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Income Mobility in a Changing Macroeconomic Environment

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Abstract
The analysis of income mobility is often constrained to short-term periods of survey panel data. This paper provides long-term income mobility trends through a continuum of short-term synthetic panels in Mexico. The examined period of analysis (1989–2018) is characterized by the lack of panel data and by a changing macroeconomic environment. The analysis builds on cross-sectional survey data using the methodology developed in Bourguignon & Moreno (2020) and employs several income mobility indicators from three complementary conceptions used in the literature: *positional* mobility, *directional* movement, and *mobility as an equalizer of longer-term incomes*. This research documents low levels of economic mobility over the course of three decades, except for the periods of rebound economic growth following the two deepest economic crises in modern times: one internal, in 1995, and one external – in 2009. These movements, however, seem to be only transitory deviations as income mobility indicators soon returned to their characteristic levels.

Keywords: Income mobility, Synthetic panels, Economic crises, Mexico

JEL Classification: O15, D31, D63, G01

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1 Introduction

Explanations of economic mobility, a subject of increasing interest, often rely on data that is static in nature. In the absence of longitudinal data, income mobility analysis relies on intertemporal comparisons over several points of the income distribution, e.g. quantiles, from independent cross-sectional surveys. This approach, however, neglects economic mobility, as it is assumed that the composition of individuals within each of these groups remains unaltered over time. This paper provides long-term income mobility trends through a continuum of short-term synthetic panels. The analysis covers the last three decades and employs multiple indicators that consider the whole income distribution in a period characterized by a lack of longitudinal data and a changing macroeconomic environment.

Few countries possess individual longitudinal data to perform a long-term, or even medium-term, analysis on the evolution of income mobility.[1] Jenkins & Van Kerm (2011), for instance, examined the patterns of income growth and its progressiveness in Britain over 13 years using data from the British Household Panel Survey from 1992 to 2005. Their study employed growth incidence curves and summary indices to show that income growth was significantly more pro-poor in the early years of the Labour government (1998–2002) than in earlier Conservative years.[2] Fiscal records are an alternative source of information. For instance, Zhang et al. (2016) found that Canadian tax-filers experienced greater income growth in the last 15 years than in the previous 15 years. However, long series of household panel data or detailed fiscal records are rather scarce in many countries.

Synthetic panels have been increasingly used to examine poverty dynamics, following a method proposed by Dang et al. (2014). This original approach employs matching and simulation techniques to construct virtual panels out of two rounds of cross-sectional data. The method delivers a lower bound and an upper bound of poverty transitions (in or out of poverty).[3] Vakis et al. (2016) used this methodology to construct a synthetic panel of around eight years, from 2004 to 2012, for 17 Latin American (LA) countries, whereas Ferreira et al. (2013) constructed medium-term synthetic panels (from 6 to 20 years) in 18 LA countries.

[1]The longest panels available (Janttï & Jenkins, 2015) are the Panel Study of Income Dynamics (PSID) (USA, from 1968 onwards), German Socioeconomic Panel (1984 onwards), British Household Panel Survey (1991–2008), Household Income and Labour Dynamics (Australia, 2001 onwards), Survey of Labor Dynamics (Canada, 1998–2011). The Mexican MXFLS survey has three waves only: 2002, 2005–2006, and 2009–2012.

[2]Bradbury (2011) used the PSID to examine mobility profiles from 1969 to 2006 for the USA. Similarly, Jenkins & Van Kerm (2006) compare two decades of mobility in USA and Germany.

[3]In a validation exercise of this methodology, Cruces et al. (2015) constructed synthetic panels with alternative lengths: one, three, and four years, for Peru, Nicaragua, and Chile, respectively.

More recently, Dang & Lanjouw (2013) improved that methodology to produce point estimates of poverty and vulnerability transitions. This method allowed them to combine those bounds of poverty mobility into a single point estimate. Dang & Lanjouw (2016) used this improvement to estimate a five-year synthetic panel for India (2004–2009) while Dang & Dabalen (2017) employed it to construct synthetic panels covering a six-year period for 21 African countries. More recently, Balcazar et al. (2018) used those two approaches to construct four synthetic panels covering ten years (2008–2016) in Colombia. Their study followed a common sample of households, with heads aged 25–60 in the baseline, to estimate poverty and vulnerability transitions.

The emerging research on income dynamics with synthetic panels shares some common ground. First, there is a strong tendency to focus on categorical analysis of poverty and vulnerability transitions (Himanshu & Lanjouw (2020) provide one the most updated and comprehensive revision of this approach in developing countries). This trend contrasts with the literature on income mobility that has managed to develop multiple indicators using the full income distribution (see Jäntti & Jenkins (2015) for a recent review of methods and indicators). The work of Berman & Bourguignon (2020) is a clear exception that compares income estimates from genuine and synthetic panels, following a copula approach, to examine five decades of growth incidence with five 10-year panels using the PSID in the USA. Second, these methods are often used to construct a *single* panel for medium- and long-term time periods (ranging from 6 to 20 years).

This paper departs from prior empirical research in several ways. The study applies the methodology described in Bourguignon & Moreno (2020), which follows an AR(1) to estimate the correlation coefficient with robust pseudo-panel methods, and applies calibration techniques to reproduce the whole income distribution. Also, the analysis builds on a sequence of short-term synthetic panels to produce long-term income mobility trends. In addition, rather than relying on poverty transitions and vulnerability profiles, this study examines the whole distribution of income through alternative conceptions and indicators of income mobility, as described in Fields (2010) and Jäntti & Jenkins (2015): *positional* movement, *directional* movement, and mobility as an *equalizer of longer-term* incomes.

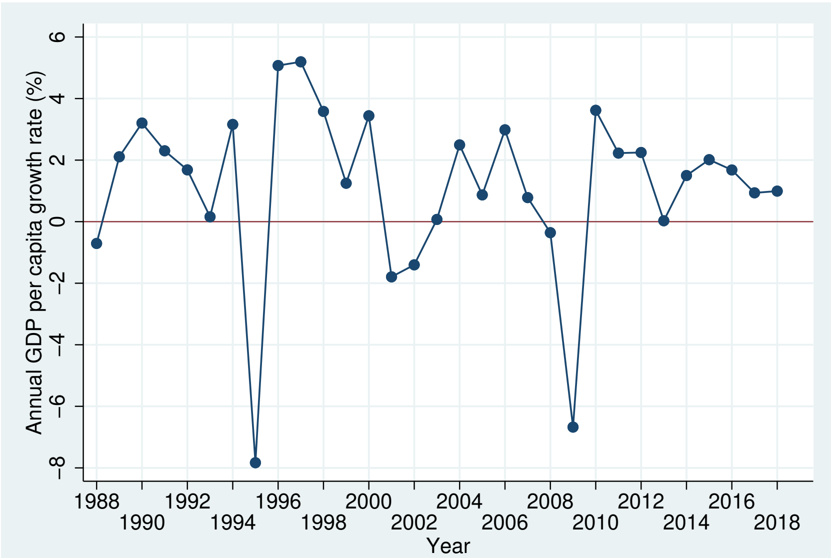
The study provides long-term trends of income mobility from a middle income country that passed through multiple and well-defined economic cycles in the last three decades.[4] This

[4]Mexico, like many other countries, lacks historical longitudinal data at the household level but possesses a continuum of comparable household income surveys that makes it suitable for the implementation of a synthetic panel methodology.

changing macroeconomic environment includes two severe episodes of economic crises – in the mid-1990s and late 2000s – followed by transient spells of economic growth. **Figure 1** highlights these periods and a fast rebound where the real GDP per-capita felt up to 8 percent during the so called Mexican peso crisis in 1995.

The study uses all the available household-income surveys over this period, yielding a continuum of 14 points, each of them referring to a synthetic panel and each referring to a two-year interval.[5] This strategy improves the quality of households' matching in every sub-period and delivers more accurate trends for the persistence parameter, or the AR(1) coefficient, which is the most sensitive input in all these synthetic panel methodologies (see Bourguignon & Moreno 2020). The use of these complementary approaches with synthetic panels is expected to provide a more comprehensive analysis of the dynamics of well-being in changing macroeconomic environments.

Figure 1: Annual GDP per capita growth rate, 1988–2018



Source: World Bank (2020) GDP per capita growth rate (national currency, constant prices)

The paper finds low levels of intra-generational mobility over the last three decades. The granularity obtained from these multiple panels reveals that these episodes of economic downturn managed to alter the rather rigid trends of income mobility differentially. *Positional* mobility indicators suggest low levels of income mobility with a sharp increase around the economic recovery from 1996–2008. *Directional* mobility indicators confirm this trend and document a clear pattern of downward mobility (severe income fall) during both economic

[5]The only exception being the first panel 1989–1992.

slumps – which was particularly abrupt in 1995. The conception of *mobility as equalizer of longer-term incomes* extends these results and verifies that the type of mobility that took place during these economic crises worked to marginally and temporarily equalize longer-term incomes.

The empirical evidence emerging from these changing economic conditions may enrich the scope of compensatory social policies in periods of economic slump. In particular those addressed to cope with households uncertainties from adverse and volatile contexts. Results can guide, for instance, the design of social protection schemes, such as employment subsidies or income transfers, in order to reduce the social costs attached to economic crises. Similarly, monetary and non-monetary interventions could be set in place to preserve the accumulation of human capital of school-aged children in these periods. Finally, results can also be used to relate economic phenomena with political responses in response to citizens' perceptions of recent economic immobility.

The paper is structured as follows. Section 2 describes the methodology and the empirical implementation. Section 3 describes mobility trends for each conception of mobility used, and Section 4 concludes.

