Journal of Population Economics (2025) 38:23
https://doi.org/10.1007/s00148-025-01066-7

ORIGINAL PAPER

Schooling mobility across three generations in six Latin American countries

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Received: 22 June 2023 / Accepted: 2 January 2025 / Published online: 5 February 2025

Abstract

This paper presents new evidence on schooling mobility across three generations in six Latin American countries. By combining survey information with national census data, we have constructed a novel dataset that includes 50,000 triads of grandparents, parents, and children born between 1890 and 1990. We estimate five intergenerational mobility measures, finding that multigenerational persistence in our six countries is twice as high as in developed countries, and 77% higher than iterating a two-generation model would predict. A theory of high and sticky persistence provides a better approximation for describing mobility across multiple generations in our sample. Even with high persistence, we uncover significant mobility improvements at the bottom of the distribution by estimating measures of absolute upward mobility and bottom-half mobility over three generations. This novel evidence deepens our understanding of long-term mobility, and we expect future research to replicate it as more multigenerational data becomes available in different contexts.

Keywords Developing countries · Latin America · Intergenerational mobility · Upward mobility · Multigenerational data · Reduced inequalities · Quality education · Educational persistence · Multigenerational mobility · Schooling mobility

This paper is dedicated to the memory of our professor Robert J. Lalonde.

Responsible editor: Alfonso Flores-Lagunes

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JEL Classification J62 · N36 · O15 · I24 · I25 · I28

1 Introduction

The intergenerational transmission of socioeconomic status has been a longstanding subject of interest in economics and social sciences (Becker and Tomes 1979; Solon 1992; Black and Devereux 2011). However, previous studies on this topic have been largely limited to examining the relationship between two adjacent generations (e.g., Hertz et al., 2008). While there is emerging evidence that extends beyond parents and their children (see Stuhler, 2023), most of it focuses on developed countries (or specific cities) with high mobility rates.[1] Consequently, there is a notable lack of published empirical multigenerational evidence for lower-income countries, despite its importance in understanding long-term economic opportunities and the persistence of social status within families.

This paper contributes to filling this gap by providing new evidence on schooling mobility across three generations in developing countries. We compile records on grades of schooling attainment for six diverse Latin American countries (LAC), linking them across multiple generations within the same family. We construct our dataset combining nationally representative surveys with census data for each country, which renders about 50,000 triads of grandparents-parents-children born between 1890 and 1990. Spanning a century of data, we study a period marked by significant political reforms and socioeconomic changes in the region.

Our methodological approach follows standard practices in the literature while incorporating recently developed methods to estimate intergenerational mobility. We estimate five different intergenerational mobility (IGM) measures. Three are measures commonly implemented in the literature: regression slope coefficients (β), Pearson (r), and Spearman (ρ) correlations; and two are more recently used measures that focus at the bottom of the distribution: absolute upward mobility (p_{25}) and bottom-half mobility (μ_0^{50}), as implemented in Chetty et al. (2014) and Asher et al. (2022),[2]

We use these IGM measures to document schooling mobility across three generations in four steps. First, we describe and compare changes in mobility over two adjacent generations of the same families: parents and grandparents, and children and parents.

Second, we document mobility patterns over the three generations computing conditional and unconditional associations between the educational attainment of grandparents and grandchildren.

Third, we use these empirical estimates to test competing theories of multigenerational persistence, namely Becker and Tomes' theory (1986) and Clark's (2014) theory

[1] See, e.g., Modalsli (2023) for Norway, Braun and Stuhler (2018) for Germany, Ferrie et al. (2021) for the United States, and Neidhöfer and Stockhausen (2019) for Germany, the United States, and the United Kingdom. For evidence on particular cities, see the relevant papers for the Swedish city of Malmo Lindahl et al. 2015 and the Italian city of Florence Barone and Mocetti 2021.

[2] Following standard definitions in the related literature (e.g., Narayan et al. 2018; Torche, 2021b), all these IGM measures capture relative mobility, except of course for Chetty et al. (2014)'s absolute upward mobility measure.

of a "universal law of social mobility" (see Becker and Tomes, 1986; Clark, 2014). Becker's theory assumes that iterating two-generation estimates is a good proxy for multigenerational mobility. Under certain conditions, this theory predicts low levels of multigenerational persistence.[3] In contrast, Clark's theory predicts high levels of multigenerational persistence that remain consistent over time and across countries. We explore both economic models and empirically examine their respective predictions using our three-generation estimates, building upon the work of Braun and Stuhler (2018) and Neidhöfer and Stockhausen (2019) in the context of developed countries.

Fourth, we conduct a three-generation analysis over time, using birth cohorts to document the evolution of mobility patterns across five decades. This analysis is closely linked to the role of institutions in explaining educational mobility (Acemoglu et al., 2014; Machin, 2007; Nybom and Stuhler, 2021), particularly due to the implementation of compulsory schooling laws in Latin America over the past century. Through this descriptive exercise, we explicitly address how reforms in schooling opportunities contribute to explaining mobility dynamics across three generations within the same family using different measures of IGM.

We devote special effort to emphasize the insights gained from incorporating a third generation to the analyses at each of these four steps. We also provide a comparative perspective contextualizing our findings within the existing two-generation literature for Latin America (e.g., Behrman et al., 2001; Neidhöfer et al., 2018; Torche, 2021a) and within the studies exploring mobility beyond two generations, generally available for the more mobile developed nations (Lindahl et al., 2015; Braun and Stuhler, 2018; Neidhöfer and Stockhausen, 2019). We present four sets of results.

First, our two-generation estimates replicate prior findings from the literature using the commonly used measures (β, r, and ρ) and add a novel result from implementing the more recent measures (p_{25} and μ_0^{50}).

Our six Latin American countries exhibit a high degree of immobility across adjacent generations of the same families, compared to the evidence cited above. This immobility decreases from 0.77 for grandparents-parents to 0.55 for parents-children when measured by regression slope coefficients (β). However, our estimated Pearson (r) and Spearman (ρ) correlations do not change from one pair of generations to the next. These findings align with important work conducted by Neidhöfer et al. (2018) and Torche (2021a), two of the most recent two-generation mobility studies for Latin America.

We add to this two-generation literature providing estimates for absolute upward (p_{25}) and bottom-half (μ_0^{50}) mobility. Our findings show significant improvements according to these measures that focus at the bottom of the distribution. For instance, the expected educational rank of the bottom half for the younger generation increases by seven points from one pair of generations to another. This result is consistent with the important educational upgrade experienced at the lower end of the schooling distribution across generations. The more commonly used IGM measures (β, r, ρ,)

[3] The iteration process implicitly imposes that the outcome follows an AR(1) process, among other conditions. If not true, then Becker and Tomes (1986)'s theoretical model could generate high multigenerational persistence. Lindahl et al. (2015) (section II) provide a clear discussion on this issue.

tend to miss this point, and therefore our estimates of p_{25} and μ_0^{50} provide a more nuanced picture of mobility in the region.

Second, we find that the association between grandparents' and their grandchildren's schooling is large and persists after conditioning on parental schooling. Our five measures of mobility display this pattern. Also, both conditional and unconditional estimates are about two times larger for our LAC compared to the available estimates for Sweden (Lindahl et al. 2015), Germany (Braun and Stuhler 2018), and Germany, the United States, and the United Kingdom (Neidhöfer and Stockhausen 2019).

For instance, the unconditional regression slope coefficient indicates that an additional year of schooling completed by grandparents is associated with an increase of 0.53 years of schooling for their grandchildren. The same estimate is 0.26 for Germany (Braun and Stuhler 2018), which is among the highest available for developed countries.[4]

Third, using our three-generation empirical estimates to test theories of multigenerational mobility renders the following two main findings. One, the Beckerian exponentiation procedure significantly over-predicts mobility for our LAC. The magnitude of the over-prediction (77%) is substantially higher than the overestimation reported for developed countries (31%). Two, we find that Clark's theory underpredicts mobility but much less than for developed countries. We estimate that Clark's measure of immobility is high (0.68 vs 0.60 for developed countries).

Overall, our empirical evidence suggests that Clark's theory of high and sticky persistence provides a better approximation for describing mobility across multiple generations in our developing countries. On the other hand, Becker's widely used prediction of low multigenerational persistence is not supported by the data.

