005-2006 to 2009-2012. Table 7 shows these estimates for both the adjusted and unadjusted income described in the previous section. Once more, the interval differences between data sets prevent a straight-forward comparison with the mobility estimates presented before.[35]

The sources of error already identified may potentially bias any conclusion derived from a direct comparison of these estimates. Given the limitations of our data, even adopting the assumptions described in Section **5.4**.1, we cannot compare directly our pseudo-panel estimates with those from the adjusted panel. However, given the relevance of this exercise, we present the corresponding figures as our best approximation to what could be expected with comparable panel data. Still, any conclusion derived from this analysis shall be taken with caution.

Under these considerations, the observed transition rates in the panel data may be seen as a proxy of the short-run mobility estimates between rounds of the RCS data. Thus, we compare the panel mobility estimates between 2002 and 2005-2006 with the pseudo-panel estimates for 2002-2004 and 2004-2006, and the panel mobility

[34]This assumes that the correlation of income decreases over time, so that the longer the interval between consecutive survey waves, the lower the correlation.

[35]If we assume that movements in and out of poverty follow a Markov chain process, it may be possible to obtain an approximation to the expected transition rates for any desired period (Rendtel et al., 1998). However, such analysis is beyond the scope of this research.

Table 7: *Observed transitions into and out of poverty in the MxFLS: 2002 to 2005-2006 and 2005-2006 to 2009-2012.*

	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]
I. Unadjusted data					
2002 to 2005-2006	45.9	13.1	17.5	23.5	30.6
	(1.060)	(0.628)	(0.855)	(0.970)	(0.973)
2005-2006 to 2009-2012	49.5	14.0	17.2	19.4	31.1
	(1.070)	(0.743)	(0.807)	(0.864)	(0.991)
II. Adjusted					
2002 to 2005-2006	30.5	20.6	12.7	36.2	33.3
	(0.959)	(0.798)	(0.735)	(1.065)	(0.984)
2005-2006 to 2009-2012	28.7	14.5	18.6	38.3	33.1
	(0.947)	(0.756)	(0.798)	(1.059)	(0.993)
III. Adjusted (80% of poverty line)[f]					
2002 to 2005-2006	24.2	21.1	12.5	42.2	33.6
	(0.892)	(0.798)	(0.736)	(1.075)	(0.984)
2005-2006 to 2009-2012	22.8	13.9	19.4	43.9	33.3
	(0.876)	(0.758)	(0.805)	(1.070)	(0.996)

Notes: Robust standard errors in parenthesis. Sample restricted to households with heads aged between 25 and 64 years old in 2002 with observations in the three waves (balanced panel, N=4,453). [a] Proportion of households identified as poor in both t and $t+1$. [b] Proportion of households identified as poor in t, but non-poor in $t+1$. [c] Proportion of households identified as non-poor in t, but poor in $t+1$. [d] Proportion of households identified as non-poor in both t and $t+1$. [e] Proportion of households with either upward or downward mobility. [f] Use 80 percent of the value of the income poverty line. I. Refers to monthly current per capita income (as defined in Székely (2005b)) in prices of 2012. II. MxFLS income adjusted to have the same mean and variance as that observed in ENIGH 2002 for MxFLS 1, ENIGH 2006 for MxFLS 2 and ENIGH 2012 for MxFLS 3. Source: author's calculations using ENIGH and MxFLS data.

rates between 2005-2006 and 2009-2012 with the pseudo-panel estimates for 2006-2008 and 2008-2010.

Table 7 reports the estimates of the poverty transitions rates calculated with panel data. In spite of the limitations already mentioned, it is noteworthy that most of the results shown in Panel II of Table 7 (corresponding to the adjusted income estimates) lie within the range defined by the DLLM's upper and lower bounds of mobility, either for the non-parametric or the parametric bounds. In addition, the persistence rates obtained with the BGK's method lie within the confidence interval of the panel estimates.

In contrast, all the pseudo-panel estimators yield non-poverty persistence rates larger than those estimated with the panel data. One possible explanation for this result is that the poverty rates in the panel data are larger than in the RCS, even after correcting for the mean and variance of the income distribution. In the case of the upward and downward mobility rates, the results are mixed; but in many cases the upward mobility rate in the pseudo-panel model seems to be underestimated, while the downward mobility appears to be closer to the levels observed in the panel data.[36]

5.4.3 Improving the pseudo-panel estimates

A final refinement of the pseudo-panel estimates follows a suggestion by DLLM, who suggest using a value of ρ obtained from suitable longitudinal information, ρ^L. This value can be used then to estimate the parametric point-estimates of mobility. In this sense, we employ $\hat{\rho}^L$ (introduced in the previous section) to evaluate the elements in M^D. Table 8 shows the parametric point-estimates of mobility using Model 3 and $\hat{\rho} = 0.442$ (from Table 6).[37] Figure 6 compares these estimates to the BGK's calculations (using Model 3 and 10-year cohorts), and the panel mobility rates.

As observed in Figure 6, using $\hat{\rho}$ from panel data, in most periods the differences between the BGK's and the DLLM's estimates are not statistically significant. In particular, from 2002-2004 both estimates fall within each other's confidence interval, being the differences more relevant in the early years. In addition, contrasting these estimates with the panel poverty persistence rates (with the limitations already described); the confidence interval of both pseudo-panel methods intersects with those of the panel estimates.

It is relevant to note as well that the BGK's method estimates seem to be more sensitive to fluctuations in the economic cycle (as evidenced by the peaks in 1996-1998 and 2008-2010, see Figure 6), while those obtained with the DLLM's approach tend to provide smoother dynamics. Although DLLM's point-estimates have narrower confidence intervals, they require a good guess of $\hat{\rho}$, which may not be available in all settings. However, the non-parametric and parametric bounds in our case do seem to enclose the observed transition rates. These results suggest that it is possible to obtain a useful approximation to the longitudinal value of $\hat{\rho}$, even in contexts with few rounds of RCS.

[36] As an *exploratory exercise*, we set the poverty line at 80 percent of its value, so that the panel poverty rates are very similar to those in the cross-sections (see Table A.5) and compute again the mobility rates (see panel III of Table 7). Despite the additional adjustment, the non-poverty persistence rates obtained with both methods fall again outside the confidence interval for the panel estimate.