2 Analytic framework

This paper's approach consists of constructing a series of short-term synthetic panels to examine long-term income mobility trends. The paper follows the methodology developed in Bourguignon and Moreno (2020) to construct synthetic panels with two rounds of cross-sectional household survey data. The following section describes this procedure briefly.

Let $y_{i\tau\tau}$ represent the income of an individual, i, observed and sampled in time τ. The sub-index τ={0,1} generically refers to the initial and terminal year, respectively. The cross-sectional income would correspond to y_{i00} and y_{i11}, for each baseline and terminal year, respectively. The goal then is to obtain the synthetic income, y_{i01}, in period 1 for an individual observed only in the first period – the baseline. The index i refers to the observational units, which in this case are households.

The procedure consists of defining a (log) income model using exclusively a set of time invariant characteristics, z_i, through OLS, as follows:

$$\hat{y}_{i\tau\tau} = z_{i\tau\tau}\hat{\beta}_{\tau\tau} + \hat{\epsilon}_{i\tau\tau}. \tag{1}$$

Where $\hat{\beta}$ represents the 'returns' of time-invariant features and $\hat{\epsilon}_i$ denotes the income residual. These two estimates are the basic inputs for the construction of synthetic panels. Fixed attributes may include deterministic characteristics at the individual or household level such as years of education, sex, or birth year – among others. The synthetic income of an individual can be reasonably defined by the following expression:

$$\tilde{y}_{i01} = z_{i00}\hat{\beta}_{11} + \check{\epsilon}_{i01}.$$

The first term on the right-hand side is the updated returns of time-invariant characteristics, whereas the second term stands for a synthetic residual, which is unknown. To deal with this problem of missing information, the methodology explicitly assumes that the residual of this basic model obeys a first-order auto-regressive process: $\epsilon_{i01} = \rho \cdot \epsilon_{i00} + u_{i01}$, where u_{i01} is an innovation term and ρ is assumed to fall into a positive interval ($0 <\mid \rho \mid< 1$).[6] These are the two elements to be determined in order to construct an artificial income.

On the one hand, rho can be obtained using two complementary approaches through pseudo-panel techniques. Both methods resort to group-based observations, g, each composed of a large number of individuals to preserve asymptotic properties. The first approach uses the variance of residuals, $\sigma^2_{\epsilon,g}$, from the income model described in Equation 1, through GLS, as follows: $\sigma^2_{\epsilon,g11} = \rho^2 \cdot \sigma^2_{\epsilon,g00} + \sigma^2_{u,g01}$. Similarly, the second approach resorts to the group-based expression of Equation 1 using the average of income, $\overline{y}_g$, and the average of time-invariant characteristics, $\overline{z}_g$, as follows: $\overline{y}_{g11} = \rho \cdot \overline{y}_{g00} + \overline{z}_{g00}\beta + \overline{u}_{g01}$. Following Bourguignon & Moreno (2020), both approaches can be used through a non-linear equation system to gain precision.

On the other hand, the distribution of the innovation terms, u_i, can be approximated using the empirical distribution of residuals in the terminal year, through simulation and calibration methods. Under this AR(1) approach, the synthetic income of an individual implies:

$$\hat{y}_{i01} = z_{i00}\hat{\beta}_{11} + \hat{\rho} \cdot \epsilon_{i00} + \tilde{u}_{i01}, \tag{2}$$

where $\tilde{u}_{i01}$ is randomly drawn from the distribution of the innovation terms with a cumulative density function denoted by $G^u_1(p_i(\cdot))$. Here $p_i(\cdot)$ refers to independent draws within a uniform distribution. $G^u_1(\cdot)$ is calibrated so that the distribution of the synthetic

[6] u_{01} is assumed to be orthogonal to ϵ_{00} and i.i.d. with zero mean and variance σ^2_u while rho is assumed to be homogeneous across groups.

residuals reproduces the distribution residuals as observed in the terminal year. This calibration is performed under a parametric approach based on the assumption that the distribution of innovation terms stems from a mixture of two normal variables, as follows: $G_1^u(U|\theta) = p_1 \cdot \mathcal{N}_1 + (1 - p_1) \cdot \mathcal{N}_2$.

The set of parameters in $\theta = (\mu_1, \sigma_1, \mu_2, \sigma_2, p_1)$, which characterize this distribution, are obtained through an optimization process that minimizes the squared difference between the cumulative density function approximation of residuals in the terminal year, denoted by $F_1(\cdot)$, and that from the empirical distribution, $H_1(\cdot)$ as follows:

$$\min_{\theta} = \sum [F_1(x_k) - H_1(x_k)]^2,$$

The term H is obtained from the following expression: $H_1(x_k) = \sum_{m=1}^{M} F_0((x_k - u)/\hat{\rho})$. Where the x_k's are a set of arbitrary values spanning the range of variation of the observed residuals in the terminal year. The term $F_0(\cdot)$ stands for the CDF Gaussian kernel approximation of residuals in the initial year.

Note from Equation (2) that the synthetic income of a household that is observed in the baseline hinges on the market return of fixed attributes, on the baseline residuals, and on a random term drawn from the distribution of innovation terms conditional on the estimated value of rho. Finally, a large number of simulations must be performed to compute the expected value of any mobility measure to avoid relying on arbitrary values from a specific set of random drawing. The empirical implementation employs 500 random samplings.

2.1 Empirical implementation

The empirical strategy consists of constructing a long series of synthetic panels to examine three decades of income mobility in changing macroeconomic environments. Together, these multiple short-term panels (each covering a period of two years except the first, which covered three due to data availability) expects to be more sensitive for detecting patterns of income mobility in alternative economic contexts.

The construction of multiple short panels expects to improve the quality of the matching, relative to longer panels, as the linear projection of income builds on a more robust criterion in the definition of time-invariant characteristics.[7] This decision allows for a more direct

[7] Conversely, the construction of a long or several medium-term synthetic panels, imposes stronger assumptions about the selection of time-invariant attributes when matching households across time. Such an approach

association between macroeconomic performance and income mobility provided that a specific auto-correlation coefficient is to be estimated for each sub-period of analysis. These improvements deliver a more sensible characterization of the mobility profile in each sub-period insofar the marginal distribution of the synthetic estimates manage to reproduce the income distribution observed in each final year.

In order to improve accuracy further, the analysis does not track the same set of households during the whole period, between these 12 panels, but it consistently follows the same group of households within each sub-period of analysis. Each of these short-term synthetic panels then tracks a set of households with heads aged between 25 and 62 years old as observed in each baseline. This means, for instance, that in the construction of the 1992–1994 synthetic panel, the analysis tracks those households whose heads were between 25 and 62 years old in 1992 – or between 27 and 64 in 1994. The next panel, 1994–1996, follows an updated cohort: those with household heads aged 25–62 in 1994 and 27–64 in 1996. This decision allows a focus on the steadiest households in terms of their formation and dissolution and covers most of the households in each sample.

2.1.1 Data and income definition

The study uses the National Survey of Household Income and Expenditures, or ENIGH henceforth by its acronym in Spanish.[8] The survey was first available in 1984 and then in 1989 but it was periodically conducted, on a two-year basis, since 1992. Its main objective is to provide information about the distribution, amount, and structure of household income. The study uses the whole set of comparable surveys from 1989 until 2018. The 1984 survey was discarded mainly due to a lack of consistency with macroeconomic indicators, as it is known to lead to inconsistent trends in social indicators relative to contemporaneous macroeconomic performance (Lustig, 1992). Moreover, the resulting five-year panel would suggest larger mobility trends relative to those being used in the rest of the work.

This survey is widely used in poverty assessment by the Mexican government, and includes information on socio-demographic characteristics, work status, housing characteristics, and household equipment. Income estimates follow the former official definition of income poverty in Mexico. Total current income considers monetary and non-monetary resources;

would also reduce the number of variables used in the income model – provided that these attributes ought to satisfy a stricter criterion of time-invariability on longer time periods and therefore reduce the proportion of the total variation of income explained by the selected model.

[8] Encuesta Nacional de Ingresos y Gastos de los Hogares.

monetary income comprises receipts from employment, owned businesses, lending of assets and public and private transfers. Non-monetary income considers gifts received and the value of services provided within the household, such as rental value of owner occupied dwelling or self-consumption. Total income is then divided by the household size in order to obtain per capita income and was deflated by the Consumer Price Index (August 2014 which is a rather stable period) to obtain real household income.

2.1.2 Income model

This study follows a homogeneous procedure to estimate the income model specification for all panels. Also, to ensure comparability in all sub-periods, the study avoids using variables that could affect the quality of the matching or unstable variables in periods of economic slowdown, such as employment status or the possession of physical assets. The selection of the variables then follows a strict criterion of time invariability and focuses on households as observational units. The model specification, however, uses both individual and household characteristics to increase the number of relevant variables.

Individual attributes include deterministic characteristics of the household head (HH), such as year of birth and sex, and other invariant attributes for adult population like years of schooling of formal education, marital status, i.e. married or with a stable couple. A second set of characteristics stem from the other household members (HM) characteristics, such as household size and its demographic composition: individuals under age 2 (introduced in the form of dummy variable), and the number of members between 3 and 24 years old, and older than age 65. The former adds flexibility to the matching as it reflects the probability of having a newborn in the household between the initial and terminal year. A final set of variables stems from local characteristics, such as the population density in the area of residence (urban or rural localities), and four regional categories (central, southeast, northeast and west). All variables follow the same definition in all periods.

Table 3-5, in the appendix, shows descriptive statistics for each year used in all the 14 panels (with sample weights), showing a notable stability in the average of these invariant characteristics. Additionally, **Tables 6-8** also in the appendix shows that all the estimates of the income model are strongly significant. In general, the model explains around 0.51 of the total variation of (log) income.