Fourth, our estimates of mobility over time show that grandparent–children mobility display a pattern that is consistent with our first set of results. Mobility improves over the span of 50 years according to the regression slope coefficients (βs) from 0.7 to 0.4 approximately, remains stable according to the Pearson (r) and Spearman (ρ) correlations, and improves when using bottom-half mobility (μ_0^{50}). The expected ranking of a child that descends from grandparents at the bottom half improves by approximately 10 percentage points over 50 years.

We explore the association between compulsory schooling laws and these mobility patterns. We do so by leveraging the variation in exposure to these reforms based on the cohorts' year of birth. Our descriptive analysis reveals that compulsory schooling laws significantly reduce the dispersion of educational attainment among the cohorts exposed to these reforms. Consequently, these results imply a rapid increase in mobility measured by regression slope coefficients but also stable mobility according to the estimated Pearson (r) and Spearman (ρ) correlations.

Our work produces new evidence on long-term mobility in developing countries. We provide three new contributions to the literature.

[4] The conditional estimates are 0.16 for our set of Latin American countries and average 0.07 for Sweden, Germany, the United States, and the United Kingdom. Our LAC conditional estimates are also larger than recent estimates reported by Kundu and Sen (2023) for males in India (0.105).

First, we produce a novel dataset for a set of developing countries, which we use to test whether adding the grandparents' generation is relevant in this context. Our findings contribute to our knowledge of immobility, which we find to be much more persistent than usual predictions based on two adjacent generations and much higher than what is documented for developed countries (see Braun and Stuhler, 2018; Lindahl et al., 2014; Lindahl et al., 2015).

In addition, we provide new evidence describing how mobility evolves across two pairs of generations of the same families. This exercise improves upon the related two-generation literature, which can document how mobility changes across cohorts but not across generations within families.

Second, our estimation of absolute upward and bottom-half mobility over three generations is novel in the literature for both developed and developing countries, thus empirically extending the recent work by Asher et al. (2022) and Chetty et al. (2014). We see this evidence contributing to a deeper understanding of long-term mobility and expect future work to replicate it in different contexts as more information spanning multiple generations becomes available.

Third, we contribute to the literature on role of institutions (Acemoglu et al., 2014; Machin, 2007; Nybom and Stuhler, 2021) at explaining mobility over three generations. Our results show that compulsory schooling laws significantly affect the distribution of schooling by shrinking the variance in schooling for generations exposed to these laws.

These findings are aligned with the evidence on the sources of intergenerational mobility in Denmark and the U.S. (Landersø and Heckman, 2017). Our new evidence is important because it highlights that educational reforms might affect the schooling attainment of generations for long periods, thus producing consequences for intergenerational mobility dynamics that persist later on (Oreopoulos et al., 2006; Björklund and Salvanes, 2011; Piopiunik, 2014).

As a final thought, we anticipate that the use of schooling as a measure of intergenerational mobility will gradually diminish as countries develop because individuals can only attain a maximum level of education. With younger generations achieving higher levels of educational attainment, the distribution of schooling becomes compressed and loses its variation. In other words, if nearly everyone attains, for instance, 16 years of schooling, then this measure becomes less informative in capturing mobility dynamics.

Our findings are robust across a wide range of empirical exercises, but we readily acknowledge that there are limitations to our analysis. While we recognize the importance of delving deeper into the mechanisms driving long-term mobility, this study primarily serves as an initial exploration of three-generation mobility. As more comprehensive and detailed data become available, researchers will likely conduct further investigations into the underlying mechanisms, similar to the progression observed in the two-generation mobility research.

Furthermore, the available data in our study does not provide rich information for each generation and is rather sparse in particular for grandparents and children. Therefore, we abstain from searching exogenous variations (in schooling or choices) or identifying grandparents' effects, and we do not draw causal claims based on our descriptive analysis.[5] Our aim is to contribute to the existing literature by presenting new empirical evidence and generating further interest in the study of three-generation mobility.

Overall, our work contributes to a strand of literature that we believe is set to increase in the following years. Researchers will likely produce further work studying mobility across multiple generations thanks to the increasing availability of data, combined with enhanced capacity to find and digitize archival records (Enamorado et al., 2019; Abramitzky et al., 2021). We expect the new evidence to be produced with emphasis for large developing countries (as in Razzu and Wambile, 2020; Kundu and Sen, 2023), going beyond studies for developed nations or small cities with detailed historic data.

2 Data

Sources. We use survey data for a set of diverse developing countries in Latin America, supplemented with national Censuses for each country. We draw on the first wave of the Longitudinal Social Protection Survey (LSPS) for Chile, Colombia, El Salvador, Mexico, Paraguay, and Uruguay.

These surveys collect harmonized information on individuals' employment and social security history for a representative sample at the national level.[6] A key feature of these surveys is that respondents report their own educational attainment, their parents' and their children's. We use these responses to link educational attainment across three generations within the same family. Following the standard practice in the literature, we construct our proxy for education using the number of years of schooling needed to complete the corresponding educational level in each country (as in Barro, 2001; Hertz et al., 2008). We provide further detail in our "Methods" section below.

Analytical sample and rank construction. We carefully build our analytical sample in two steps. First, we keep respondents born between 1920 and 1970 to balance the time span of our analysis across countries,[7] We also follow common practices and keep respondents with children who are at least 23 years old, when their schooling accumulation is mostly completed. Using these procedures, we end up with a sample of about 50,000 triads of grandparents-parents-children with the oldest grandparents born in 1890 and the youngest children born in 1990, thus spanning a century of data for families linked across three generations.

[5] Important studies using instrumental variables to estimate grandparental effects are Behrman and Taubman (1985) and Lindahl et al. (2014).

[6] Mexico does not have a LSPS, but we decided to include this important Latin American country using a similar survey called the Mexican Health and Aging Study (MHAS). The Longitudinal Social Protection Survey database is maintained by the Inter-American Development Bank's Labor Markets Division and is harmonized to "promote the use of country datasets through comparable variables." The data has information for Chile, Colombia, El Salvador, Paraguay, and Uruguay. All datasets are public; to access the LSPS data, visit this link; to access the MHAS data, visit this link. For further details, see IADB (2016).

[7] This is a standard procedure in the literature implementing cross-country analyses. Although the surveys were conducted in different years (2001 in Mexico, 2002 in Chile, 2012 in Colombia and Uruguay, 2013 in El Salvador, 2015 in Paraguay), we use the same birth cohorts for each country (as in, e.g., Hertz et al. 2008).

A second step in building our analytical sample uses auxiliary Census data for each country and generation to compute rank (percentiles) of schooling. We constructed our ranks separately for each country and separately for each generation. Within each country and for each generation, we computed the rank for 10-year birth cohorts from census records. For instance, consider a survey respondent who was born between 1940 and 1950 and who reports 8 years of schooling. We use the census data to compute the corresponding percentile for 8 years of schooling within that birth cohort, subsequently imputing this value into the survey dataset. We proceed this way because the survey data typically lacks enough sample size to compute representative estimates for small subgroups, in this case, for specific birth cohorts. This is one of the main benefits of using the census data in our analyses.

We use all censuses from IPUMS-International (MPC 2020), implemented in each country since 1960, to construct the distribution of schooling within country and the corresponding percentiles, covering all birth cohorts included in our survey data.[8]

Descriptive statistics. Previous studies of two generations have documented that children attain higher levels of education than their parents. The first question we ask in describing our data is how this educational upgrading behaves once we add the grandparent generation to the analysis.

We find that the educational attainment steadily increases across three generations of the same families in our set of Latin American countries. In what follows, we always refer to this sample of six countries when we write LAC, otherwise noted. Grandparents average 2.7 years of completed schooling, which more than doubles to 5.6 years of schooling for parents and then increases to 9.8 years for children, as we show in Fig. 1.[9]

Going beyond averages, Fig. 1 also plots the schooling distribution for each generation in LAC. The graphs display how the distribution of schooling has steadily moved to the right across three generations. This is also the case for every individual country in our analysis, with the average schooling consistently increased in all countries over three generations.[10]

A second question is how the distribution of schooling changed across the three generations. Grandparents display low and relatively equal levels of schooling, while parents have a higher average but more unequally distributed education. Figure 1 shows that their children enjoy an even higher level of education with a similar overall dispersion (4.5 vs 4.6) and higher dispersion in most countries.