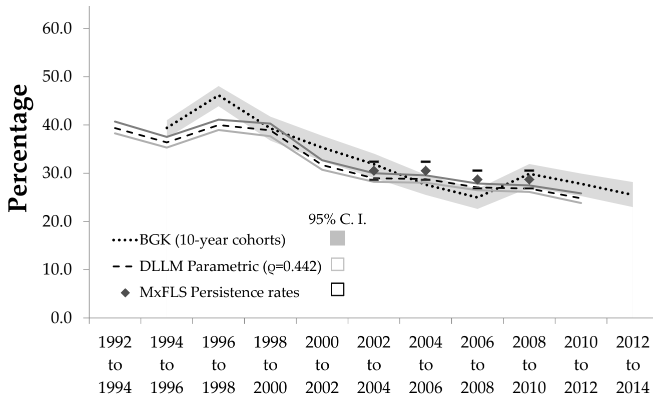
[37] In this case, we use the two-year estimate of the annualised $\hat{\rho}$, selecting $\hat{\rho}_{2005-2006to2009-2012}$ as the relevant correlation term over the period. The selection of $\hat{\rho}_{2005-2006to2009-2012}$ does not follow a particular criteria, we choose a value roughly resembling the mean value of $\hat{\rho}$ in panel III of Table 6. However, using other values provides similar conclusions.

Table 8: *Estimates of poverty mobility based on (Dang et al., 2014)'s approach. Parametric estimates with* $\rho = 0.442$. *Model 3. (Percentages)*

Period	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]
1992-1994	39.4	20.6	4.8	35.2	25.4
	(0.647)	(0.258)	(0.117)	(0.721)	(0.345)
1994-1996	36.4	16.6	6.9	40.1	23.5
	(0.537)	(0.136)	(0.162)	(0.534)	(0.285)
1996-1998	40.0	8.0	15.1	37.0	23.1
	(0.544)	(0.132)	(0.185)	(0.601)	(0.300)
1998-2000	38.9	9.9	12.5	38.7	22.4
	(0.685)	(0.208)	(0.183)	(0.819)	(0.374)
2000-2002	31.7	9.3	13.3	45.6	22.7
	(0.512)	(0.181)	(0.198)	(0.711)	(0.359)
2002-2004	29.0	8.7	14.6	47.7	23.3
	(0.483)	(0.139)	(0.167)	(0.579)	(0.287)
2004-2006	28.8	10.6	12.6	48.0	23.2
	(0.404)	(0.159)	(0.119)	(0.530)	(0.251)
2006-2008	27.1	16.4	8.3	48.3	24.7
	(0.338)	(0.133)	(0.097)	(0.409)	(0.210)
2008-2010	26.8	12.6	11.1	49.5	23.7
	(0.344)	(0.104)	(0.125)	(0.420)	(0.205)
2010-2012	24.8	8.8	14.9	51.5	23.7
	(0.520)	(0.181)	(0.230)	(0.713)	(0.383)

Notes: Bootstrapped standard errors in parenthesis (399 replications). Sample restricted to households with heads aged 25 to 64 years, in cohorts with at least 100 observations in each period. The value of $\rho = 0.442$ comes from Table 6. Description of columns is the same presented in Table A.3. Source: author's calculations using MxFLS and ENIGH data.

Figure 6: *Comparison of the poverty persistence rates based on Bourguignon et al. (2004) and Dang et al. (2014)'s methods.*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details). Bourguignon et al. (2004)'s estimates obtained using 10-year cohorts and Model 3 (see Table 6 for details). Dang et al. (2014)'s estimates use the two-year estimate of the annualised $\hat{\rho}$, selecting $\hat{\rho}_{2005-2006to2009-2012}$ as the relevant correlation term (refer to panel III of Table 6). The MxFLS Persistence rates correspond to those reported in Panel II of Table 7. Source: author's calculations using ENIGH and MxFLS data.

In spite of the similarities between the pseudo-panel and panel estimates of the poverty persistence rates, other mobility rates have important discrepancies. In particular, the rates of non-poverty persistence, which are appreciably higher with the pseudo-panel methods. It is unclear, however, if this is due to problems in the data (e.g., the questionnaire, measurement error, or attrition bias), or issues associated with the pseudo-panel methodologies. The similarities between the pseudo-panel approaches and the panel estimates suggest that as much as 30 percent of the population moves in and out of poverty over short periods of time, which is consistent with previous results by Antman & McKenzie (2007a,b).

In addition, our estimations suggest that the non-poverty persistence rates have increased over the period—although slowly—and by 2012 they already were in similar levels to those observed before 2008. However, the growth of the non-poverty persistence rates has been insufficient to reduce the general poverty rates and, as a result of this trend, the predicted share of the population moving in and out of poverty seems to have increased over the last decade.

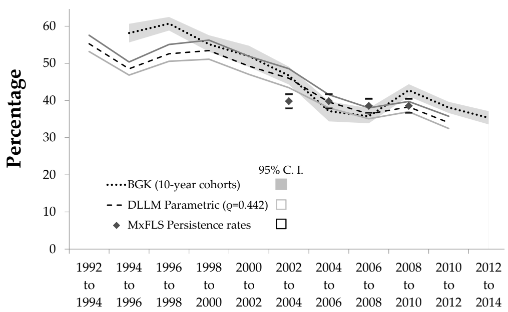
In this context, pseudo-panel methods can become a powerful diagnostic tool to provide short-term assessments of the dynamics of poverty, that is easy to update when new cross-sectional data become available. In the next section, we show how several groups of the population differ in terms of their poverty mobility rates, so as to provide a first approximation to the heterogeneity of poverty dynamics in the Mexican population.

6. Subgroup analysis

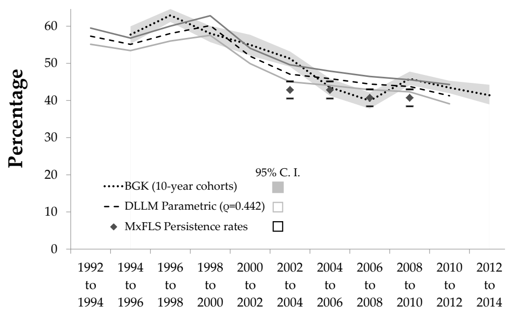
The results of the previous section provide a 20-year perspective of the dynamics of poverty in Mexico. However, the aggregate trends may hide important social heterogeneities in terms of how persistent are the experiences of poverty for certain groups or individuals, or how likely they are to fall or escape successfully from this condition. In this section, we estimate the rates of poverty persistence for some groups of the population that traditionally have been considered of interest for social policy: households in rural or remote areas, individuals with low levels of formal education,

Figure 7: *Poverty persistence rates in households living in rural areas or with low levels of formal education. Estimates based on Bourguignon et al. (2004) and Dang et al. (2014) methodologies.*

(a) *Communities with less than 15,000 inhabitants (rural areas).*



(b) *Household head never attended school or have less than primary school.*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details). Bourguignon et al. (2004)'s estimates obtained using 10-year cohorts and Model 3 (see Table 6 for details). Dang et al. (2014)'s estimates use the two-year estimate of the annualised $\hat{\rho}$, selecting $\hat{\rho}_{2005-2006to2009-2012}$ as the relevant correlation term (refer to panel III of Table 6). The MxFLS Persistence rates correspond to those reported in Panel II of Table 7. Source: author's calculations using ENIGH and MxFLS data.