2.1.3 Rho and the calibration parameters

Following Bourguignon & Moreno (2020), the estimation of the AR(1) parameter was performed through a system of non-linear equations. In this empirical implementation each pseudo-panel builds on 35 groups (g) from the interaction of seven birth-year cohorts (each covering a six-year interval) and five education groupings. These age groups are individuals aged 22–27, 28–33, 34–39, 40–45, 46–51, 52–57, and 58–63, as observed in each baseline. The education groups are the following: incomplete primary education, complete primary but incomplete secondary education, complete secondary but incomplete high school, complete high school but incomplete university, and university or more. The resulting groups contain a large number of observations (n_g) to preserve the asymptotic properties of the estimated parameters. In general, the group with the least number of observations (the oldest group with higher levels of education) contains around 300 observations.

Figure 2: Rho estimates in 14 sub-periods, 1989–2018

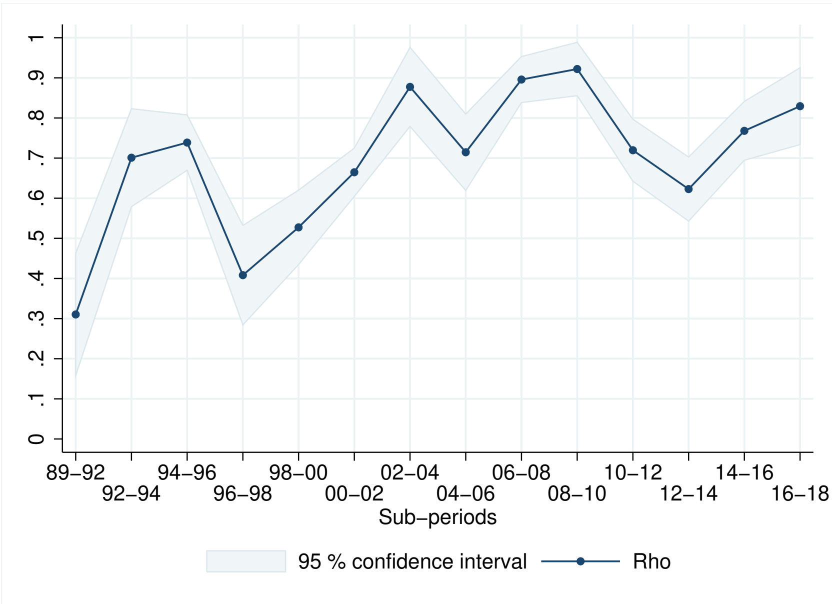
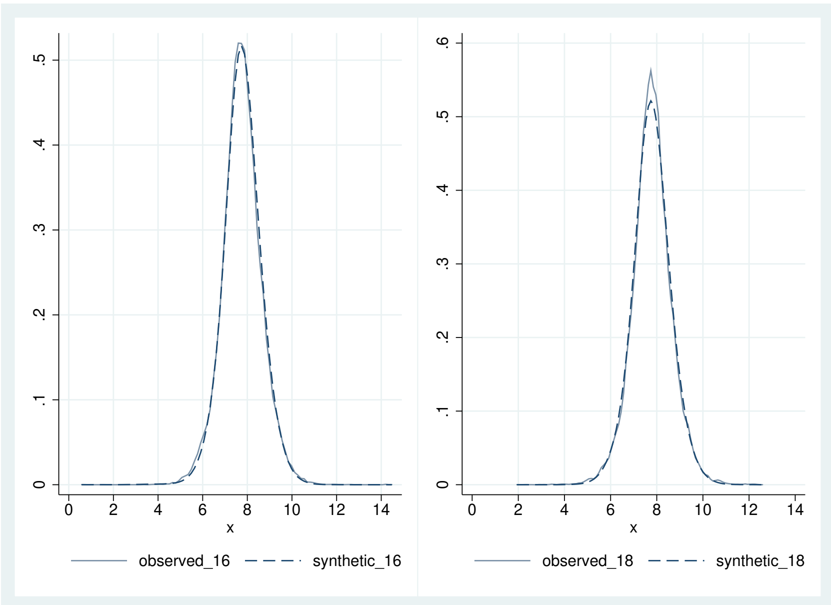


Figure 2 displays the rho estimates and the 95% confidence interval. All estimates are highly significant, have the expected signs, and order of magnitude, and reasonably lie between zero and one. This series starts at a rather low value right after the 1980s economic crisis but follows an increasing trend that is abruptly disrupted after the crises of 1994–1996 and 2008–2010. An attenuated expression of this fall is also observed after the period of economic downturn of 2002–2004. Indeed, the value of this persistence parameter was significantly higher on the eve of the international crisis of 2008 (ρ around 0.90) as compared to that for

the so-called *Tequila* crisis (ρ around 0.70). The value of rho is still far from suggesting a null correlation regarding the baseline conditions. However, results imply that this value tends to fall in the aftermath of these periods of economic crisis. More importantly, this evidence do suggest that rho significantly varied during these periods of changing macroeconomic conditions. [9]

These estimates were employed to obtain the calibration parameters. **Table 1** shows the calibration parameters from independent optimization processes. Results shows that the distribution of synthetic residuals are characterized by a mean of zero with a standard deviation different from one in all years which implies that assuming a standard normal distribution would have alter the accuracy of results relative to the target. These parameters were the last input required to compute the synthetic income. **Figure 3** show the resulting marginal distribution for synthetic income along with the target income (log) of the last two years of this series: 2016 and 2018 (see the **figures 7-9** in the appendix for all the previous years). These estimates constitute the expected value at each income level from 500 simulations. In all cases the estimates for each synthetic panel closely approximates the level and the shape of the targeted distribution at each income level.

Figure 3: Estimated and observed kernel densities, 2016 and 2018



[9]In the aftermath of these periods of economic downturn the value of rho is still far from suggesting a null correlation regarding the baseline conditions. If anything these estimates suggest that the income dynamics are closer to a random walk process rather than a process governed by a perfect correlation with respect to the prevailing conditions at the origin.

Table 1: Rho and calibration parameters by period

Periods	ρ	μ_1	σ_1	p_1	μ_2	σ_2
1989–1992	0.31	0.023	0.62	0.64	-0.042	1.29
1992–1994	0.70	0.011	0.43	0.69	-0.024	0.89
1994–1996	0.74	0.011	0.48	0.86	-0.068	0.75
1996–1998	0.41	0.016	0.75	0.66	-0.032	1.28
1998–2000	0.53	0.022	0.55	0.69	-0.048	1.14
2000–2002	0.66	0.010	0.52	0.66	-0.020	0.80
2002–2004	0.88	0.018	0.48	0.64	-0.032	1.06
2004–2006	0.71	0.010	0.47	0.73	-0.028	0.84
2006–2008	0.90	0.004	0.33	0.70	-0.009	0.67
2008–2010	0.92	0.064	0.55	0.69	-0.142	1.01
2010–2012	0.72	0.006	0.51	0.75	-0.018	0.59
2012–2014	0.62	0.033	1.16	0.29	-0.013	0.66
2014–2016	0.77	0.004	0.33	1.00	-1.113	0.57
2016–2018	0.83	0.009	0.34	0.44	-0.007	0.52

3 Long-term trends of income mobility

Income mobility can be broadly conceived as a transformation from an initial, or first, income distribution to a second, or terminal, income distribution. There are, however, several approximations within this complex concept. This paper's analysis bases its categorizations of income mobility on Jäntti & Jenkins (2015) and Fields (2010) and shows estimates for the following concepts: *positional change*, *income growth*, and *long-term inequality*.

3.1 Mobility and positional change

Positional change refers to a change in the concentration of households at different points along the income distribution. The concept of relative mobility refers to the exchange of observational units between positions where 'changes in income affect *positional mobility* only insofar as these changes alter each person's position relative to the position of others' (Jäntti & Jenkins, 2015). A common device to examine this conception of mobility is the transition matrix, which assigns each individual into a number of fixed categories depending on their initial and final incomes.

The analysis here uses income quintiles so that each transition matrix cross-tabulates the relative frequencies of households in both periods, taking the baseline's income limits as a reference. Each matrix cell, m_{ij}, then refers to the relative frequency of individuals in the baseline quintile (initial) and the corresponding real income bracket in the terminal year (final). **Table 2** shows the estimated transition matrices with the corresponding 95% confidence intervals in a protracted format: instead of using the typical matrix form, results appear in single columns for each synthetic panel to facilitate longitudinal comparison. The first five cells in any column, or sub-period, represent the poorest quintile of households, i.e. the sum of households in m_{11} - m_{15} adds up 20%, whereas the subsequent group of five elements refers to a richer quintile according to the baseline income. For example, the first quintile in the 1989–1992 synthetic panel was spread over the full distribution of income in the terminal year although nearly half remained in the poorest group (9.7 percent of households) and only a small fraction made it to the richest group (0.4 percent).[10] In this setting, an extreme case of perfect immobility corresponds to a situation where the percentage of every cell in the leading diagonal (elements in m_{11}, m_{22}, m_{33}, m_{44}, m_{55}) equals 20 percent of households. Any departure from this situation describes *positional* mobility.

The table shows contrasting patterns of upward and downward mobility during alternative macroeconomic environments. This is more clearly observed in the extreme tails of the income distribution (which only admits one-directional movements). Take, for instance, the case of the share of population that remained at the bottom and at the top of the income distribution. In the case of the poorest groups, the emerging pattern is one of limited or null upward mobility in periods of economic crisis (in 1994–1996 and 2008–2010) while there is a clear pattern of upward mobility in the subsequent periods of economic expansion (i.e. 1989–1992 or 1996–1998).