These results can be directly observed from Fig. 1. The first graph shows that the grandparent's distribution is skewed to the left, with a standard deviation of 3.1 years. This outcome reflects that grandparents in our sample grew up when legislation had

[8] For Paraguay and El Salvador, we construct the percentiles using the survey data. The reason is that the latest publicly available data accessible at IPUMS International dates from 2002 and at the time the 1980–2000 birth cohorts were still too young and accumulating schooling. We show in the Appendix that the estimates for the other countries in our sample are robust to using these survey percentiles.

[9] We compute the statistics for each country using the corresponding survey weights, and the estimates for LAC are a simple average of these statistics over countries.

[10] We provide country-specific plots and statistics in the Appendix.

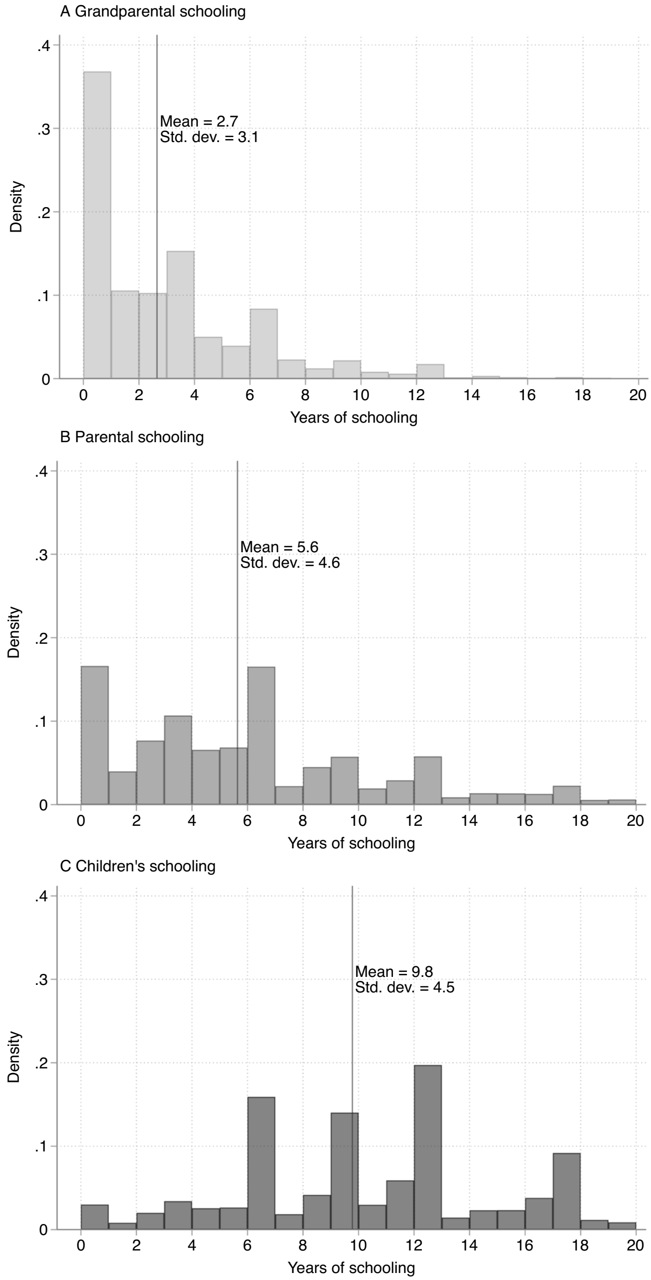

Fig. 1 Distribution of schooling across three generations in six Latin American countries. Notes: Fig. 1 plots the distribution of years of schooling for each generation (grandparents, parents, and children). Each graph shows a vertical line indicating the mean of the distribution. The graphs and statistics are computed averaging across the six countries under study (Chile, Colombia, El Salvador, Mexico, Paraguay, and Uruguay). In the Appendix, we provide the country-specific and statistics separately

either not yet established compulsory schooling laws or, if established, mandated very few years of minimum education.[11]

The distribution for the generation of parents is wider, with a standard deviation of 4.6 years, as shown in the second graph. This result suggests that the important increase in schooling from grandparents to parents was accompanied by an increase in inequality (proxied by larger dispersion) from one generation to the next. In the Appendix, we show that this pattern of increased dispersion from grandparent to parents is common for all countries in our sample.

Children's average schooling increases importantly compared to their parents' schooling, but in this case, the dispersion remains constant at 4.5 years. While there is some heterogeneity across countries, changes in the dispersion from parents' to children's schooling are markedly smaller than changes from grandparents to parents.

A third question is how the relative educational attainment by men and women changed over three generations of the same families. We find that this gender gap measured in terms of average schooling vanishes from grandparents to children. On average, grandfathers in our data are more educated than grandmothers (3.1 vs 2.5 years of schooling, respectively). Fathers achieve roughly one more year of schooling than mothers (6.1 vs 5.3), and daughters and sons attain similar levels of average schooling (9.8 years both). The relative increase in the schooling of females is a result that is common for all countries under analysis.

Robustness to additional data choices. *Computing grandparental schooling*. In all surveys, respondents provide information on the educational background of their parents, i.e., grandfathers and grandmothers in our analysis. We compute grandparental schooling using the average of grandfathers and grandmothers. Following Hertz et al. (2008) procedures, if the information is available only for one of the grandparents, we use that specific data to determine the educational attainment of the grandparents in question.[12] The fraction of respondents with missing data on either parent is low (about 94% have non-missing data), and our results are not sensitive to this choice.

We also test the robustness of our results to computing grandparental schooling using the maximum schooling of grandfathers and grandmothers instead of their average. We do so because using the information for the respondent's parent with the highest educational degree is also common practice in the literature (Black and Devereux 2011). In the Appendix, we show that our results are robust to the choice of how to compute grandparental schooling.

Cohabitation. Our data does not suffer from issues related to cohabitation between respondents and their parents, because the survey asks about the older generation in a retrospective questionnaire module. There are also no coresidence issues in the analysis including respondents and their offspring for Chile and Mexico because the survey asks respondents about all their children (coresident and non-coresident). For the other countries, the surveys collect information on coresident children.

[11] We provide further detail on compulsory schooling laws in Section 4.4.

[12] In Hertz et al. (2008), authors report that the respondent's paternal and maternal information on education was available 87 and 92% of the time. In our data, we have even higher rates, of 88 and 94%, respectively.

We use the Chilean and Mexican data to assess the importance of cohabitation on mobility measures and find that the estimates are generally robust. In the Appendix, we describe in detail the exercise of comparing mobility estimates using restricted (co-resident children) and unrestricted data. The results show very little differences among estimates and, if anything, suggest that our main findings are a lower bound, i.e., that the immobility could be slightly larger when using the full sample of children.

Comparing the schooling distribution of the respondents versus Census data. We test whether the selection of our analytical sample leads to the sampling of a particular subgroup within the respondent generation. For example, respondents might consist of parents with low levels of schooling compared to the respective population. We compare the mean and standard deviation of schooling of our sample with the same birth cohorts using Census data. Our sample of Latin American countries average 5.64 years of schooling versus 5.54 using Census data (as we show in the Appendix), suggesting that on average our sample does not follow a particular selection pattern.

Comparing schooling in our data versus published studies. In an additional effort to check the quality of our data, we directly compare our schooling levels with two of the more recent studies on intergenerational schooling mobility in Latin America. Figure 2 plots the average schooling by generation, for cohorts born in 1940 to 1980 using data from Neidhöfer et al. (2018) (left), Torche (2021b) (center) and our study (right). The figure highlights two results. First, our data display similar levels of average schooling compared to these important studies. Second, we contribute with information that was missing from the literature by adding a new generation (grandparents) to the empirical intergenerational studies based on parents and children.