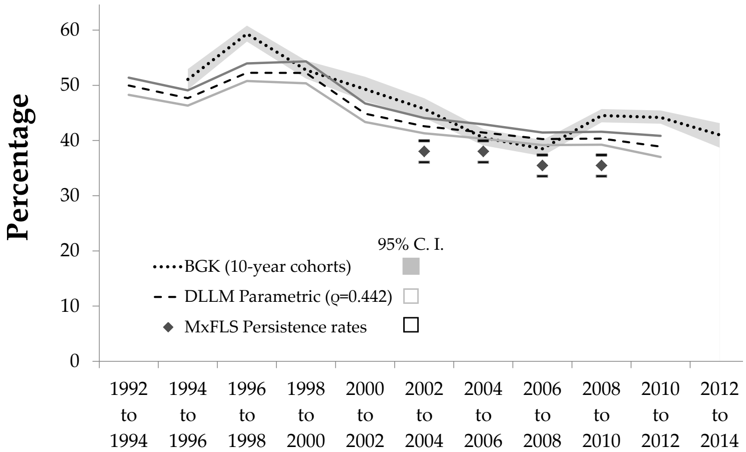
families with children, and workers in the informal sector or self-employed.[38] In addition, we explore geographical variations, comparing the poverty dynamics of the population living in the south and north of the country. We present mobility estimates using the BGK's method (using Model 3 of the income equation and 10-year cohorts), as well as the DLLM's parametric approach (with $\rho = 0.422$, obtained from Table 6). As reference, we also present the poverty mobility rates estimated with panel data. However, we should keep in mind the considerations mentioned before.

The main objective of this exercise is to show the flexibility and limitations of the pseudo-panel methods to measure poverty mobility in different settings. Thus, in this section we only provide a short description of the main trends for each group; we also point out the most relevant differences with respect to the national trends, and the other groups under analysis. For simplicity, we focus on the poverty persistence rate; however, the whole set of mobility estimates is available upon request. [39]

[38] In this exercise we use household-level information, so that we use the characteristics of the household's head as reference in the analysis of individual traits. See Appendix **A.1**

[39] Appendix **A.1** provides details of the definitions of these variables, and Table A.1 includes the corresponding descriptive statistics. Table A.6 shows the cross-sectional poverty rates for each group.

Figure 8: *Poverty persistence rates among households with children (0 to 11 years old). Estimates based on Bourguignon et al. (2004) and Dang et al. (2014) methodologies.*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details). Bourguignon et al. (2004)'s estimates obtained using 10-year cohorts and Model 3 (see Table 6 for details). Dang et al. (2014)'s estimates use the two-year estimate of the annualised $\hat{\rho}$, selecting $\hat{\rho}_{2005-2006 to 2009-2012}$ as the relevant correlation term (refer to panel III of Table 6). The MxFLS Persistence rates correspond to those reported in Panel II of Table 7. Source: author's calculations using ENIGH and MxFLS data.

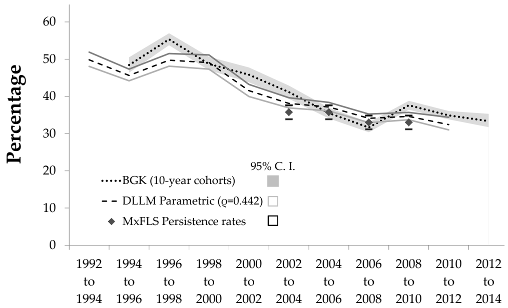
6.1 Rural areas, education and children

Figure 7a shows the poverty persistence estimates for the population living in rural areas (i.e., in communities with less than 15,000 inhabitants). In the case of this group, both pseudo-panel methods suggest that, from 1992-1994 to 2002-2004, the poverty persistence rates were close to 50 percent. However, between 1998-2000 and 2004-2006 the poverty persistence rates decreased faster than in all the other groups, although the reason for that reduction is not clear. However, after 2004-2006, the poverty persistence rates have stabilised around a value of 40 percent, which is still far larger that that of the general population (approximately 30 percent).

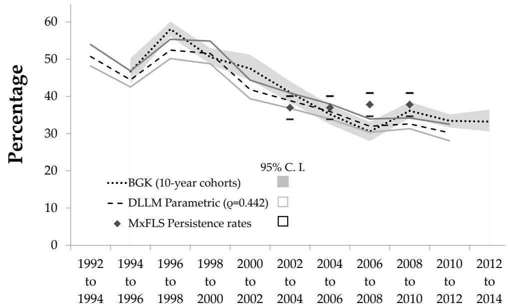
The population living in households whose heads did not finish primary school, or never studied at all, is the group with the highest rates of poverty in our analysis (see Table A.6). In addition, this group presents the highest rates of poverty persistence, as shown in Figure 7b. In the 1990's, these households had poverty persistence rates close to 70 percent, but in the early years of the 2000's their poverty persistence rates slowly started to decrease. However, unlike the trends observed in rural areas, the reduction in the poverty persistence rates for these households has been quite modest. By 2012, the proportion of this population living in poverty and expected to remain

Figure 9: *Poverty persistence rates among households with heads self employed or working in the informal sector. Estimates based on Bourguignon et al. (2004) and Dang et al. (2014) methodologies.*

(a) *Households with heads who work, but do not have access to social security through their job (informal workers).*



(b) *Households with heads who work on their own business, have people on their charge or are independent professionals.*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details). Bourguignon et al. (2004)'s estimates obtained using 10-year cohorts and Model 3 (see Table 6 for details). Dang et al. (2014)'s estimates use the two-year estimate of the annualised $\hat{\rho}$, selecting $\hat{\rho}_{2005-2006 to 2009-2012}$ as the relevant correlation term (refer to panel III of Table 6). The MxFLS Persistence rates correspond to those reported in Panel II of Table 7. Source: author's calculations using ENIGH and MxFLS data.

poor was about 50 percent.

Among households with children aged 0 to 11 years old< the poverty persistence rates are similar to those of the general population. Even so, the poverty persistence rates for these households are significantly higher than the national trend (see Figure 8). For households with children, the poverty persistence rates calculated with panel data were of about 38 percent, whilst those for the general population were of approximately 30 percent. In the case of the pseudo-panel estimates, while the poverty persistence rates of these households were close to 40 percent: 10 percentage points higher than the national figures in most years. The higher poverty persistence rates found in households with children suggest that these households may be facing vulnerabilities specific to child bearing, not reflected in the static poverty headcount rates.