The less mobile period corresponds to the global crisis of 2008 where the vast majority of households in the first quintile, nearly 93 percent, remained in the poorest group. Conversely, the most mobile episode for the left tail of the income distribution corresponds to the expansion period observed in 1989–1992 where most of the poorest households in this group seemed to have reached the next income group. In fact, it is during the expansion period of 1996–1998 that the group of households that move from the first to the second quintile, m_{12}, is the largest (nearly 25 percent of the poorest groups).

[10]The sum of cells within the first quintile adds up to one-fifth of households (9.7+5.2+3.1+1.6+ 0.4=20%).

It gets harder to identify a clear pattern of mobility for the richest quintile. In the case of the Tequila crisis, only 57 percent maintained their membership to the top income group. This share is largest in the global economic crisis of 2008 where 75 percent managed to maintain their relatively affluent position. Similarly, a clear pattern for periods of expansion is less evident. This is a simple and intuitive examination that masks important movements that occurred all across the income distribution.

Two intuitive measures of exchange mobility summarize this information further. The first of these measures uses the Pearson correlation, r, which describes the direction and strength in the association of (log) incomes between each pair of years. The second relies on the beta coefficient, β, obtained from an OLS regression of the (log) synthetic income in the terminal year on the (log) income of the baseline. These measures are connected by the ratio of the standard deviations, σ, in both years according to the following expression: $r = \beta(\sigma_0/\sigma_1)$. This means that the correlation coefficient adjusts for the inequality observed in each year, which is useful when the marginal distribution of income varies across time. These two simple measures are the basis of more familiar measures of mobility that take into account the fact that a perfect linear relationship between the incomes in both the initial and terminal years (r=1) refers to absolute persistence (immobility).

Figure 4 plots two simple measures of income mobility (1-β and 1-r) over the continuum of points across all sub-periods and the corresponding confidence intervals. Four remarks are in order. First, both indices confirm a rather low level of mobility, around 0.1, and a parallel dynamic ranging from 0.05, during the slowdown of 2002–2004, to 0.3 during the expansion of 1996–1998. The highest levels are observed during the periods of economic growth observed right after the *internal* economic downturn of 1995.[11] Interestingly the expansion period after the *external* crisis of 2008, seems to have had an enduring trend of rising mobility that extended until 2012–14, where both indicators reached the second largest peak of the whole period (nearly to 0.3 again).

Second, the gap between these indices, during the expansion period of 1996–98, illustrates the inter-linkage between income mobility and income inequality. The gap in this period implies that inequality in the terminal year rose significantly relative to that from the baseline, i.e. the mobility with r is greater than that with β, which is consistent with the increase of income inequality in Mexico during this period.[12] Third, the rather low income mobility is consistent with empirical evidence from the USA – Mexico's most important business

[11] After this point, the mobility seems to have returned to its steady trend, around 0.10

[12] Where $\sigma_0 < \sigma_1$ and the difference is statistically significant from zero (see Campos, Esquivel & Lustig, 2012)

Table 2: Transition matrix for each synthetic panel, 1989–2018

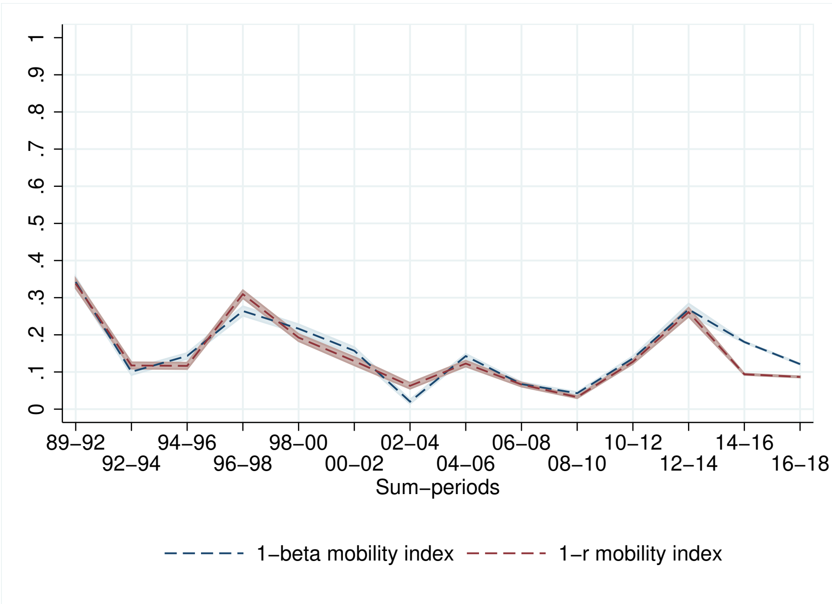
m_{ij}	89–92	92–94	94–96	96–98	98–00	00–02	02–04	04–06	06–08	08–10	10–12	12–14	14–16	16–18
1-1	9.7	15.2	17.2	11.6	12.2	14.3	16.4	13.0	15.9	18.6	13.3	14.5	13.4	14.7
	(9.1–10.2)	(14.7–15.7)	(16.8–17.6)	(11.1–12.1)	(11.7–12.8)	(13.8–14.8)	(16–16.8)	(12.5–13.5)	(15.5-16.2)	(18.4-18.8)	(13-13.7)	(13.9–15)	(13.3–13.5)	(14.6–14.8)
1-2	5.2	3.8	2.5	4.6	5.2	4.6	3.3	5.1	3.7	1.4	4.9	3.7	5.4	4.5
	(4.6–5.7)	(3.3–4.3)	(2.1–2.9)	(4.1–5.1)	(4.7–5.8)	(4.1–5.1)	(2.9–3.7)	(4.6–5.6)	(3.3–4.1)	(1.2–1.6)	(4.5–5.2)	(3.2–4.2)	(5.3–5.5)	(4.4–4.6)
1-3	3.1	0.9	0.3	2.4	2.0	1.0	0.3	1.6	0.4	0.0	1.5	1.4	1.1	0.7
	(2.7–3.6)	(.6–1.2)	(.1–.4)	(2–2.7)	(1.6–2.3)	(.7–1.3)	(.1–.4)	(1.3–1.9)	(.3–.6)	(0-0)	(1.3–1.7)	(1.1–1.7)	(1.1–1.2)	(.7–.8)
1-4	1.6	0.1	0.0	1.2	0.5	0.1	0.0	0.3	0.0	0.0	0.3	0.4	0.1	0.1
	(1.2–1.9)	(0–.2)	(0–.1)	(.9–1.4)	(.4–.7)	(0-.3)	(0-0)	(.1–.4)	(0–0)	(0–0)	(.2–.4)	(.3–.6)	(.1–.1)	(0–.1)
1-5	0.4	0.0	0.0	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	(.3–.6)	(0–0)	(0–0)	(.1–.4)	(0–.1)	(0–0)	(0–0)	(0–0)	(0–0)	(0–0)	(0–0)	(0–.1)	(0–0)	(0–0)
2-1	4.5	5.4	9.0	5.7	3.9	4.4	4.5	3.7	4.6	5.9	4.1	8.4	2.7	3.5
	(4–5.1)	(4.8–6)	(8.4–9.6)	(5.2–6.2)	(3.4–4.4)	(3.8–5)	(4.1–5)	(3.3–4.2)	(4.1–5)	(5.6–6.2)	(3.8–4.4)	(7.8–9.1)	(2.6–2.8)	(3.5–3.6)
2-2	5.1	8.1	7.9	5.4	6.8	8.3	10.4	7.6	9.8	12.3	7.5	5.9	8.9	9.3
	(4.5–5.7)	(7.4–8.8)	(7.3–8.6)	(4.9–5.9)	(6.2–7.4)	(7.6–9.1)	(9.8–11)	(7–8.2)	(9.2–10.4)	(11.9–12.6)	(7.1-7.9)	(5.2–6.5)	(8.8–9)	(9.1–9.4)
2-3	4.8	5.1	2.6	4.4	5.6	5.3	4.5	6.1	4.9	1.8	5.8	3.6	6.6	5.7
	(4.3–5.4)	(4.4–5.7)	(2.2–3.1)	(3.9–4.9)	(5–6.1)	(4.6–5.9)	(4–5)	(5.5–6.7)	(4.5–5.4)	(1.6–2.1)	(5.5–6.2)	(3–4.1)	(6.5–6.7)	(5.6–5.8)
2-4	3.8	1.3	0.4	3.3	3.1	1.8	0.6	2.4	0.7	0.0	2.4	1.8	1.8	1.4
	(3.2–4.3)	(1–1.6)	(.2–.6)	(2.9–3.7)	(2.7–3.6)	(1.4–2.3)	(.4–.8)	(2–2.8)	(.5–.9)	(0–0)	(2.1–2.6)	(1.4–2.2)	(1.7–1.8)	(1.3–1.5)
2-5	1.8	0.1	0.0	1.2	0.6	0.1	0.0	0.2	0.0	0.0	0.2	0.3	0.1	0.0
	(1.4–2.1)	(0–.1)	(0–0)	(.9–1.5)	(.4–.8)	(0–.3)	(0–0)	(.1–.3)	(0–0)	(0–0)	(.1–.3)	(.1–.5)	(0–.1)	(0-.1)
3-1	2.2	1.2	2.8	2.7	1.2	1.0	0.4	0.8	0.5	0.2	0.9	4.6	0.3	0.5
	(1.7–2.6)	(.9–1.5)	(2.4–3.3)	(2.3–3.1)	(.9–1.5)	(.7–1.3)	(.3–.6)	(.6–1)	(.3–.7)	(.1–.3)	(.7–1.1)	(4-5.2)	(.3–.4)	(.5–.5)
3-2	3.9	5.0	7.9	4.3	4.3	5.1	5.1	4.1	5.0	7.1	4.3	5.7	4.0	4.6
	(3.4–4.5)	(4.5–5.6)	(7.3–8.6)	(3.8–4.8)	(3.8–4.8)	(4.5–5.8)	(4.6–5.5)	(3.7–4.6)	(4.5-5.4)	(6.8–7.5)	(3.9–4.6)	(5–6.3)	(3.9–4.1)	(4.5–4.7)
3-3	5.1	7.8	6.6	4.9	6.2	7.3	9.3	7.4	9.3	11.0	7.1	5.0	8.5	8.4
	(4.5–5.7)	(7.1–8.4)	(6–7.3)	(4.4–5.4)	(5.6–6.8)	(6.5–8.1)	(8.7–9.8)	(6.8–7.9)	(8.8–9.9)	(10.6–11.4)	(6.7–7.5)	(4.4–5.6)	(8.4–8.7)	(8.2–8.5)
3-4	5.3	5.2	2.4	5.1	6.1	5.5	5.0	6.5	5.0	1.7	6.3	3.7	6.4	5.9
	(4.7–5.9)	(4.7–5.8)	(2–2.9)	(4.6–5.7)	(5.5–6.7)	(4.9–6.2)	(4.5–5.5)	(6–7)	(4.5–5.5)	(1.4–1.9)	(5.9–6.7)	(3.1–4.2)	(6.3–6.5)	(5.8–6)
3-5	3.5	0.8	0.2	3.0	2.1	1.0	0.2	1.2	0.2	0.0	1.4	1.0	0.7	0.6
	(3–4)	(.5–1)	(0–.3)	(2.6–3.4)	(1.8–2.5)	(.7–1.3)	(.1–.4)	(.9–1.5)	(.1–.3)	(0–0)	(1.2–1.6)	(.7–1.4)	(.7–.8)	(.6–.7)
4-1	0.9	0.1	0.5	1.0	0.3	0.1	0.0	0.1	0.0	0.0	0.1	2.0	0.0	0.0
	(.6–1.2)	(0–.3)	(.3–.7)	(.8–1.3)	(.1–.4)	(0–.3)	(0–0)	(0–.2)	(0–.1)	(0–0)	(0–.2)	(1.6–2.4)	(0–0)	(0–0)
4-2	2.4	1.5	3.6	2.6	1.8	1.7	0.6	1.1	0.6	0.4	1.2	4.0	0.7	0.9
	(1.9–2.8)	(1.1–1.9)	(3.1–4.1)	(2.2–3)	(1.4–2.1)	(1.3–2.1)	(.4–.8)	(.8–1.4)	(.4–.8)	(.3–.5)	(1–1.4)	(3.5–4.5)	(.7–.8)	(.8–.9)
4-3	4.2	5.2	7.4	4.1	4.3	5.1	4.4	4.3	4.6	6.8	4.3	5.2	4.4	4.5
	(3.6–4.7)	(4.6–5.8)	(6.7–8)	(3.6–4.6)	(3.8–4.8)	(4.5–5.7)	(3.9–4.8)	(3.8–4.8)	(4.2–5)	(6.5–7.2)	(3.9–4.6)	(4.6–5.8)	(4.3–4.5)	(4.4–4.6)
4-4	6.0	8.9	7.1	6.1	7.7	8.6	11.1	9.2	11.3	11.7	8.7	5.9	10.3	10.2
	(5.4–6.7)	(8.2–9.6)	(6.4–7.8)	(5.6–6.7)	(7–8.3)	(7.9–9.4)	(10.4–11.7)	(8.7–9.8)	(10.8–11.8)	(11.3–12.1)	(8.3–9.2)	(5.3–6.5)	(10.2–10.4)	(10–10.3)
4-5	6.6	4.3	1.5	6.1	6.0	4.4	3.9	5.3	3.4	1.0	5.6	2.9	4.5	4.4
	(6–7.1)	(3.8–4.8)	(1.1–1.8)	(5.6–6.6)	(5.4–6.5)	(3.8–5)	(3.5–4.4)	(4.9–5.7)	(3–3.7)	(.9–1.2)	(5.3–6)	(2.4–3.4)	(4.4–4.6)	(4.3–4.5)
5-1	0.2	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0
	(0–.4)	(0–0)	(0–0)	(.1–.3)	(0–.1)	(0–0)	(0–0)	(0–0)	(0–0)	(0–0)	(0–0)	(.1–.5)	(0–0)	(0–0)
5-2	0.8	0.1	0.3	0.7	0.2	0.1	0.0	0.0	0.0	0.0	0.1	1.2	0.0	0.0
	(.5–1.1)	(0–.1)	(.1–.5)	(.5–1)	(.1–.4)	(0–.2)	(0–0)	(0–.1)	(0–0)	(0–0)	(0–.1)	(.8–1.5)	(0–0)	(0–0)
5-3	1.9	0.7	1.8	1.8	1.1	0.8	0.1	0.5	0.2	0.1	0.6	2.6	0.4	0.4
	(1.5–2.4)	(.4–.9)	(1.5–2.2)	(1.4–2.1)	(.8–1.4)	(.5–1.1)	(0–.2)	(.3–.7)	(.1–.3)	(.1–.2)	(.5–.8)	(2.1–3.1)	(.3–.4)	(.3–.4)
5-4	4.4	4.0	6.3	4.4	4.3	4.3	2.7	3.7	3.5	4.8	3.6	5.8	3.7	3.7
	(3.9–5)	(3.4–4.5)	(5.8–6.9)	(3.9–4.9)	(3.8–4.8)	(3.6–4.9)	(2.3–3)	(3.3–4.1)	(3.2–3.8)	(4.6–5.1)	(3.3–3.9)	(5.1–6.4)	(3.6–3.8)	(3.6–3.7)
5-5	12.7	15.3	11.5	12.9	14.3	14.8	17.2	15.7	16.3	15.0	15.7	10.1	15.9	16.0
	(12.1–13.2)	(14.8–15.9)	(11–12)	(12.4–13.4)	(13.7–14.8)	(14.1–15.4)	(16.8–17.5)	(15.3–16.2)	(16–16.6)	(14.8–15.3)	(15.4–16)	(9.4–10.9)	(15.8–16)	(15.9–16.1)
Sum	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Note: Each entry, m_{ij}, corresponds to a cell in a 5X5 transition matrix.