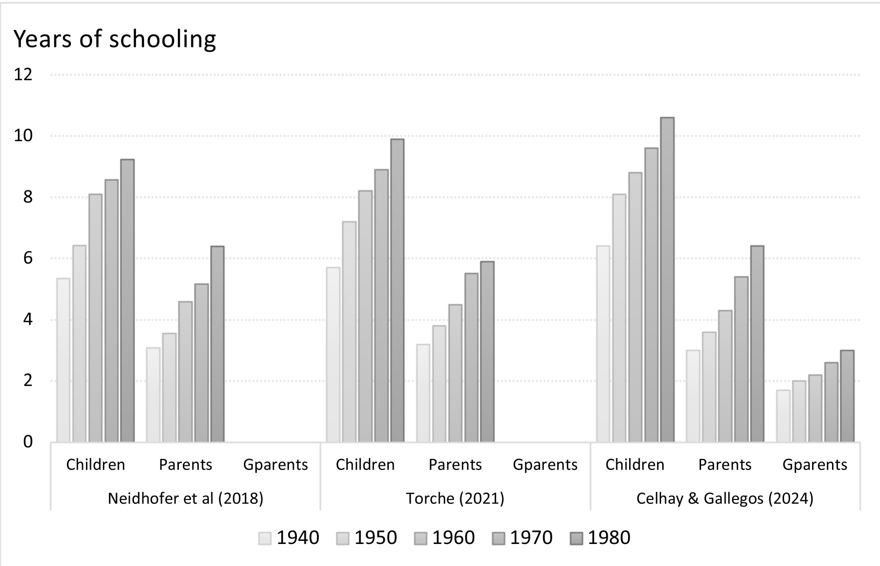

Fig. 2 Adding a new generation to the empirical studies. Notes: Fig. 2 plots the average schooling for children, parents, and grandparents for cohorts of children born in 1940 to 1980 using data from three studies: Neidhofer et al. (2018), Torche (2021b), and our study, which is the only one with data on grandparents

3 Methods

Our methodological procedures carefully follow the standard practices in the literature, complemented with recently developed methods to estimate intergenerational mobility. We present and discuss our methodological choices below.

3.1 Schooling as our variable of interest

This paper studies intergenerational mobility using years of schooling as the main variable of interest. Following common practice in the literature, we coded schooling as the number of years associated with the educational attainment (highest grade completed) reported in our data, as in Hertz et al. (2008). We consider this schooling variable to be a proxy for education, as in Barro (2001). The related literature studying mobility also examines other relevant outcome variables, like income, occupation, health, or even mortality, all of which are important proxies of welfare.[13]

We use educational attainment due to the availability of the information in the survey data and because it comes with a series of widely known advantages. For instance, schooling is highly correlated with long-term incomes and is less susceptible to outliers, recall error, or underreporting in survey data. In addition, because human capital accumulation typically ends at a relatively young age, educational attainment does not vary importantly over the life cycle.

We acknowledge that these benefits come with some costs. For example, education might be bottom-coded or coarsely measured. We borrow from recent literature that has developed methods to address these issues, as we explain below.

3.2 Measuring intergenerational mobility

Studies of intergenerational mobility use different measures depending on the corresponding research question and analysis being done.[14] In this paper, we use a host of different methods to measure mobility, which provide a range of estimates that are useful to place our findings within the related literature.

We estimate five different intergenerational mobility (IGM) measures. Three are measures commonly implemented in the literature: regression slope coefficients (β), Pearson (r), and Spearman (ρ) correlations; and two are more recently used measures that focus at the bottom of the distribution: absolute upward mobility (p_{25}) and bottom-half mobility (μ_0^{50}), as implemented in Chetty et al. (2014) and Asher et al. (2022). We provide further details on each measure next.

[13] We cite important related papers studying educational mobility in the main text, but of course, there is a long literature studying intergenerational mobility. Some important articles in economics using income as the measure of mobility are Acciari et al. (2022); Chetty et al. (2014); Lee and Solon (2009); Mazumder (2005); Nybom and Stuhler (2017, 2016); Olivetti et al. (2018); Solon (1992). For studies using occupational mobility, see, for instance, Corak and Piraino (2011); Torche (2015). For research with child mortality as the main variable, see the recent paper by Lu and Vogl (2023).

[14] Articles that explicitly discuss methods of measurement are, for instance, Fields and Ok (1996); Asher et al. (2022); Deutscher and Mazumder (2021) and Munoz and Siravegna (2021).

Regression slope coefficients (β). These are the most commonly used measures of intergenerational mobility. We compute the regression slope coefficients relying on econometric specifications that follow standard descriptive analyses of mobility between adjacent generations. These are based on the estimation of a reduced form equation derived from the microeconomic model in Becker and Tomes (1979, 1986). We first estimate a linear regression of years of education of generation (t) on years of education of an older generation ($t - s$) in the same family of the form

$$S_{it} = \beta_0 + \beta_1 S_{i,t-s} + f(age_{it}, age_{i,t-s}) + \mathbf{X}\gamma + \eta_{it} \quad (1)$$

where i indexes a family and $t - s$ indexes a generation for $s \in \{0, 1, 2\}$. The function $f(age_{it}, age_{i,t-s})$ summarizes the fact that we include a flexible functional form for each generation's age in the regression; $\mathbf{X}$ is a vector of controls that includes gender for generation t and t-s; and η_{it} is an error term. In this setting, the regression slope β_1 is a measure of immobility as it indicates how an additional year of education in generation $t - s$ is associated to education for generation t.

We first estimate Eq. 1 for two pairs of adjacent generations per family. With these results, we can describe how mobility evolves across pairs of generations of the same family. This exercise improves upon the related two-generation literature, which can use only one pair of generations at once and can document how mobility changes across cohorts but not within families.

Next, we directly include the three generations in our estimations of mobility. We trivially extend Eq. 1 above adding the possibility of grandparent contribution in the following reduced form equation:

$$S_{it} = \beta'_0 + \beta'_1 S_{i,t-1} + \beta'_2 S_{i,t-2} + f(age_{it}, age_{i,t-1}, age_{i,t-2}) + \mathbf{X}\gamma' + \varepsilon_{it} \quad (2)$$

which previous researchers have estimated for developed countries (e.g., Behrman and Taubman, 1985 for the U.S., Lindahl et al., 2015 for Sweden, and Braun and Stuhler, 2018 for Germany). In specification Eq. 2, we labeled the parameters with a prime ($'$) to differentiate them from parameters in Eq. 1. Therefore, β'_1 is the association between parental education and children's education, conditioning on grandparental education; β'_2 reflects the association between grandparents' and children's education, conditional on parental education. We are interested in testing the null hypothesis $H_0 : \beta'_2 = 0$. If rejected, it suggests evidence of higher than two order levels of persistence in educational outcomes.

Pearson (r) **and Spearman** (ρ) **correlations**. Regression slope coefficients are sensitive to changes in the distribution of years of schooling over time and changes in relative status. For instance, changes in the distribution of education across generations may cause mechanical shifts in mobility estimates obtained from regression slope coefficients, but not necessarily changes in the relative position of family members within their reference distribution.

The Pearson and Spearman correlations are two standard measures of relative mobility that make adjustments taking into account changes in the distributions of schooling between generations. The Pearson correlation comes from adjusting the regression slope coefficients by the ratio of standard deviations of the dependent and independent variables.

The Spearman correlation aims to measure the positional change from one generation to the next. It can be derived from implementing two steps. First, running a version of Eq. 1 but using schooling in terms of percentiles of the respective distribution for each generation. Then, the Spearman correlation comes from adjusting the coefficient from this rank-rank regression by the ratio of standard deviations of the dependent and independent variables measured in percentiles.[15]

Absolute upward mobility (p_{25}). The three previous measures provide insights into relative mobility. While this is informative, we are also interested in exploring whether individuals experience absolute mobility over time. We follow the definition of absolute upward mobility (p_{25}) as in Chetty et al. (2014) and estimate it as the expected rank of a child who was born to parent at the 25th percentile of their distribution of reference, i.e., $\hat{p_{25}} = \hat{\alpha} + 0.25 * \hat{\beta}$, where $\hat{p_{25}}$ represents the expected rank of a child, and $\hat{\alpha}$ and $\hat{\beta}$ are derived from estimating rank-rank regressions. This computation produces the predicted rank of a third-generation child born to someone at the 25th percentile in the previous generation.