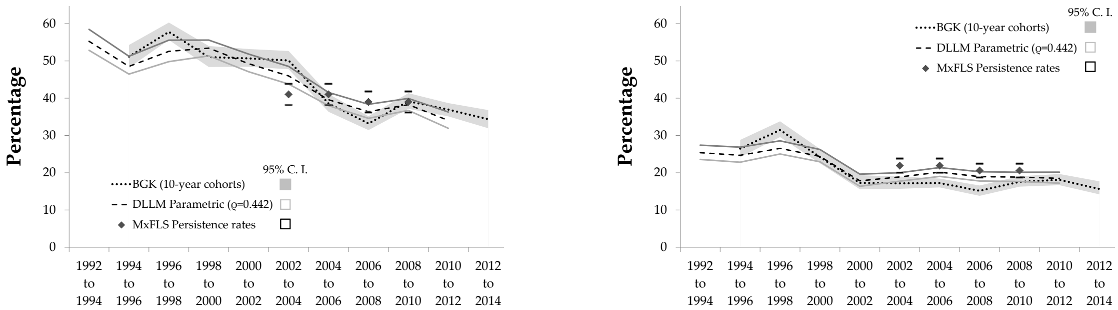
6.2 Labour market characteristics

In a different perspective, we study how the labour market characteristics of the household head correlate with different trends of poverty dynamics. We study two of these characteristics: work in the informal sector and self-employment.[40] As shown in Ta-

[40]Refer to Appendix **A.1** for definitions of the variables used in the analysis.

Figure 10: *Poverty persistence rates among households in the south and north of the country. Estimates based on Bourguignon et al. (2004) and Dang et al. (2014) methodologies.*

(a) *Population in southern states of Mexico.* **(b)** *Population in northern states of Mexico.*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details). Southern states: Campeche, Chiapas, Guerrero, Oaxaca, Puebla, Quintana Roo, Tabasco, Veracruz de Ignacio de la Llave y Yucatán. Northern states: Baja California, Baja California Sur, Coahuila de Zaragoza, Chihuahua, Durango, Nuevo León, Tamaulipas, Sinaloa and Sonora. Bourguignon et al. (2004)'s estimates obtained using 10-year cohorts and Model 3 (see Table 6 for details). Dang et al. (2014)'s estimates use the two-year estimate of the annualised $\hat{\rho}$, selecting $\hat{\rho}_{2005-2006 to 2009-2012}$ as the relevant correlation term (refer to panel III of Table 6). The MxFLS Persistence rates correspond to those reported in Panel II of Table 7. Source: author's calculations using ENIGH and MxFLS data.

ble A.6, both kinds of households are characterised by higher levels of poverty than those of the general population. Figures 9a and 9b introduce the poverty persistence rates for these households.

As shown in Figures 9a and 9b, these groups exhibit similar trends of poverty persistence, with markedly higher poverty persistence rates than those of the general population. However, although the differences are not as prominent as those observed for rural areas, or households with low levels of formal education. Even though, in recent years that difference has shrunk, and in recent years the confidence intervals have started to intersect. The main difference between these groups is the width of the confidence interval for households with self-employed heads, which reflects the higher income heterogeneity in this group. These results are consistent with previous studies suggesting that workers in the informal sector, or self-employed, are more likely to have lower remunerations and job quality, affecting their chances to transit towards a formal or better paid job (Bargain & Kwenda, 2011, Gong et al., 2004).

6.3 Geographical variation

Regional variations, such as those associated with the access to infrastructure or economic activity, can be reflected as well in contrasting dynamics of poverty. Figures 10a and 10b show the poverty persistence rates for the population living in southern and northern states of Mexico. [41] Whilst states in the north of the country have low and stable levels of poverty persistence (around 20 percent, as shown in Figure 10b); in the south, more than 50 percent of the population was identified as poor and expected to remain poor in 2010-2012, a level similar to that of rural areas.

7. Concluding remarks

In this paper we use recent methodological developments to investigate the dynamics of poverty in Mexico over a 20-year period. In recent years, a number of studies have provided relevant insights in this area, but most of these have used short panels or with few waves of information. We contribute to this discussion providing a medium-term perspective of the magnitude of the movements in and out of poverty in Mexico, taking advantage of a series of repeated cross-sections, nationally-representative and comparable, from 1992 to 2012.

Although this is a relatively new area of research, the literature already offers several approaches to estimate pseudo-panel measures of poverty mobility. However, different assumptions and requirements of information create considerable complication to compare the different methods, so that it is unclear under which conditions one should be preferred over other. Thus, from a methodological point of view, it is relevant to investigate further the differences between these methods, as well as the conditions where their estimates converge or differ.

We use two pseudo-panel methods, Dang et al. (2014) and Bourguignon et al. (2004), which are the most frequently referred in the literature. Although each of these approaches have already been validated and applied in previous studies, to our knowledge there is only one other study, by Fields & Viollaz (2013), that has directly compared their results. Thus, we estimate and compare the poverty mobility rates with each method, and then we compute bootstrapped standard errors and confidence intervals to assess the differences between these approaches.

Our findings suggest that the income correlation parameter is a key element to understand the differences between pseudo-panel methods. However, using a similar

[41] Southern states: Campeche, Chiapas, Guerrero, Oaxaca, Puebla, Quintana Roo, Tabasco, Veracruz de Ignacio de la Llave y Yucatán. Northern states: Baja California, Baja California Sur, Coahuila de Zaragoza, Chihuahua, Durango, Nuevo León, Tamaulipas, Sinaloa and Sonora.

correlation parameter results in analogous conclusions about poverty mobility with both methods. Unlike Fields & Viollaz (2013), we find that using a relatively large number of waves of RCS data, it is possible to obtain an estimate of ρ reasonably similar to that calculated with panel data. Even though, the large magnitude of the pseudo-panel $\hat{\rho}$'s standard errors may indicate the existence of small sample problems (due to a reduced number of RCS). Another considerable source of differences is the sensitivity to shocks in the economic cycle, as the biggest differences between methods occur in periods of economic turmoil. However, in most cases the estimations of both methods are not statistically different from each other.

In addition, most applications of these pseudo-panel methodologies have either used panel data (treating them as cross-sections), or only the repeated cross-sectional data. The first case is useful, as it allows the comparison of the observed and estimated mobility rates with the same sample and quality of information, albeit in many applications the main source of information would be exclusively the repeated cross-sections (the second case). Thus, it is relevant to explore if pseudo-panel estimates obtained only with cross-sectional data can produce mobility estimates similar to those of a true panel.

Although the comparison of two different sources of information requires addressing several possible causes of discrepancies between surveys (such as sampling strategies, questionnaire design, frequency of the information, and so forth), we propose a series of assumptions to harmonise the cross-sectional information with the longest and most comprehensive panel study in the country. Under these assumptions, our results suggest that the pseudo-panel methods have the potential to produce poverty persistence figures similar to the ones observed with panel data (even if they apparently over-estimate the rates of non-poverty persistence). Even so, further research is required to provide a direct comparisons of these estimates.

Although pseudo-panel methods do not provide the richness of information usually available in longitudinal surveys, our findings suggest that pseudo-panel methods can be used to provide diagnostics of the trends of poverty mobility, which is of particular interest for policy analysis, as cross-sectional information is usually available for longer periods of time, with higher frequency and with bigger sample-sizes than typical panel surveys. In particular, countries where cross-sectional data is the only or most frequent source of information, pseudo-panel methods may be used to readily generate short-term assessments of the dynamics of poverty.