partner. Indeed, Bradbury (2011) also documented a trend of low income mobility using the 1-beta estimates, from around 0.30 in the mid-80s to 0.25 in the mid-90s, using larger, 10-year panels and the Panel Study of Income Dynamics.

Lastly, mobility appears to be greater in the first and longer period, 1989–1992; however, this may be the effect of comparing alternative time intervals. Indeed, Gittleman and Joyce (1999) find that this type of positional mobility increases as the interval grows. This means that the level from the first period (which had a 3-year interval) might not be strictly comparable with the rest. Because of this, the analysis here focused on periods from 1992 to 2012 with a homogeneous two-year length.

Figure 4: Exchange mobility, 1989–2018



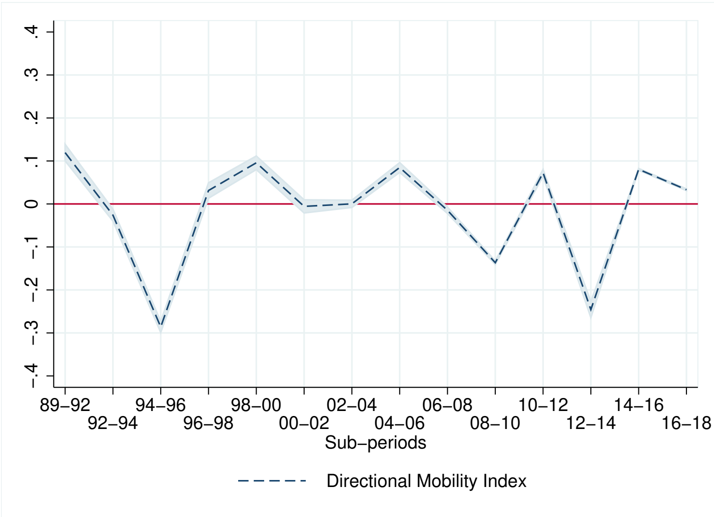
3.2 Mobility and income growth

A second conception of mobility refers to *income growth* and relies on aggregate measures of changes in income observed at the individual level between two points in time. Growth here is defined as the distance between the first and the second period. This measure adds new information relative to the *positional change* approach as it takes into account the direction of the change.

The analysis builds on the D1 index of directional income growth from Fields & Ok (1999), which is the most well-known aggregate measure of directional mobility (Jäntti & Jenkins, 2015). This index is concerned with 'the extent to which incomes are rising or falling' and so the direction stems simply from $d(y_0,y_1)=\log(y_1)-\log(y_0)$. The index is $D1=(1/n)\sum d(y_0,y_1)$ with a straightforward interpretation (Fields, 2010): there is more income movement when this measure increases – or less mobility conversely.

Figure 5 shows the evolution of directional movement over the whole period of analysis. The index first confirms the trends of low mobility with respect to income changes (not only in individual rank positions) in almost all periods except those of economic crises. It mainly highlights the abrupt downward mobility that occurred during both episodes of economic slump, particularly in 1995. According to this, the income fall experienced during the internal crises of the mid-1990s was at least twice as large as the one experienced during the externally driven crises.

Figure 5: Directional income growth, 1989–2018



4 Mobility and long-term inequality

The last conception of income mobility to be examined in this paper is concerned with the long-term effect of mobility on the reduction of inequality. It relies on the average income of two points of time relative to cross-sectional inequality. Measures of this type of mobility rely on aggregate measures of inequality and because of that the direction of mobility (upward or downward) is not directly examined in this last set of indexes.