An important assumption in computing this estimation is the linearity of the conditional expectation function (CEF) that connects the rank of a child with the rank of their parent or grandparent. While this assumption may be appropriate for certain outcomes, such as income, it may not hold when examining educational attainment.[16] The next measure takes this caveat into consideration.

Bottom-half mobility (μ_0^{50}). Finally, we implement a non-linear measure based on work by Asher et al. (2022). They develop a new measure called *bottom-half mobility*, which corresponds to the expected educational rank of a child whose parent was at the 50^{th} percentile of their distribution of reference.

The motivating idea is that standard estimators are not ideal when the variable of interest is coarsely measured or bottom-coded, which tends to be the case for education in developing countries. If so, percentiles of the distribution of interest might not be observed (they would be "interval-censored") which would make it difficult to use rank-based measures of mobility, such as Chetty et al. (2014)'s absolute mobility measure. Asher et al. (2022) argue that their proposed μ_0^{50} can be bounded tightly even in contexts with extreme interval censoring and has a similar interpretation to other measures of upward mobility.[17]

[15] It is true that theoretically, these standard deviations should be nearly the same. However, there are small discrepancies probably related to the empirical sampling variation, and this is why we make adjustment by the ratio of standard deviations. This adjustment is also implemented in the related literature, e.g., in Neidhöfer et al. (2018). For completeness, we show in the Appendix the descriptive statistics on the percentiles of schooling for each generation and country.

[16] In the Appendix, we show that the relationship between child and parent rank displays a shallower slope at lower parent ranks and a steeper slope after the 50th percentile of parent's rank.

[17] We compute all bottom-half mobility estimates using the code provided by Asher et al. (2022). We thank the authors for providing access to their code, which can be accessed through this link.

3.3 Testing competing theories of multigenerational persistence

Our empirical estimates of mobility are valuable for documenting patterns and facilitating cross-country comparisons, but they can also be used for important applications. Following relevant related work for developed countries (Lindahl et al. 2014; Vosters 2018; Braun and Stuhler 2018; Neidhöfer and Stockhausen 2019), we use our three-generation estimates to empirically test the predictions from the Beckerian theory of long-run mobility (Becker and Tomes 1979, 1986) and from Clark's universal law of social mobility (Clark 2014). We briefly discuss both models below.

3.3.1 Becker's extrapolation method

Becker's extrapolation method proposes to estimate long-term mobility through a simple iteration process. If the outcome follows an AR(1) process, then this assumption implies that mobility estimates remain constant across generations. This piece of information allows us to produce an estimate of multigenerational mobility when there is no data available for further, non-adjacent generations.

Consider a simple example where we are interested in the association between childrens' and grandparents' outcomes, but we only have access to data for children and their parents. Using Eq. 1 with no additional controls for the sake of simplicity $S_{it} = \beta_0 + \beta_1 S_{i,t-1} + \eta_{it}$. If we assume the exact same process for the past generation, then $S_{i,t-1} = \beta_0 + \beta_1 S_{i,t-2} + \eta_{i,t-1}$. Replacing this expression in the former, we get $S_{it} = \alpha_0 + \alpha_1 S_{i,t-2} + \varepsilon_{it}$ where $\alpha_0 = \beta_0 + \beta_1, \quad \alpha_1 = \beta_1^2$, and $\varepsilon_{it} = \beta_1 \eta_{i,t-1} + \eta_{i,t}$.

Without data for non-adjacent generations, we cannot directly estimate the parameter of interest α_1 above. But using data for adjacent generations, we can estimate β_1 and then square it to approximate α_1. This result mechanically dissipates the immobility rapidly from one generation to the next. In our setup, we empirically estimate the transmission coefficient from a regression of G3 on G1 and compare it with the Beckerian theoretical benchmark.[18]

The assumptions behind Becker's extrapolation method have already been challenged by the literature both theoretically (Stuhler 2012; Solon 2018; Stuhler 2023) and also empirically for developed countries (Lindahl et al. 2014; Braun and Stuhler 2018; Colagrossi et al. 2020). In the "Results" section, we place our estimates in context with those of advanced nations. A priori, we expect the prediction error to be higher for our set of much less mobile, developing countries.

3.3.2 Clark's universal law of social mobility

Clark (2014) uses family surnames to estimate the persistence of social status across generations in various countries. His main finding is that social status is highly persistent and consistently so across countries and historical periods. Clark's results and interpretation suggest that long-term immobility tends to persist and that it is resistant to policy interventions.

[18] Another way of proceeding is using data for non-adjacent generations to compute a prediction, using the product of the G3-G2 and G2-G1 regression coefficients.

Following Braun and Stuhler (2018)'s latent factor model, the correlation of socioeconomic status between generations t and $t-s$ is given by $\beta_{-s} = p^2\lambda^s$

where p is the current generation's ability to transform endowments into socioeconomic status and λ is the heritability of unobserved endowments. Note that the ratio between β_{-2} and β_{-1} identifies Clark's λ,

$$\frac{\beta_{-2}}{\beta_{-1}} = \frac{p^2\lambda^2}{p^2\lambda^1} = \lambda$$

We follow exactly the method used by Braun and Stuhler (2018) to compute estimates for β_{-2} and β_{-1} and then produce estimates for Clark's λ (with bootstrapped standard errors). We estimate β_{-2} by computing the Pearson correlation (with no covariates) between G1 and G3. We compute an estimate for β_{-1} as the average of the two parent–child Pearson correlations in our data (i.e., the average of the intergenerational correlations between G1 and G2 and between G2 and G3).[19]

Clark (2014)'s three hypotheses of multigenerational persistence state that λ is larger than β_{-1}, close to a constant of 0.75, and stable across countries and over time. We estimate and compare λ with those available for other countries such as Germany, Sweden, United States, and the United Kingdom. A priori, we expect the heritability of unobserved endowments (λ) to be substantially higher for our six LAC than estimates for developed countries.

3.4 Trends in intergenerational mobility

We examine patterns of multigenerational mobility over a span of 50 years. To investigate these trends, we use the respondent's birth cohorts as a reference which is the common practice in the literature. We categorize these cohorts into five 10-year groups spanning from 1920–1929 to 1960–1969 and estimate the following equation:

$$S_{it} = \beta_0 + \sum_{c=1}^{5} D_c \cdot \beta_c \cdot S_{i,t-s} + f(age_{it}, age_{i,t-s}) + \mathbf{X}\gamma + \mu_{it} \tag{3}$$

where D_c represents a dummy variable that takes a value of one if the respondent is born in the birth cohort c, where c ranges from 1920–1929 to 1960–1969, for a total of five groups. The vector $\mathbf{X}$ represents a set of control variables, which includes gender for both generation t and $t-s$ and a binary indicator for each cohort group. The term η_{it} denotes an error term.

To obtain the regression slope coefficients, we directly estimate Eq. 3. We compute the Pearson correlations by adjusting each β_c by the ratio of standard deviations within cohorts. The Spearman correlations are computed analogously but estimating a rank-rank regression as described in Section 3.2. In this exercise, we document changes in the bottom-focused measures computing the estimates for each cohort of birth

[19] To keep comparability with Braun and Stuhler (2018)'s estimates, we compute simple Pearson correlations without controlling for covariates. Note that this procedure results in numbers that are marginally different than the Pearson correlations in Table 1.

separately. As in Asher et al. (2022), we report the midpoint of the intervals and contrast them against the other measures of intergenerational mobility.

3.4.1 Compulsory schooling laws and the evolution of intergenerational mobility

We implement a descriptive decomposition that specifically focuses on the role of compulsory schooling laws as a potential source of differences between estimates in the evolution of mobility, following Landersø and Heckman (2017).