From a substantive point of view, our results indicate that a large proportion of the Mexican population change of poverty status over short periods, despite the apparent stability of the overall poverty headcount rates. These findings, in combination with the modest changes in the levels of poverty shown in Figure 1, suggest that an increasing fraction of the population are able to move out of poverty, but are unable to remain out of it. This result calls attention to the design of specific policies to protect this population , although further research is needed on better strategies to achieve this end.

Finally, we find evidence of clear differences between groups of the population usually considered in higher risk of poverty (such as households with low levels of human capital or in rural areas). Although the all the studied groups have similar patterns of poverty mobility, the pace and magnitude of the mobility rates differs significantly. In households with low levels of human capital, the pace of reduction of the poverty persistence rate seems to be far slower than for the other groups. In contrast, the population in households with children under 12 years old presents poverty rates similar to the general population, but their estimated poverty persistence rates are more than 10 percentage points larger. In contrast, the population in the north of the country have significantly lower persistence rates, stable over most of the period of analysis. These results suggest that recognising the specificities and characteristics of the dynamics of poverty of different groups can significantly contribute to define appropriate policies to improve the poverty alleviation efforts oriented to these populations.

This is the first analysis of its kind to provide a medium-term perspective on the evolution of poverty persistence and the magnitude of movements in and out of poverty in Mexico. Our results show that the analysis of poverty dynamics can contribute with significant insights to improve the social policy design, highlighting priority areas for policy makers (the population moving in and out of poverty), as well as the heterogeneity behind the national trends. In this context, pseudo-panel methods can become a powerful diagnostic tool to provide short-term assessments of the dynamics of poverty.

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A. Appendices

A.1 Variables definition

In this appendix we present the definition of all the variables considered in the estimation of equations 1 and 7.

Access to water service: Dummy variable identifying with value 1 those households with access to water from the public service, either in or outside the property, and 0 otherwise.

Age: Age declared at the time of the interview.

Computer: Dummy variable identifying with value 1 those households who have a computer, and 0 otherwise.

Dirt floors: Dummy variable identifying with value 1 those households in dwellings with dirt floors, and 0 otherwise.

Educational level: Categorical variable indicating the maximum educational level of the household head in five groups: less than full primary school (control category), full primary school or incomplete secondary school, full secondary school or incomplete high-school, full high-school or incomplete college, and college or higher.

Fridge: Dummy variable identifying with value 1 those households who own a fridge or other electronics, and 0 otherwise.

Income: Per capita current income (see). All monetary values are expressed in constant prices of 2012.

Informal sector worker: Dummy variable identifying with value 1 the household heads who work, but do not receive health services as a job benefit, and 0 otherwise.

Labour force participation: Dummy variable identifying with value 1 the household heads who worked at least one hour the week prior to the interview or had a job but did not work, and 0 otherwise.

Literacy: Dummy variable identifying with value 1 the household heads who cannot read or write a message, and 0 otherwise.

Locality size: Dummy variable identifying with value 1 those households in localities with less than 15,000 inhabitants, and 0 otherwise.

Marital status: Dummy variable identifying with value 1 those household heads who are married or partnered, and 0 otherwise.

North, states in the north of Mexico: Baja California, Baja California Sur, Coahuila de Zaragoza, Chihuahua, Durango, Nuevo León, Tamaulipas, Sinaloa and Sonora.

Number of children in the household: Number of children (0 to 12 years old) in the household.

Number of rooms: Number of rooms in the dwelling.

Per capita current income: Corresponds to division of the total current income of the household to the number of individuals in the household. The total current income of the household is the sum of the income of all household members from the the following sources: labour income, self-consumption, rent of property and dividends, in-kind payments and transferences, gifts and imputed rent of the dwelling. All monetary values are expressed in constant prices of 2012.

Self-employment: Dummy variable identifying with value 1 households where the head work in her own business, have people in her charge or is an independent professional, and 0 otherwise.

Sex: Dummy variable identifying with value 1 if the head of the household is a female, and 0 otherwise.

South, states in the south of Mexico: Campeche, Chiapas, Guerrero, Oaxaca, Puebla, Quintana Roo, Tabasco, Veracruz de Ignacio de la Llave y Yucatán.

Vehicles: Dummy variable identifying with value 1 if the household has a vehicle (car, truck, motorcycle), and 0 otherwise.

All estimations include, in addition, state-level fixed effects and the following characteristics of the municipality according to Census data (2000):

Indigenous population: Percentage of the population who speaks an indigenous language in the municipality.

Vehicles: Percentage of the population in households who own a vehicle (car, truck or motorcycle) in the municipality.

Post-primary school education: Percentage of the population with education beyond primary school in the municipality.

High earnings: Percentage of the population who earns 10 times or more the minimum wage in the municipality.

A.2 Inference

The pseudo-panel methods described in Section **3** rely on the combination of multiple estimates, obtained in several steps. This makes particularly difficult to find a tractable expression for the variance of each of these estimators. In order to make statistical inference, we use bootstrap sampling methods as described in Cameron & Trivedi (2005). Using the estimation sample for each year, we obtained B bootstrap sampling weights, which we used to estimate the whole set of parameters. We use $B = 399$ as suggested by (Davidson & MacKinnon, 2000), which let us provide inference at level $\alpha = 0.05$.

Once we obtained the $\hat{\theta}_1^* \ldots \hat{\theta}_B^*$ bootstrap replications of each parameter $\hat{\theta}$, the bootstrap estimate of the variance is given by:

$$s^2_{\hat{\theta},Boot} = \frac{1}{B-1} \sum_{b=1}^{B} \left(\hat{\theta}_b^* - \bar{\hat{\theta}}^* \right)^2, \tag{A.1}$$

where

$$\bar{\hat{\theta}}^* = B^{-1} \sum_{b=1}^{B} \hat{\theta}_b^*. \tag{A.2}$$

The bootstrap estimate of the standard error, $s_{\hat{\theta},Boot}$, can be obtained taking the square root of $s^2_{\hat{\theta},Boot}$.