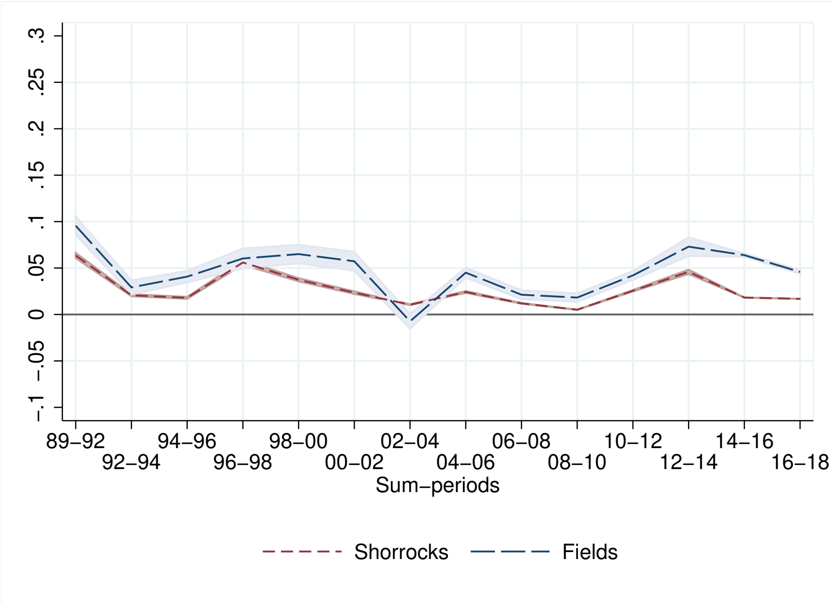
This paper first follows the seminal work of Shorrocks (1978), who proposed a measure of income rigidity, R. This measure stems from the ratio of inequality of averaged incomes to the weighted average of cross-sectional inequality as follows: R_s=I(y_m)/$\sum$ [w_t*I(y_t)]. Here I(·) refers to some measure of inequality; y_t is the cross-sectional income in some period 't' (in this case t=1 and t=2); and y_m is the longitudinal average of initial and final income for each individual. The weights, w_t, stem from the proportion of aggregate income received in each period (w_t=μ_t/μ) and sum to unity. In complete rigidity, this index equals unity and inequality remains the same in both periods. Once more, mobility is conceived as the complement of rigidity: M_s = 1 - Rs.

Fields (2010) followed a variant of this approach with an index of '*Mobility as an Equalizer of Longer-term Incomes*'. His measure of rigidity, R_f, is defined by the ratio of inequality of averaged incomes to the cross-sectional inequality in the baseline: R_f=I(y_m)/I(y_t)]. Similarly, the corresponding mobility index is M_f = 1 - R_f. Complete rigidity, I(y_m)=I(y_i), now implies zero equalization of longer-term incomes relative to initial income. The index is unbounded but takes a positive (negative) value to indicate that the average incomes between two points in time are more (less) equally distributed than the base-year income. This indicator describes to what extent the income changes that took place during a specific period make the distribution of incomes more equal than the initial distribution.

Figure 6 plots these indexes using the Gini index as a measure of inequality. Both approaches follow a common trend that is positive for most of the period of analysis except during the economic slowdown of 2002. This suggests that the mobility observed during these years worked to equalize longer-term incomes relative to the inequality observed in each baseline. The low levels of mobility that took place appear to have almost no effect on longer-term inequality. The levels of mobility in these indexes are consistent with those computed from Hungerford (2011) for the United States. According to their results, the Fields index for the periods 1979–1988 and 1989–1998 are 0.02 and 0.08. However, his estimates for the corresponding Shorrocks index appear slightly larger (0.109 and 0.111, respectively).

As expected, the Shorrocks index describes a smoother pattern and identifies a larger persistence ($R_s > R_f$), or less mobility, given the smaller weight attached to the initial conditions (relative to the Fields index, which is more influenced by initial inequality). Despite this, both indexes reached a peak during the period of economic growth that occurred right after these two economic crises. This brief and weak equalizing trend lost its momentum during the economic slowdown of 2002–2004 with practically neutral equalizing effects. This equalizing trend recurred during the period of recovery after the 2009 crisis. Despite this, the extremely low levels of mobility that took place during the more equalizing periods may have limited effects on longer-term inequality.

Figure 6: Mobility as an equalizer of longer-term incomes, 1989–2018



5 Concluding remarks

This paper examines long-term trends of income mobility through a sequence of 14 synthetic panels from a middle income country. This series of artificial panels is obtained from standard cross-sectional household income surveys covering multiple periods with alternative macroeconomic environments. During this period, the Mexican economy went through all stages of the economic cycle, including two significant periods of economic slowdown – an *internal* one in 1995 and a *global* one in 2009 that produced major declines in annual economic activity of around 8% and 7% per capita, respectively.

Differing from previous research that focused on poverty or vulnerability transitions, this paper examined the full income distribution using concepts of income mobility widely found in the literature: *positional* movement, *directional* movement, and mobility as an *equalizer of longer-term incomes*. Furthermore, the methodology employed to construct synthetic panels developed in Bourguignon & Moreno (2020) allowed supplementary indicators of income mobility to be computed within each of these concepts.

This paper documents low and steady levels of income mobility over the last three decades. The most notable exceptions, however, are the periods of economic growth that occurred right after these periods of economic decline. This is particularly the case during the so-called Mexican peso crisis where the granularity obtained by the implemented empirical strategy showed a profound fall in household income. In fact, the impact of this internal crisis on *directional mobility* indicators was much larger than the one triggered by the global crisis of 2009. Additionally, *positional mobility* indicators showed pro-cyclical upward mobility in some of the poorest income groups. These indicators confirmed a clear pattern of null mobility during this financial crisis and some upward mobility in the following period of economic growth.

All in all, the type of mobility observed after these economic crises may have worked to marginally and temporarily reduce the inequality observed in each baseline. In other words, the concurrence of downward positional mobility (rank fall) and negative directional mobility (income fall) that followed these economic crises could have worked to equalize *longer-term* incomes. However, these movements seem to be only transitory deviations as each of these mobility indicators soon returned to their characteristically low long-term levels.

These results show the potential utility of using a series of short-term synthetic panels for making the analysis of long-term income mobility more feasible, given the wide availability of cross-sectional household surveys in most countries. These types of analysis may improve our understanding of the effects of macroeconomic cycles on the long-term trends of income mobility and support the need for anti-cyclical social protection schemes in periods of severe economic uncertainty. Similarly, comparative analysis of international economic crisis in similar regions is a potential avenue of future research.

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Table 3: Descriptive statistics (1/3), 1989–2018

Synthetic panel Year	Panel 1 1989	Panel 1 1992	Panel 2 1992	Panel 2 1994	Panel 3 1994	Panel 3 1996	Panel 4 1996	Panel 4 1998	Panel 5 1998	Panel 5 2000
Income (log)	7.678	7.873	7.867	7.887	7.881	7.604	7.599	7.667	7.660	7.843
	(0.952)	(0.965)	(0.955)	(0.985)	(0.981)	(0.960)	(0.957)	(0.999)	(0.998)	(0.982)
HH female	0.121	0.130	0.123	0.134	0.128	0.150	0.144	0.159	0.154	0.160
	(0.326)	(0.337)	(0.329)	(0.341)	(0.334)	(0.357)	(0.351)	(0.366)	(0.361)	(0.367)
HH birthyear	1,948	1,950	1,952	1,952	1,953	1,954	1,955	1,955	1,957	1,957
	(10.93)	(10.98)	(10.84)	(11.34)	(11.01)	(11.12)	(10.88)	(11.21)	(10.88)	(11.04)
HH schooling	6.179	6.289	6.457	6.442	6.604	6.706	6.824	6.863	6.984	7.398
	(4.976)	(4.962)	(4.914)	(5.060)	(5.036)	(5.080)	(5.051)	(5.068)	(5.040)	(5.119)
Hm below 2	0.518	0.516	0.357	0.361	0.333	0.374	0.342	0.328	0.300	0.292
	(0.719)	(0.740)	(0.574)	(0.595)	(0.568)	(0.596)	(0.569)	(0.569)	(0.538)	(0.539)
Hm 3–24	2.686	2.300	2.609	2.379	2.510	2.314	2.436	2.199	2.298	2.039
	(1.954)	(1.710)	(1.849)	(1.760)	(1.831)	(1.750)	(1.831)	(1.680)	(1.718)	(1.571)
Hm 65+	0.0696	0.0461	0.0564	0.0538	0.0599	0.0494	0.0541	0.0430	0.0453	0.0388
	(0.275)	(0.225)	(0.253)	(0.246)	(0.259)	(0.231)	(0.241)	(0.216)	(0.225)	(0.203)
Urban	0.652	0.641	0.641	0.642	0.643	0.617	0.620	0.625	0.628	0.652
	(0.476)	(0.480)	(0.480)	(0.479)	(0.479)	(0.486)	(0.485)	(0.484)	(0.483)	(0.476)
Region	1.481	1.482	1.475	1.474	1.475	1.432	1.434	1.445	1.451	1.494
	(1.025)	(1.034)	(1.035)	(1.041)	(1.041)	(1.075)	(1.077)	(1.075)	(1.078)	(1.037)
HH married	0.830	0.828	0.832	0.807	0.813	0.794	0.801	0.783	0.790	0.782
	(0.375)	(0.378)	(0.374)	(0.395)	(0.390)	(0.404)	(0.400)	(0.412)	(0.407)	(0.413)