Several Latin American countries have implemented compulsory schooling laws over the past century. Chile mandated compulsory schooling of 8 years in 1965 as part of the program *Bases Generales para el Planeamiento de la Educacion Chilena*. This reform impacted cohorts born around 1952, who were in their eighth grade when the law became effective. In Colombia, education became mandatory for children between the ages of 5 and 15 and comprised at least 9 years of education in 1991. Children born around 1977 or later were exposed to this law. Similarly, El Salvador established that schooling would be mandatory for at least 9 years during a constitutional process in 1983, with the first cohort eligible for this change born in 1968. Paraguay promoted mandatory and universal schooling after the return to democracy in 1993 and established a law that mandated 9 years of schooling in the first year of this transition. Birth cohorts born around 1979 were the first to be exposed to this law. Mexico expanded primary level education throughout the country and mandated its completion by law in 1959, with the first cohort exposed to this reform born in 1951. Uruguay underwent a constitutional change in 1967 that established mandatory schooling for at least 12 years, with the first cohort eligible for this change born in 1949.[20]

Our analysis does not aim to establish causal effects of compulsory schooling laws (e.g., Machin et al. (2012)). Instead, similar to the approach taken by Nybom and Stuhler (2021), we describe how mobility patterns evolve in response to the implementation of compulsory laws.

We focus on laws implemented around cohorts of the children generation who were affected by these changes in compulsory schooling policies and those that were not.[21]

We use an event study approach, pooling all countries together and incorporating country fixed effects. We compute the number of years that a child was exposed to a compulsory schooling law within each country and construct eight birth cohort groups for estimation. This variable captures the extent of exposure to the law based on the child's age at the time of its implementation. For example, children who were older than 18 years when a compulsory schooling law was passed would (most likely) never have been exposed to it. On the other hand, a 6-year-old child who turns 6 years old would have been fully exposed to the law. The eight birth cohort groups are children born 10 or more years before, 9 to 5 years before, 0 to 4 years before, 1 to 5 years after, 6 to 10 years after, 11 to 15 years after, 16 to 20 years after, and 21 or more years

[20] Details of Chile's 1965 reform can be found in Biblioteca Nacional de Chile (1965); for Colombia, see Constitución Política de Colombia (1991); for El Salvador, see Constitución Política de la República de El Salvador (1983); for Paraguay, see Elías (2014); for Mexico, see Olivera Campirán (2011); for Uruguay, see De los Campos and Ferrando (2013).

[21] We examine the children's generation because we are interested in observing how mobility patterns change when there is a change in the distribution of the dependent variable in Eq. 1

after the implementation of the compulsory schooling law. We interact the variables on the right-hand side of the regression equation with binary indicators for these cohort groups. The reference group is set as the cohort born 0 to 4 years before the law was enacted. In particular, we run the following regression:

$$S_{icj}^{Ch} = \phi_j + \sum_{c=-2\ /\ c\neq 0}^{8} \beta_c \cdot S_{icj}^{(G)P} \cdot D_{icj}^{Ch} + f(age_{icj}^{Ch}, age_{icj}^{(G)P}) + \mathbf{X}\gamma + \omega_{icj} \quad (4)$$

where S_{icj}^{Ch} is years of schooling for children (Ch) i in cohort group c in country j, ϕ_j are country fixed effects, $S_{icj}^{(G)P}$ is years of schooling for parent (P) or grandparent (G), and D_{icj}^{Ch} are binary indicators that equal to one if the child belongs to birth cohort group c, where $c \in \{-2, -1, 0, 1, 2, 3, 4, 5\}$ according to the eight groups defined above where cohorts born 0 to 4 years before are normalized to 0. $\mathbf{X}$ includes the gender of child and parent and binary indicators for each D_{icj}^{Ch}, and $f(age_{icj}^{Ch}, age_{icj}^{(G)P})$ are flexible functional forms of age for the children and parent generations.

The β_c coefficients can be interpreted as differences in mobility between each cohort and the reference cohort. Using this approach, we examine changes in mobility before and after the implementation of compulsory schooling reforms in LAC. Additionally, we explore whether compulsory schooling laws have varying effects using our different linear mobility measures.

4 Results

In this section, we present and discuss our estimates of intergenerational mobility. Our first set of results describes and compares changes in mobility over two adjacent generations of the same families: parents and grandparents, and children and parents. We then document mobility over the three generations and use these empirical estimates to test theories of multigenerational persistence. We end up with a three-generation analysis over time, using birth cohorts to document how mobility patterns have developed in the last decades.

4.1 Mobility over adjacent generations of the same families

We start describing how mobility evolves across pairs of generations of the same families. This evidence adds to the related two-generation literature for Latin America, which documents changes across cohorts after measuring mobility using children and parents, i.e., one pair of adjacent generations (see, e.g., Behrman et al., 2001; Neidhöfer et al., 2018; Narayan et al., 2018; Torche, 2021a; Torche, 2021b).

We first estimate five mobility measures using data for three generations, i.e., for two pairs of adjacent generations. Then, we document changes from one pair (grandparents and parents) to another (parents and children). Table 1 reports these results in panels 1 and 2, respectively.

Table 1 Educational intergenerational mobility measures for six Latin American countries

	LAC	Chile	Colombia	El Salvador	Mexico	Paraguay	Uruguay
Panel A: Parents on grandparents (G2 on G1)							
Slope coefficient (β)	0.774	0.682	0.812	0.995	1.005	0.716	0.590
	(0.011)	(0.016)	(0.036)	(0.055)	(0.044)	(0.044)	(0.046)
Pearson correlation (r)	0.523	0.589	0.478	0.567	0.566	0.554	0.464
Spearman's rank correlation (ρ)	0.472	0.505	0.470	0.514	0.511	0.571	0.413
Bottom-half mobility (μ_0^{50})	33.67	31.40	32.71	34.10	31.63	28.75	27.09
Absolute upward mobility (p_{25})	0.366	0.367	0.352	0.371	0.342	0.311	0.303
Observations	16,469	4362	2600	1175	6523	1,227	582
Panel B: Children on parents (G3 on G2)							
Slope coefficient (β)	0.551	0.453	0.521	0.553	0.672	0.459	0.351
	(0.007)	(0.010)	(0.017)	(0.030)	(0.020)	(0.034)	(0.041)
Pearson correlation (r)	0.519	0.576	0.504	0.545	0.528	0.419	0.393
Spearman's rank correlation (ρ)	0.482	0.522	0.514	0.556	0.516	0.509	0.398
Bottom-half mobility (μ_0^{50})	35.87	35.04	44.20	32.53	36.06	31.98	28.84
Absolute upward mobility (p_{25})	0.415	0.416	0.433	0.345	0.408	0.321	0.336
Observations	48,899	12,004	3462	1499	29,702	1595	637
Panel C: Children on grandparents (G3 on G1)							
Slope coefficient (β)	0.534	0.376	0.579	0.675	0.842	0.331	0.343
	(0.012)	(0.015)	(0.033)	(0.054)	(0.037)	(0.060)	(0.054)
Pearson correlation (r)	0.340	0.409	0.321	0.377	0.385	0.240	0.301
Spearman's rank correlation (ρ)	0.327	0.352	0.339	0.380	0.368	0.334	0.292

Table 1 continued

	LAC	Chile	Colombia	El Salvador	Mexico	Paraguay	Uruguay
Bottom-half mobility (μ_0^{50})	42.10	43.96	43.20	37.46	44.34	34.81	28.20
Absolute upward mobility (p_{25})	0.452	0.454	0.469	0.395	0.434	0.349	0.352
Observations	48,899	12,004	3462	1499	29,702	1595	637
Panel D: Children on grandparents conditional on parents (G3 on G1|G2)							
Slope coefficient (β)	0.158	0.103	0.185	0.164	0.316	−0.009	0.177
	(0.012)	(0.015)	(0.031)	(0.053)	(0.039)	(0.062)	(0.055)
Pearson correlation (r)	0.101	0.112	0.103	0.128	0.144	−0.007	0.156
Spearman's rank correlation (ρ)	0.135	0.118	0.123	0.141	0.165	0.065	0.156
Bottom-half mobility (μ_0^{50})	32.04	36.18	35.97	31.63	26.13	27.09	24.61
Absolute upward mobility (p_{25})	0.324	0.327	0.328	0.253	0.306	0.189	0.253
Observations	48,899	12,004	3462	1499	29,702	1595	637

Notes: Table 1 displays a host of intergenerational mobility (IGM) measures for Latin America and the six countries under study. The estimates for our LAC come from pooling all six surveys using country fixed effects, while results for each country are computed using the country-specific subsample and sampling weights provided by the respective survey. The table is organized in four panels. Each panel reports five intergenerational mobility measures: regression slope coefficients, Pearson's and Spearman's correlations, Chetty et al. (2014)'s absolute upward mobility (p^{25}), and the midpoint of the interval for bottom-half mobility. The complete set of Asher et al. (2022)'s estimates is available in the Appendix. In an effort to avoid crowding the table, we provide standard errors (in parentheses) only for the regression slope coefficients, but all estimates are statistically significant at conventional levels (the exceptions are the regression slope and correlation estimates for Paraguay in panel 4). The bottom-half estimates in panel D condition on children whose parents (G2) are below the 50th percentile of their schooling distribution

All five estimated measures confirm that Latin America is a region with high levels of persistence. This high immobility declines across generations of the same family per our estimated regression slope coefficients, but is constant according to the estimated Pearson and Spearman correlations. This set of results closely replicates the empirical findings from the literature based on two generations that examine changes across cohorts in Latin America.