We use confidence intervals to produce tests of hypotheses. We use $s_{\hat{\theta},Boot}$ to build the confidence intervals of $\hat{\theta}$ building first the B bootstrap replications of the t-statistic, $t_1^* \ldots t_B^*$, given by:

$$t_b^* = \left(\hat{\theta}_b^* - \hat{\theta} \right) / s_{\hat{\theta},Boot}. \tag{A.3}$$

In ascending order, the $t_1^* \ldots t_B^*$ bootstrapped t-statistics can be used to find the lower and upper bootstrap critical values at level α, $t^*_{[1-\alpha/2]}$ and $t^*_{[\alpha/2]}$, respectively. Thus, the percentile confidence interval at level α is given by the following expression:

$$\left(\hat{\theta} - t^*_{[1-\alpha/2]} \times s_{\hat{\theta}}, \hat{\theta} - t^*_{[\alpha/2]} \times s_{\hat{\theta}} \right), \tag{A.4}$$

where $\hat{\theta}$ and $s_{\hat{\theta}}$ are the estimate and its standard error in the full sample. However, given that in our case no estimate of $s_{\hat{\theta}}$ is available for many of the relevant parameters, we use $s_{\hat{\theta},Boot}$ instead. This last approach is still asymptotically valid, but without asymptotic refinement (Cameron & Trivedi, 2005, Horowitz, 2001). As mentioned before, we use $\alpha = 0.05$, so that the lower critical value correspond to $\alpha/2 = 0.025$ and the upper critical value to $1 - \alpha/2 = 0.975$. In order to compare two different estimates, we compare the extreme values of the confidence intervals, so that if they intersect we reject $Ho : \theta = \theta_0$.

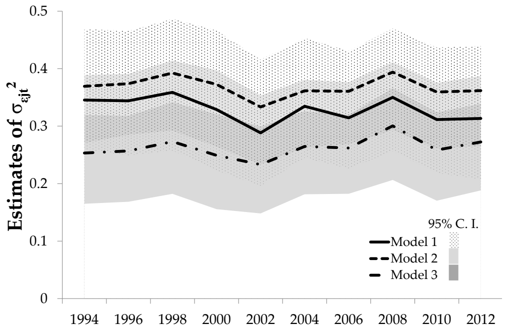
As an alternative approach, in cases where the interest is in testing hypotheses like $Ho : \theta_{BGK} = \theta_{DLLM}$, we study the differences in each repetition, that is, we define $\hat{\delta}_b = \hat{\theta}_b^{BGK} - \hat{\theta}_b^{DLLM}$ and obtain $\hat{\delta}_1 \ldots \hat{\delta}_B$. We then used equations A.1, A.3 and A.4 to test the significance of $\hat{\delta}_b$ using the confidence interval.[42]

[42] Typically, this procedure is used to test if the confidence interval of $\hat{\delta}_b$ includes zero or not, so as to test the null hypothesis $Ho : \theta_0 = \theta_1$.

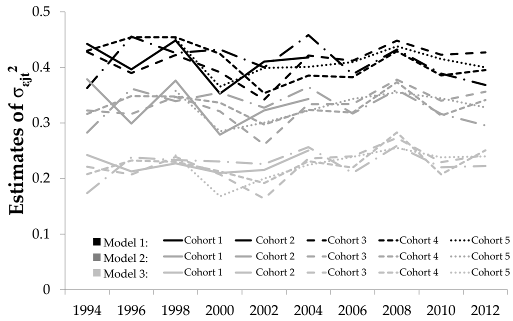
A.3 Additional tables and figures

Figure A.1: *Estimates of $\hat{\sigma}^2_{\epsilon jt}$ based on Bourguignon et al. (2004)'s approach.*

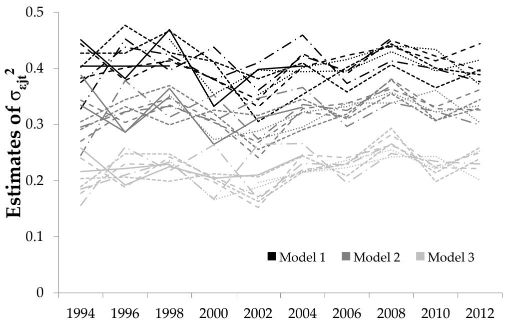
(a) *Whole sample*



(b) *10 years cohorts*



(c) *5 years cohorts*



Notes: Bootstrapped 95% confidence intervals with 399 repetitions (see Appendix **A.2** for details) Sample restricted to households with heads aged between 25 and 64 years old in cohorts with at least 100 observations in each period. See Section **4.4** for a description of the variables included in the estimation of the income equation. Source: author's calculations using ENIGH data.

Table A.1: *Descriptive statistics of the variables used in the cross-sectional models, 1992-2012. (Percentages)*

Variables	1992	1996	2000	2002	2006	2008	2010	2012
Characteristics of the household's head								
Age*	41.0	42.3	43.4	43.9	44.2	45.7	46.7	48.2
	(0.111)	(0.101)	(0.122)	(0.092)	(0.081)	(0.067)	(0.067)	(0.119)
Female	12.3	14.9	16.4	19.0	23.4	23.2	22.9	24.1
	(0.361)	(0.331)	(0.414)	(0.334)	(0.332)	(0.283)	(0.300)	(0.558)
Married	83.6	77.7	79.5	77.5	75.6	76.2	75.1	72.6
	(0.407)	(0.387)	(0.451)	(0.356)	(0.336)	(0.285)	(0.308)	(0.582)
Literacy	88.3	87.1	91.3	90.4	92.6	93.2	93.1	92.9
	(0.354)	(0.311)	(0.315)	(0.251)	(0.205)	(0.169)	(0.180)	(0.335)
Educational level								
Less than primary school	42.8	39.1	31.5	31.6	25.4	26.5	23.7	23.1
	(0.544)	(0.453)	(0.520)	(0.396)	(0.341)	(0.296)	(0.303)	(0.550)
Primary school or	25.8	25.7	25.7	24.5	24.4	23.6	24.1	22.9
incomplete Secondary school	(0.481)	(0.406)	(0.489)	(0.367)	(0.336)	(0.285)	(0.305)	(0.548)
Secondary school or	15.5	19.7	23.6	24.6	26.3	26.0	27.5	27.6
incomplete High school	(0.398)	(0.370)	(0.475)	(0.367)	(0.345)	(0.294)	(0.319)	(0.583)
High school or	8.4	8.3	8.5	7.8	11.1	11.0	11.3	13.3
incomplete College	(0.304)	(0.256)	(0.313)	(0.229)	(0.246)	(0.210)	(0.226)	(0.443)
College or higher	7.5	7.1	10.6	11.4	12.8	12.8	13.5	13.0
	(0.290)	(0.239)	(0.345)	(0.271)	(0.261)	(0.224)	(0.244)	(0.439)
Labour market characteristics								
Employed	89.2	87.6	89.8	89.6	88.9	86.0	84.6	85.4
	(0.342)	(0.306)	(0.338)	(0.260)	(0.246)	(0.233)	(0.258)	(0.460)
Self-employed	20.4	23.6	22.5	24.1	22.0	25.0	24.2	27.7
	(0.443)	(0.394)	(0.468)	(0.365)	(0.324)	(0.290)	(0.306)	(0.583)
Informal worker	52.2	54.7	54.4	53.4	54.1	54.0	53.0	57.2
	(0.549)	(0.462)	(0.557)	(0.425)	(0.390)	(0.334)	(0.356)	(0.646)
Characteristics of the household								
Number of children	1.60	1.43	1.21	1.13	1.07	1.02	0.93	0.81
in the household (0 to 12 y.o.)*	(0.016)	(0.013)	(0.014)	(0.010)	(0.009)	(0.008)	(0.008)	(0.014)
Dirt floors	15.7	12.3	9.2	8.8	6.9	6.0	4.0	3.3
	(0.400)	(0.305)	(0.323)	(0.242)	(0.199)	(0.160)	(0.140)	(0.232)
Without access to water service	18.5	13.9	8.5	9.7	9.3	11.4	7.6	8.9
	(0.427)	(0.322)	(0.312)	(0.252)	(0.228)	(0.213)	(0.189)	(0.371)
Rooms in the dwelling*	2.75	2.89	3.04	3.03	2.92	2.99	3.07	3.04
	(0.017)	(0.014)	(0.017)	(0.013)	(0.013)	(0.011)	(0.012)	(0.021)
Household has one or more	28.9	31.8	35.8	31.8	36.6	38.4	46.9	47.1
cars or trucks	(0.498)	(0.432)	(0.537)	(0.397)	(0.377)	(0.326)	(0.356)	(0.651)
Household has a computer	2.3	3.5	12.0	15.6	22.1	25.9	30.6	35.1
	(0.166)	(0.172)	(0.364)	(0.309)	(0.325)	(0.294)	(0.329)	(0.623)
Household has a fridge	62.0	67.6	76.2	78.3	82.7	84.3	85.8	84.3
	(0.534)	(0.435)	(0.477)	(0.351)	(0.296)	(0.244)	(0.249)	(0.475)
Community size								
Rural areas	35.8	35.0	34.3	34.8	33.4	34.3	34.0	34.0
	(0.527)	(0.443)	(0.531)	(0.406)	(0.369)	(0.318)	(0.338)	(0.618)
Observations	8,277	11,598	7,987	13,755	16,311	22,245	19,646	5,877