Table 4: Descriptive statistics (2/3), 1989–2018

Synthetic panel Year	Panel 6 2000	Panel 6 2002	Panel 7 2002	Panel 7 2004	Panel 8 2004	Panel 8 2006	Panel 9 2006	Panel 9 2008	Panel 10 2008	Panel 10 2010
Income (log)	7.844	7.873	7.867	7.916	7.913	8.095	8.085	7.982	7.974	7.925
	(0.983)	(0.931)	(0.928)	(0.917)	(0.913)	(0.888)	(0.886)	(0.922)	(0.919)	(0.894)
HH female	0.154	0.184	0.179	0.216	0.213	0.223	0.220	0.228	0.225	0.223
	(0.361)	(0.387)	(0.383)	(0.411)	(0.409)	(0.416)	(0.414)	(0.420)	(0.417)	(0.417)
HH birthyear	1,958	1,958	1,959	1,961	1,962	1,963	1,964	1,964	1,965	1,966
	(10.74)	(10.94)	(10.71)	(10.95)	(10.73)	(10.74)	(10.61)	(10.86)	(10.66)	(10.88)
HH schooling	7.546	7.363	7.462	7.886	8.012	8.920	8.968	8.241	8.357	8.594
	(5.104)	(5.064)	(5.030)	(4.980)	(4.934)	(4.561)	(4.529)	(4.890)	(4.841)	(4.920)
Hm below 2	0.270	0.277	0.258	0.283	0.241	0.273	0.248	0.247	0.234	0.238
	(0.517)	(0.521)	(0.512)	(0.523)	(0.494)	(0.514)	(0.498)	(0.498)	(0.483)	(0.492)
Hm 3–24	2.123	2.011	2.090	1.933	2.022	1.846	1.932	1.891	1.968	1.787
	(1.619)	(1.542)	(1.578)	(1.507)	(1.550)	(1.434)	(1.487)	(1.493)	(1.518)	(1.433)
Hm 65+	0.0419	0.0400	0.0452	0.0444	0.0474	0.0501	0.0525	0.0480	0.0508	0.0443
	(0.213)	(0.212)	(0.226)	(0.217)	(0.224)	(0.236)	(0.242)	(0.231)	(0.240)	(0.222)
Urban	0.653	0.646	0.651	0.650	0.651	0.685	0.681	0.655	0.656	0.657
	(0.476)	(0.478)	(0.477)	(0.477)	(0.477)	(0.465)	(0.466)	(0.475)	(0.475)	(0.475)
Region	1.494	1.485	1.485	1.491	1.489	1.532	1.529	1.497	1.496	1.491
	(1.037)	(1.043)	(1.045)	(1.046)	(1.047)	(1.038)	(1.039)	(1.046)	(1.046)	(1.045)
HH married	0.786	0.766	0.771	0.745	0.746	0.730	0.733	0.738	0.741	0.731
	(0.410)	(0.423)	(0.420)	(0.436)	(0.435)	(0.444)	(0.442)	(0.440)	(0.438)	(0.443)

Table 5: Descriptive statistics (3/3), 1989–2018

Synthetic panel Year	Panel 11 2010	Panel 11 2012	Panel 12 2012	Panel 12 2014	Panel 13 2014	Panel 13 2016	Panel 14 2016	Panel 14 2018
Income (log)	7.919	8.000	8.001	7.701	7.699	7.755	7.754	7.787
	(0.893)	(0.898)	(0.903)	(0.936)	(0.936)	(0.867)	(0.865)	(0.847)
HH female	0.219	0.232	0.225	0.208	0.205	0.222	0.220	0.233
	(0.414)	(0.422)	(0.418)	(0.406)	(0.403)	(0.416)	(0.414)	(0.423)
HH birthyear	1,967	1,967	1,969	1,969	1,970	1,971	1,972	1,973
	(10.67)	(11.19)	(11.08)	(10.57)	(10.29)	(10.54)	(10.31)	(10.64)
HH schooling	8.727	8.758	8.926	8.684	8.806	8.914	9.009	9.165
	(4.874)	(4.831)	(4.759)	(4.670)	(4.606)	(4.576)	(4.512)	(4.541)
Hm below 2	0.227	0.229	0.214	0.297	0.274	0.294	0.270	0.281
	(0.481)	(0.477)	(0.463)	(0.541)	(0.520)	(0.534)	(0.515)	(0.526)
Hm 3–24	1.859	1.667	1.741	2.169	2.260	2.120	2.199	2.062
	(1.469)	(1.390)	(1.443)	(1.494)	(1.532)	(1.468)	(1.508)	(1.438)
Hm 65+	0.0473	0.0403	0.0460	0.0556	0.0595	0.0522	0.0587	0.0569
	(0.232)	(0.205)	(0.218)	(0.251)	(0.260)	(0.240)	(0.256)	(0.249)
Urban	0.654	0.658	0.660	0.772	0.770	0.769	0.769	0.756
	(0.476)	(0.475)	(0.474)	(0.420)	(0.421)	(0.421)	(0.422)	(0.429)
Region	1.486	1.505	1.503	1.477	1.478	1.480	1.478	1.482
	(1.044)	(1.045)	(1.044)	(1.042)	(1.044)	(1.045)	(1.047)	(1.045)
HH married	0.735	0.710	0.716	0.798	0.801	0.789	0.792	0.779
	(0.441)	(0.454)	(0.451)	(0.402)	(0.399)	(0.408)	(0.406)	(0.415)

Table 6: Income model estimates (1/3), 1989–2018

Synthetic panel Year	Panel 1 1989	Panel 1 1992	Panel 2 1992	Panel 2 1994	Panel 3 1994	Panel 3 1996	Panel 4 1996	Panel 4 1998	Panel 5 1998	Panel 5 2000
HH female	-0.181***	-0.127***	-0.122***	-0.198***	-0.202***	-0.156***	-0.176***	-0.196***	-0.217***	-0.185***
	(0.0351)	(0.0372)	(0.0368)	(0.0299)	(0.0298)	(0.0309)	(0.0310)	(0.0341)	(0.0343)	(0.0321)
HH birthyear	-0.0113***	-0.0126***	-0.0127***	-0.0131***	-0.0129***	-0.0121***	-0.0115***	-0.0108***	-0.0112***	-0.0125***
	(0.000714)	(0.000732)	(0.000711)	(0.000618)	(0.000616)	(0.000630)	(0.000628)	(0.000731)	(0.000737)	(0.000713)
HH schooling	0.0699***	0.0862***	0.0840***	0.0901***	0.0879***	0.0838***	0.0812***	0.0796***	0.0782***	0.0824***
	(0.00169)	(0.00182)	(0.00177)	(0.00155)	(0.00153)	(0.00150)	(0.00148)	(0.00177)	(0.00175)	(0.00164)
Hm below 2	-0.207***	-0.257***	-0.230***	-0.246***	-0.214***	-0.266***	-0.227***	-0.261***	-0.201***	-0.223***
	(0.0105)	(0.0103)	(0.0126)	(0.0109)	(0.0111)	(0.0111)	(0.0114)	(0.0134)	(0.0140)	(0.0138)
Hm 3–24	-0.134***	-0.115***	-0.142***	-0.135***	-0.148***	-0.151***	-0.163***	-0.150***	-0.163***	-0.163***
	(0.00383)	(0.00430)	(0.00392)	(0.00368)	(0.00351)	(0.00375)	(0.00358)	(0.00452)	(0.00439)	(0.00469)
Hm 65+	-0.241***	-0.172***	-0.191***	-0.179***	-0.189***	-0.225***	-0.224***	-0.187***	-0.204***	-0.264***
	(0.0252)	(0.0333)	(0.0296)	(0.0253)	(0.0238)	(0.0267)	(0.0252)	(0.0338)	(0.0323)	(0.0351)
Urban	0.442***	0.364***	0.350***	0.475***	0.469***	0.342***	0.332***	0.422***	0.410***	0.336***
	(0.0167)	(0.0165)	(0.0161)	(0.0140)	(0.0138)	(0.0139)	(0.0138)	(0.0165)	(0.0163)	(0.0157)
Region	0.0792***	0.0799***	0.0766***	0.0869***	0.0855***	0.0773***	0.0745***	0.105***	0.106***	0.131***
	(0.00702)	(0.00739)	(0.00720)	(0.00607)	(0.00597)	(0.00588)	(0.00581)	(0.00725)	(0.00718)	(0.00640)
HH married	-0.321***	-0.305***	-0.290***	-0.367***	-0.359***	-0.361***	-0.364***	-0.349***	-0.372***	-0.327***
	(0.0308)	(0.0329)	(0.0322)	(0.0260)	(0.0258)	(0.0275)	(0.0275)	(0.0308)	(0.0309)	(0.0293)
Constant	29.64***	32.18***	32.45***	33.19***	32.72***	31.20***	30.01***	28.64***	29.37***	32.06***
	(1.388)	(1.422)	(1.385)	(1.202)	(1.200)	(1.227)	(1.224)	(1.426)	(1.438)	(1.390)
Observations	9,668	8,677	8,869	10,711	10,663	10,961	10,968	8,430	8,359	8,354
R-squared	0.477	0.502	0.511	0.564	0.575	0.525	0.533	0.527	0.537	0.514