While the correlations suggest stagnant mobility across generations, we find improvements according to our estimated measures of bottom-half and absolute upward mobility. We interpret this result as natural given the important educational upgrade experienced at the bottom of the schooling distribution across generations, as shown in Fig. 1. The improvement according to these measures focused on the bottom of the distribution is a novel finding and provides a more nuanced picture of mobility in the region.

We provide further detail on each of these findings next.

4.1.1 Latin America's high immobility is declining across generations, when measured by regression slope coefficients

The estimated regression slope coefficient for Latin America indicates that an additional year of education in the grandparent generation (G1) is related to 0.77 years of schooling in the next generation (G2). The coefficient decreases to 0.55 for the association between children' and parents' education (G3 on G2), suggesting that there is more mobility as families advance across generations.

This improvement occurs in all six countries under study. At high levels of immobility, Uruguay and Chile display the highest mobility, while Mexico and El Salvador exhibit the lower mobility rates. We interpret the overall decrease in regression slope coefficients as children's educational outcomes becoming less dependent on their parents' backgrounds than their parents' outcomes were on their grandparents'. The improvements in mobility are large, with a drop of approximately 30% in the slope coefficients from one generation to the next.

4.1.2 Mobility remains constant across generations, when measured by Pearson and Spearman correlations

Both Pearson (r) and Spearman (ρ) estimated correlations remain constant at $r = 0.52$ and $\rho = 0.47$ for the associations between parents and grandparents and children and parents. With the exception of Paraguay, most countries display this pattern of stagnant relative mobility across generations.

This finding suggests that the relative position of families within their reference distribution does not change significantly from one pair of generations to the other, despite improvements in schooling levels. These results for mobility across generations resemble the findings for mobility across cohorts, which we discuss below.

4.1.3 Our mobility estimates across generations closely replicate the available estimates across cohorts for Latin America found in other studies

This is the case for regression slope, Pearson and Spearman estimates described above. For instance, Hertz et al. (2008) report an average coefficient of 0.79 for LAC, similar to our slope coefficient of 0.77.[22] For younger cohorts, Neidhöfer et al. (2018) find a regression slope coefficient of 0.60 (and decreasing), resembling the 0.55 regression slope coefficient from our G3 on G2 estimation.

Hertz et al. (2008) and Torche (2021b) report the intergenerational coefficient correlation (which is equivalent to our Pearson estimate) to be constant over time in LAC. In the same vein, Neidhöfer et al. (2018)'s Pearson and Spearman correlations are stable at 0.5 throughout a period of 40 years of birth cohorts.

This evidence supports two important takeaways. First, the results confirm that our estimates are consistent in direction and magnitude with those in the related literature. Second, the estimates suggest that we can learn about changes in mobility across two pairs of generations of the same family using the changes across cohorts of one pair of generations.[23] This finding complements the related literature, as Berman (2022) recently documented a similar result for a host of developed countries.

4.1.4 There is higher mobility for the bottom of the distribution, according to the measures of absolute upward and bottom-half mobility

Our estimated p_{25} and μ_0^{50} show important improvements across generations. These results contribute to the available evidence discussed above because they suggest that the lower end of the schooling distribution has experienced increased mobility in our Latin American countries.

In Table 1, we display the expected ranking of (grand)child that descends from a (grand)parent at the 25th percentile of the schooling distribution. These estimates show that the expected educational rank of the younger generation born to someone at the 25th percentile of their reference distribution increases from the 36th (for G2-G1) to the 42nd percentile (for G3-G2). As a benchmark, Asher et al. (2022) estimate intervals of [39.9; 47.1] for p_{25} using similar cohorts of G2 and G3 in India.

As in Asher et al. (2022), we report the midpoint of the interval for bottom-half mobility measures in Table 1. The estimates presented in panels 1 and 2 show that the expected educational rank of the bottom half for the younger generation increases by seven points from one pair of generations to another. More specifically, a parent (G2) is expected to be in the 34th percentile if she was born to grandparent (G1) in the bottom half of the education distribution. Using the next pair of generations (G3 and G2), we find that the children born to parents in the lower half of the education

[22] Hertz et al. (2008) use G2's cohorts born around the same years as in our data for the G2 on G1 estimation. See Table 2, column 2 in Hertz et al. (2008), pp. 15.

[23] Note that this is an exercise that is different from Becker's exponentiation method. The proposed exercise uses different cohorts to compute different measures of mobility across adjacent generations. The Beckerian procedure assumes that mobility is constant across adjacent generations to predict mobility for non-adjacent generations.

distribution are expected to be situated at the 41st percentile. As a benchmark, Asher et al. (2022) estimate intervals of [36.6; 39.0] for μ_0^{50} in India.

Overall, we find that the estimates of p_{25} and μ_0^{50} display a common pattern in all Latin American countries under study. These findings are consistent with the upgrading of schooling benefiting the bottom of the distribution across the board and provide a perspective that complements the results from the measures more widely documented in the existing literature.

4.2 Documenting mobility over three generations

We now go beyond two adjacent generations and document longer run dependence by studying how grandparents' education relates to their grandchildren's schooling. We find that the association is large and persists after conditioning on parental education. Table 1 reports these results in panels 3 and 4. The estimated long-run immobility is especially high when compared with the available three-generation evidence for other countries.

4.2.1 We find large unconditional associations between the educational attainment of grandparents and grandchildren

The regression slope coefficients indicate that an additional year of grandparental schooling is associated to 0.53 years of schooling for their grandchildren in Latin America (see results for G3 on G1 in panel 3 from Table 1). This large estimate is similar to the transmission coefficient of 0.55 between parents and children, shown in panel 2. At high levels of persistence, there is some variation across countries; the regression slope decreases in Chile and Paraguay, remains constant in Uruguay, and increases in Colombia, El Salvador, and Mexico. The data suggest that this cross-country variation is partly due to changes in the variance of the schooling across generations, as we explain below.

The Pearson and Spearman correlations between childrens' and grandparents' education are also relatively high compared to the available evidence (at 0.34 and 0.32, respectively). However, the magnitude of the G3 on G1 estimates decreases consistently for all countries compared to the estimates of G3 on G2. Given that the correlations abstract from changes in the variance across generations, this finding suggests that, at high level of immobility, grandparents have less influence in the relative position of children than parents in LAC.

The measures that focus at the bottom of the distribution describe a similar picture. When we compute absolute upward mobility, the results show that the expected rank of a child born to a grandparent at the 25th percentile is 0.452 (vs the 0.415 percentile for G3 on G2). This result is similar when we compute bottom-half mobility estimates for G3 on G1 indicate that children who descend from grandparents at the bottom half of her education distribution are expected to be at the 47th percentile, which is an improvement in mobility with respect to the same estimate of G3 on G2 (41th percentile). These findings are in line to those shown by the first three estimators, but focusing on children who start at lower levels of schooling according to their grandparental background.

4.2.2 The association between grandparents and grandchildren decreases but persists after conditioning on parental education

If the grandparental schooling influence acts only through the parents' education, then the coefficient on grandparents' education would be statistically indistinguishable from zero when we estimate Eq 2. However, panel 4 shows that the conditional grandparent's slope coefficient, Pearson and Spearman correlations, all remains statistically significant with a sizable magnitude for LAC (0.16, 0.10, and 0.14, respectively).