Notes: Robust standard errors in parenthesis. Sample restricted to households with heads aged between 25 and 64 years old in cohorts with at least 100 observations in each period. Employed individuals are those who worked at least one hour in the prior week to the survey interview. Informal workers are those who do not receive health care services (public or private) as a job benefit. Rural areas are those with less than 15,000 inhabitants. *Averages reported instead of percentages. Source: author's calculations using ENIGH data.

Table A.2: *Descriptive statistics of the variables used in the longitudinal models. 2002, 2005-2006, and 2009-2012. (Percentages)*

Variables	2002	2005-2006	2009-2012
Characteristics of the household's head			
Age*	43.8	46.7	50.8
	(0.162)	(0.161)	(0.163)
Female	20.3	21.1	23.8
	(0.606)	(0.615)	(0.641)
Married	82.3	79.2	79.8
	(0.576)	(0.612)	(0.605)
Literacy	88.5	88.1	87.0
	(0.480)	(0.488)	(0.506)
Educational level			
Less than primary school	38.2	38.9	38.8
	(0.732)	(0.735)	(0.734)
Primary school or	24.6	26.5	23.9
incomplete Secondary school	(0.649)	(0.665)	(0.642)
Secondary school or	19.2	18.5	19.8
incomplete High school	(0.593)	(0.585)	(0.601)
High school or	9.3	7.9	9.9
incomplete college	(0.438)	(0.406)	(0.450)
College or higher	8.6	8.2	7.6
	(0.423)	(0.413)	(0.398)
Labour market characteristics			
Employed	84.9	81.3	77.5
	(0.540)	(0.587)	(0.629)
Self-employed	25.6	21.4	21.5
	(0.657)	(0.618)	(0.619)
Informal worker	64.8	62.9	57.1
	(0.720)	(0.728)	(0.746)
Characteristics of the household and dwelling			
Number of children	1.37	1.34	1.09
in the household (0 to 12 y.o.)*	(0.021)	(0.021)	(0.020)
Dirt floors	12.1	13.2	8.4
	(0.491)	(0.510)	(0.419)
Without access to water service	14.9	14.8	10.0
	(0.537)	(0.535)	(0.452)
Rooms in the dwelling*	2.88	3.06	3.12
	(0.017)	(0.022)	(0.018)
Household has one or more	34.8	38.1	49.0
cars or trucks	(0.718)	(0.732)	(0.753)
Household has a fridge	92.7	88.9	91.3
	(0.391)	(0.473)	(0.426)
Community size			
Rural areas	43.1	44.7	45.2
	(0.746)	(0.749)	(0.750)
Observations	4,406	4,406	4,406

Notes: Robust standard errors in parenthesis. The sample is restricted to households with heads aged between 25 and 64 years old in 2002. Employed individuals are those who reported to work at least one hour in the prior week to the survey interview. Informal workers are those who do not receive health care services (public or private) as a job benefit. Rural areas are those with less than 15,000 inhabitants. *Averages reported instead of percentages. Source: author's calculations using MxFLS data.

Table A.3: *Estimates of poverty mobility based on (Bourguignon et al., 2004)'s approach. Year of birth cohorts (10-year intervals). Model 1. (Percentages)*

Period	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]
1994-1996	34.2	9.8	22.8	33.2	32.7
	(1.034)	(0.873)	(0.858)	(0.989)	(1.593)
1996-1998	40.3	19.8	12.0	28.0	31.7
	(1.031)	(0.920)	(0.824)	(0.984)	(1.660)
1998-2000	33.6	21.4	11.5	33.5	32.9
	(1.161)	(0.963)	(0.948)	(1.055)	(1.752)
2000-2002	29.7	15.7	15.8	38.8	31.5
	(1.223)	(1.044)	(1.011)	(1.211)	(1.858)
2002-2004	25.9	16.5	15.8	41.8	32.3
	(1.170)	(1.067)	(1.127)	(1.347)	(1.985)
2004-2006	21.6	18.2	14.7	45.5	32.9
	(1.084)	(1.015)	(1.014)	(1.205)	(1.968)
2006-2008	19.0	16.1	16.6	48.3	32.7
	(1.055)	(1.007)	(1.023)	(1.138)	(1.975)
2008-2010	23.6	16.8	17.6	41.9	34.4
	(1.142)	(1.094)	(1.051)	(1.113)	(2.099)
2010-2012	21.6	20.8	13.8	43.9	34.5
	(1.126)	(1.074)	(1.101)	(1.179)	(2.116)
2012-2014	19.3	23.6	11.6	45.5	35.2
	(1.209)	(1.167)	(0.973)	(1.252)	(1.932)

Notes: Bootstrapped standard errors in parenthesis (399 replications). Sample restricted to households with heads aged 25 to 64 years, in cohorts with at least 100 observations in each period. See Section **4.4** for a description of the variables included in the estimation of the income equation. [a] Proportion of households poor in period t, expected to remain poor in $t+1$. [b] Proportion of households identified as poor in period t, expected to be not poor in $t+1$. [c] Proportion of households identified as non-poor in period t, expected to be poor in $t+1$. [d] Proportion of households identified as non-poor in period t, expected to be not poor in $t+1$. [e] Proportion of households with either upward or downward mobility. Source: author's calculations using ENIGH data.