Table 7: Income model estimates (2/3), 1989–2018

Synthetic panel Year	Panel 6 2000	Panel 6 2002	Panel 7 2002	Panel 7 2004	Panel 8 2004	Panel 8 2006	Panel 9 2006	Panel 9 2008	Panel 10 2008	Panel 10 2010
HH female	-0.218***	-0.173***	-0.171***	-0.133***	-0.121***	-0.114***	-0.126***	-0.143***	-0.148***	-0.0940***
	(0.0316)	(0.0225)	(0.0226)	(0.0175)	(0.0173)	(0.0180)	(0.0178)	(0.0144)	(0.0143)	(0.0151)
HH birthyear	-0.0121***	-0.0119***	-0.0117***	-0.0133***	-0.0128***	-0.0135***	-0.0129***	-0.0143***	-0.0135***	-0.0132***
	(0.000711)	(0.000529)	(0.000529)	(0.000468)	(0.000465)	(0.000498)	(0.000497)	(0.000419)	(0.000419)	(0.000417)
HH schooling	0.0808***	0.0804***	0.0792***	0.0942***	0.0926***	0.0913***	0.0894***	0.0853***	0.0841***	0.0824***
	(0.00162)	(0.00123)	(0.00122)	(0.00105)	(0.00104)	(0.00117)	(0.00117)	(0.000966)	(0.000965)	(0.000951)
Hm below 2	-0.182***	-0.263***	-0.231***	-0.248***	-0.219***	-0.242***	-0.196***	-0.244***	-0.211***	-0.265***
	(0.0141)	(0.0103)	(0.0103)	(0.00928)	(0.00967)	(0.0101)	(0.0103)	(0.00885)	(0.00900)	(0.00888)
Hm 3–24	-0.173***	-0.154***	-0.163***	-0.171***	-0.182***	-0.169***	-0.178***	-0.155***	-0.168***	-0.160***
	(0.00454)	(0.00345)	(0.00334)	(0.00328)	(0.00318)	(0.00357)	(0.00344)	(0.00294)	(0.00290)	(0.00310)
Hm 65+	-0.249***	-0.221***	-0.207***	-0.214***	-0.211***	-0.264***	-0.273***	-0.164***	-0.176***	-0.153***
	(0.0334)	(0.0240)	(0.0228)	(0.0209)	(0.0201)	(0.0228)	(0.0218)	(0.0185)	(0.0176)	(0.0187)
Urban	0.323***	0.419***	0.413***	0.331***	0.326***	0.310***	0.307***	0.339***	0.329***	0.318***
	(0.0156)	(0.0120)	(0.0119)	(0.0113)	(0.0113)	(0.0115)	(0.0114)	(0.00976)	(0.00969)	(0.00992)
Region	0.129***	0.0959***	0.0976***	0.0959***	0.0947***	0.0645***	0.0634***	0.0568***	0.0576***	0.0744***
	(0.00634)	(0.00497)	(0.00494)	(0.00434)	(0.00430)	(0.00470)	(0.00465)	(0.00410)	(0.00407)	(0.00404)
HH married	-0.354***	-0.308***	-0.301***	-0.309***	-0.295***	-0.316***	-0.322***	-0.312***	-0.312***	-0.298***
	(0.0286)	(0.0209)	(0.0209)	(0.0166)	(0.0164)	(0.0172)	(0.0171)	(0.0140)	(0.0139)	(0.0145)
Constant	31.24***	30.89***	30.49***	33.60***	32.60***	34.05***	33.02***	35.78***	34.18***	33.42***
	(1.388)	(1.033)	(1.034)	(0.914)	(0.911)	(0.974)	(0.974)	(0.821)	(0.821)	(0.817)
Observations	8,293	14,271	14,173	18,734	18,540	15,698	15,670	24,111	23,777	22,434
R-squared	0.524	0.541	0.547	0.560	0.568	0.536	0.541	0.504	0.513	0.521

Table 8: Income model estimates (3/3), 1989–2018

Synthetic panel Year	Panel 11 2010	Panel 11 2012	Panel 12 2012	Panel 12 2014	Panel 13 2014	Panel 13 2016	Panel 14 2016	Panel 14 2018
HH female	-0.0961***	-0.110***	-0.115***	-0.00543	-0.00350	-0.0364***	-0.0384***	-0.0456***
	(0.0151)	(0.0250)	(0.0250)	(0.00666)	(0.00669)	(0.00512)	(0.00510)	(0.00476)
HH birthyear	-0.0128***	-0.0104***	-0.0103***	-0.0104***	-0.0104***	-0.00950***	-0.00940***	-0.00922***
	(0.000421)	(0.000740)	(0.000737)	(0.000182)	(0.000186)	(0.000148)	(0.000150)	(0.000143)
HH schooling	0.0809***	0.0779***	0.0767***	0.0788***	0.0774***	0.0727***	0.0712***	0.0695***
	(0.000959)	(0.00178)	(0.00179)	(0.000434)	(0.000441)	(0.000368)	(0.000372)	(0.000360)
Hm below 2	-0.213***	-0.257***	-0.231***	-0.153***	-0.124***	-0.152***	-0.121***	-0.148***
	(0.00922)	(0.0163)	(0.0164)	(0.00344)	(0.00353)	(0.00281)	(0.00288)	(0.00278)
Hm 3–24	-0.172***	-0.174***	-0.185***	-0.0903***	-0.105***	-0.0969***	-0.109***	-0.0879***
	(0.00304)	(0.00560)	(0.00545)	(0.00126)	(0.00125)	(0.00103)	(0.00101)	(0.00102)
Hm 65+	-0.147***	-0.157***	-0.157***	-0.151***	-0.155***	-0.141***	-0.121***	-0.152***
	(0.0179)	(0.0369)	(0.0353)	(0.00753)	(0.00724)	(0.00622)	(0.00584)	(0.00591)
Urban	0.312***	0.345***	0.331***	0.376***	0.371***	0.256***	0.255***	0.283***
	(0.00994)	(0.0169)	(0.0168)	(0.00451)	(0.00454)	(0.00325)	(0.00325)	(0.00312)
Region	0.0750***	0.0529***	0.0567***	0.0668***	0.0680***	0.111***	0.112***	0.118***
	(0.00405)	(0.00738)	(0.00733)	(0.00172)	(0.00173)	(0.00135)	(0.00135)	(0.00132)
HH married	-0.289***	-0.301***	-0.310***	-0.0849***	-0.0794***	-0.106***	-0.105***	-0.116***
	(0.0145)	(0.0239)	(0.0238)	(0.00677)	(0.00681)	(0.00528)	(0.00527)	(0.00489)
Constant	32.62***	28.10***	27.86***	27.50***	27.49***	25.86***	25.72***	25.34***
	(0.826)	(1.450)	(1.447)	(0.357)	(0.365)	(0.290)	(0.295)	(0.281)
Observations	22,059	7,113	7,008	183,753	180,068	217,524	214,110	225,278
R-squared	0.525	0.501	0.514	0.313	0.317	0.323	0.328	0.322

Figure 7: Synthetic and observed kernel densities (1/3), 1992–1998

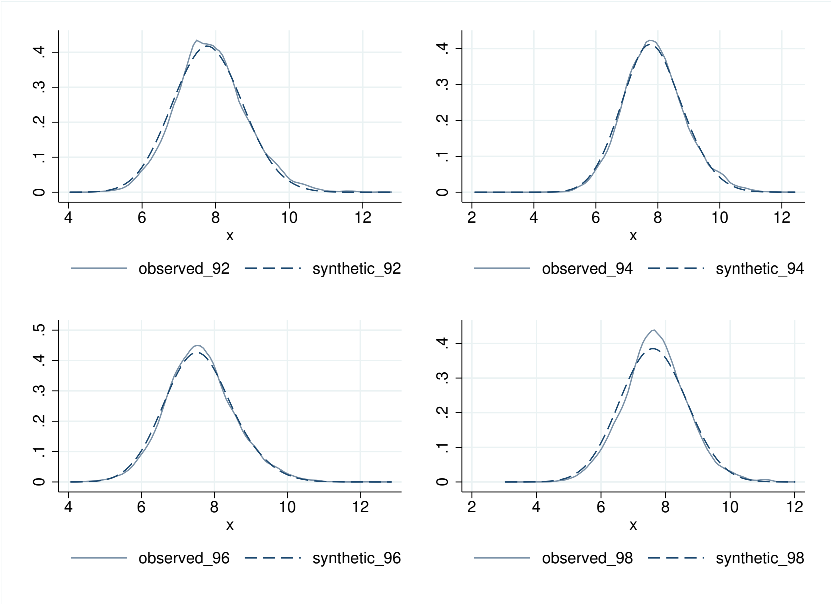

Figure 8: Synthetic and observed kernel densities (2/3), 2000–2006

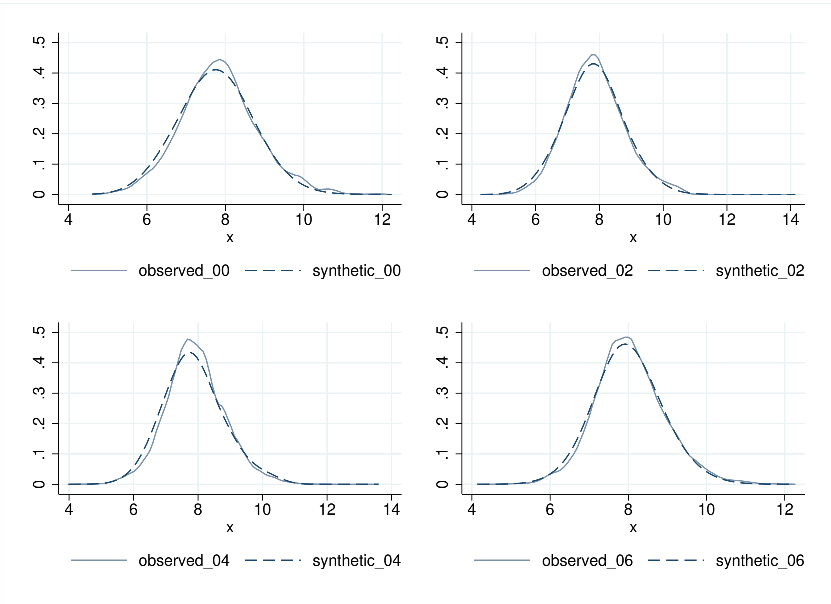

Figure 9: Synthetic and observed kernel densities (3/3), 2008–2014