Table A.4: *Estimates of poverty mobility based on (Bourguignon et al., 2004)'s approach. Year of birth cohorts (10-year intervals). Model 2. (Percentages)*

Period	Poverty Persistence[a]	Upward Mobility[b]	Downward Mobility[c]	Non-poverty Persistence[d]	Total Mobility[e]
1994-1996	36.3	7.7	20.6	35.4	28.3
	(0.873)	(0.639)	(0.646)	(0.814)	(1.111)
1996-1998	42.6	17.4	10.3	29.7	42.6
	(0.869)	(0.715)	(0.588)	(0.776)	(0.869)
1998-2000	35.5	19.5	9.4	35.7	35.5
	(1.024)	(0.824)	(0.693)	(0.888)	(1.024)
2000-2002	31.4	14.0	13.8	40.8	31.4
	(1.068)	(0.842)	(0.769)	(1.039)	(1.068)
2002-2004	28.1	14.3	13.7	43.9	28.1
	(1.000)	(0.847)	(0.884)	(1.132)	(1.000)
2004-2006	23.9	15.8	12.6	47.7	23.9
	(0.908)	(0.789)	(0.747)	(0.973)	(0.908)
2006-2008	21.1	13.9	14.9	50.1	21.1
	(0.854)	(0.800)	(0.757)	(0.914)	(0.854)
2008-2010	26.0	14.4	16.1	43.5	26.0
	(0.947)	(0.882)	(0.789)	(0.868)	(0.947)
2010-2012	23.9	18.4	11.9	45.8	30.3
	(0.929)	(0.871)	(0.859)	(0.969)	(1.668)
2012-2014	21.9	21.1	10.3	46.8	31.4
	(1.107)	(1.055)	(0.840)	(1.138)	(1.570)

Notes: Bootstrapped standard errors in parenthesis (399 replications). Sample restricted to households with heads aged 25 to 64 years, in cohorts with at least 100 observations in each period. See Section **4.4** for a description of the variables included in the estimation of the income equation. Description of columns is the same presented in Table A.3. Source: author's calculations using ENIGH data.

Table A.5: *Observed poverty rates in MxFLS: 2002, 2005-2006 and 2009-2012.*

Source	MxFLS (Panel)			ENIGH (Cross-section)		
	2002	2005-2006	2009-2012	2002	2006	2010
I. Unadjusted data						
	48.2	52.4	56.8	42.4	35.1	42.4
	(0.753)	(0.752)	(0.746)	(0.420)	(0.370)	(0.350)
II. Adjusted[a]						
2002 to 2005-2006	49.7	43.2	47.2			
	(0.753)	(0.746)	(0.752)			
III. Adjusted (80% of poverty line)[b]						
2002 to 2005-2006	44.0	36.7	42.2			
	(0.748)	(0.726)	(0.744)			

Notes: Robust standard errors in parenthesis. Sample restricted to households with heads aged between 25 and 64 years old in 2002 with observations in the three waves (balanced panel, N=4,453). [a] Income adjusted to have the same mean and variance as that observed in ENIGH 2002 for MxFLS 1, ENIGH 2006 for MxFLS 2 and ENIGH 2012 for MxFLS 3. [b] Use 80 percent of the value of the income poverty line. Source: author's calculations using ENIGH and MxFLS data.

Table A.6: *Poverty rates for the sub-groups of the population analysed in Section **6**, 1992-2012. (Percentages)*

Year	National[a]	Rural areas[b]	Children in the household[c]	Head with less than primary school[d]	Self-Employed[e]	Informal Sector Worker[f]	Northern states[g]	Southern states[h]
1992	53.7	67.7	43.4	71.0	64.2	64.7	38.6	68.3
	(0.548)	(0.753)	(1.165)	(0.718)	(1.106)	(0.704)	(1.115)	(1.089)
1994	52.7	70.7	40.6	71.7	60.4	61.9	40.6	66.7
	(0.548)	(0.651)	(1.008)	(0.639)	(0.941)	(0.631)	(0.987)	(0.867)
1996	69.0	81.2	61.9	84.8	79.6	77.3	55.2	80.3
	(0.429)	(0.550)	(0.920)	(0.506)	(0.750)	(0.512)	(1.007)	(0.670)
1998	63.2	76.4	56.7	82.1	74.3	72.7	49.4	74.4
	(0.517)	(0.697)	(1.091)	(0.667)	(0.942)	(0.632)	(1.123)	(0.974)
2000	53.2	69.4	46.0	74.8	64.8	64.3	34.7	70.8
	(0.558)	(0.778)	(1.134)	(0.804)	(1.096)	(0.713)	(1.077)	(0.827)
2002	50.3	65.8	44.4	71.5	60.4	60.7	34.9	69.9
	(0.426)	(0.662)	(0.853)	(0.649)	(0.834)	(0.564)	(0.803)	(0.728)
2004	47.3	57.8	40.9	66.9	54.2	57.0	37.0	61.3
	(0.367)	(0.673)	(0.714)	(0.667)	(0.796)	(0.504)	(0.618)	(0.734)
2006	42.5	54.7	35.7	61.8	47.9	51.4	33.5	54.6
	(0.387)	(0.656)	(0.749)	(0.711)	(0.811)	(0.525)	(0.736)	(0.705)
2008	47.5	61.3	42.6	66.2	54.5	57.3	35.2	61.0
	(0.337)	(0.568)	(0.667)	(0.620)	(0.682)	(0.460)	(0.690)	(0.648)
2010	49.7	59.5	48.9	69.6	55.2	59.4	41.9	61.8
	(0.359)	(0.620)	(0.722)	(0.650)	(0.697)	(0.475)	(0.846)	(0.574)
2012	50.2	61.2	51.2	70.5	60.2	61.1	39.9	62.1
	(0.652)	(0.903)	(1.330)	(1.137)	(1.149)	(0.819)	(1.248)	(1.182)

Notes: Robust standard errors in parenthesis. Sample restricted to households with heads aged between 25 and 64 years old in cohorts with at least 100 observations in each period that present the relevant characteristic. a. Considers all the households in the sample, differences with Figure 1 are due missing values in the estimation variables. b. Households in communities of less than 15,000 inhabitants. c. Households with one or more children (0 to 11 years old). d. Household head did not attended any formal education or did not finished primary school. e. Household head work in her own business or independent. f. Household head work, but do not receive health benefits. g. Includes: Baja California, Baja California Sur, Coahuila de Zaragoza, Chihuahua, Durango, Nuevo León, Tamaulipas, Sinaloa and Sonora. h. Includes: Campeche, Chiapas, Guerrero, Oaxaca, Puebla, Quintana Roo, Tabasco, Veracruz de Ignacio de la Llave y Yucatán. Source: author's calculations using ENIGH data.