The estimates that focus at the bottom of the distribution describe once again a similar pattern. Mobility is reduced compared to the unconditional association, but it stays meaningful. The conditional estimates for absolute upward mobility suggest that children who descend from grandparents and parents at the 25th percentile are expected to be at the 32th percentile of her distribution of reference. Our results for bottom-half mobility indicate that the expected percentile of children born to grandparents *and* parents in the bottom half of the distribution is the 37th percentile (vs the 47th percentile in the unconditional case).

4.2.3 These estimates for (conditional) mobility over three generations are novel in the literature

Our absolute upward and bottom-half mobility over three generations estimates are novel in the literature for both developed and developing countries, thus empirically extending the recent work by Asher et al. (2022) and Chetty et al. (2014).

We see this evidence contributing to a deeper understanding of long-term mobility and expect future work to replicate it in different contexts as more information spanning multiple generations becomes available. Next, we discuss our findings in perspective with results from the available three-generation literature.

4.2.4 The persistence over three generations is especially high in our LAC from a comparative perspective

Figure 3 plots the regression slope coefficients for our LAC presented in Table 1 with analog estimates published for Sweden, Germany, the U.S., and the U.K. The Swedish estimates come from Lindahl et al. (2015), while the estimates for Germany(NS), the U.S., and the U.K. come from Neidhöfer and Stockhausen (2019). We also included Germany(BS), which are estimates from Braun and Stuhler (2018).[24] In our LAC, the large regression slope coefficient of 0.55 for adjacent generations (G3 on G2) remains very similar when computed for non-adjacent generations (G3 on G1). This result contrasts with the findings for other countries, where the immobility decreases sharply from G3 on G2 to G3 on G1.

[24] We discuss the regression slope coefficients because these are commonly reported across studies, but results using the Pearson and Spearman correlations paint the same picture. We present the few available results that are comparable in the Appendix.

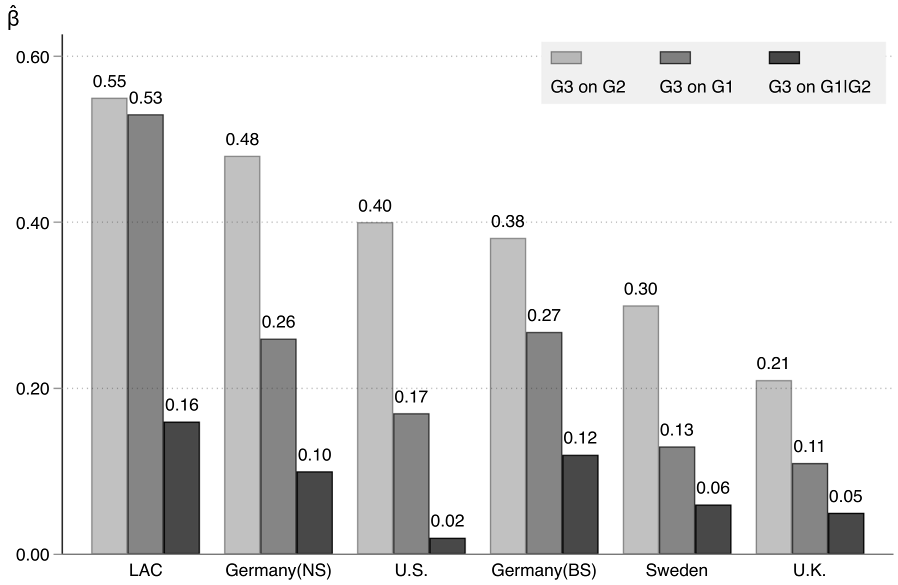

Fig. 3 Three-generations estimates in a comparative perspective. Notes: Fig. 3 plots the regression slope coefficients reported in Table 1 with analog estimates published for Sweden, Germany, the U.S., and the U.K. The Swedish estimates come from Lindahl et al. (2015), while the estimates for Germany(NS), the U.S., and the U.K. come from Neidhöfer and Stockhausen (2019). We also included Germany(BS), which are estimates from Braun and Stuhler (2018) using the NEPS-2 data. All coefficients are statistically significant at conventional levels

Overall, the unconditional persistence between children and grandparents in LAC (0.53) is at least two times larger than the same coefficient computed for other countries (0.26 and 0.27 for Germany, 0.17 for the U.S., 0.13 for Sweden, and 0.11 for the U.K.).

Figure 3 also plots the conditional persistence between children and grandparents (G3 on $G1|G2$). For LAC, it remains high at 0.16. The magnitude of this estimate is markedly smaller in other countries, ranging from 0.12 for Germany(BS) to 0.02 for the United States.[25]

The main takeaway is that the three-generation mobility estimates for LAC are substantially large compared to results for other countries, even after conditioning on parental education. We use these empirical estimates to test theories of multigenerational persistence in the next section.

4.3 Theories of multigenerational mobility: from shirtsleeves to shirtsleeves or a universal law of social status?

Using our three-generation empirical estimates to test theories of multigenerational mobility renders the following two main findings: First, the Beckerian AR(1)

[25] Our LAC conditional estimates are also larger than recent estimates for males in India (0.105) reported by Kundu and Sen (2023) in their Appendix C2, Table C5. We could not include their results in our Fig. 3 because they do not report the G3 on G1 coefficient in their paper.

exponentiation procedure over-predicts mobility for LAC. The magnitude of the over-prediction is substantially higher than the overestimation reported for developed countries.

Second, we find that Clark's theory under-predicts mobility but much less than for developed countries. We estimate that Clark's measure of immobility (λ) is high (0.68 vs 0.60 for developed countries) with some important variation across Latin American countries. We elaborate on both results below.

4.3.1 Becker's over-prediction

Becker's extrapolation method proposes to estimate long-term mobility through a simple iteration process. Under specific conditions, then regression to the mean in outcomes is rapid, and therefore the advantages or disadvantages of ancestors would disappear in three generations (Becker and Tomes 1986), thus consistent with the *shirtsleeves to shirtsleeves in three generations* adage.[26]

It is already well documented that this procedure over-predicts mobility for some developed countries (see Stuhler (2023) for a complete summary), but there is no evidence for developing countries. In this section, we compute the Beckerian prediction for LAC and compare it with our actual three-generation estimates in perspective with the results for developed countries.

Figure 4 compares the estimates of the regression slope coefficients with the prediction from extrapolation by iteration, for Latin America and Sweden, Germany, the U.S., and the U.K. We computed the prediction by squaring the coefficient from adjacent generations, displayed before in Fig. 3.

The actual three-generation estimate is 77% higher than the Beckerian predicted coefficient for LAC.[27] The magnitude of the overestimation is much larger than comparable estimates for Sweden, Germany(NS), the U.S., and the U.K that average to 31%. The over-prediction is similar to the result for Germany(BS), yet at a much lower immobility.[28]

Overall, these findings indicate that the iteration of two-generation measures is far from providing a good approximation for mobility across multiple generations in developing countries. The Beckerian theory, widely used thus far, appears to provide a better fit with the empirical results only for the world's most mobile countries. This result supports the idea that we need a theory consistent with stronger persistence in the patterns of multigenerational transmission, specially for developing countries. Clark (2014)'s universal law of socioeconomic status provides a theory with those characteristics, which is why we discuss it next.

[26] As Lindahl et al. (2015) (section II) discuss, the outcome needs to follow an AR(1) process—with uncorrelated endowments. If not true, then Becker and Tomes (1986)'s theoretical model could generate high multigenerational persistence.

[27] We compute the percent of over-prediction following the same procedure as in Braun and Stuhler (2018) to keep the results comparable. In our data, the G3 on G2 estimated coefficient for LAC is 0.55. The prediction from extrapolation by iteration is $0.55^2 = 0.30$. Therefore, the actual estimate of 0.53 is 77%=(0.53−0.30)/0.30 larger than the prediction. Using the product of the G3-G2 and G2-G1 regression coefficients, we obtain a prediction of 0.42, which is still 11 percentage points below the actual estimate.

[28] The average over-prediction considering both Germany(BS) and Germany(NS), plus Sweden, the U.S., and the U.K, is 46% still way beyond the 77% for LAC.

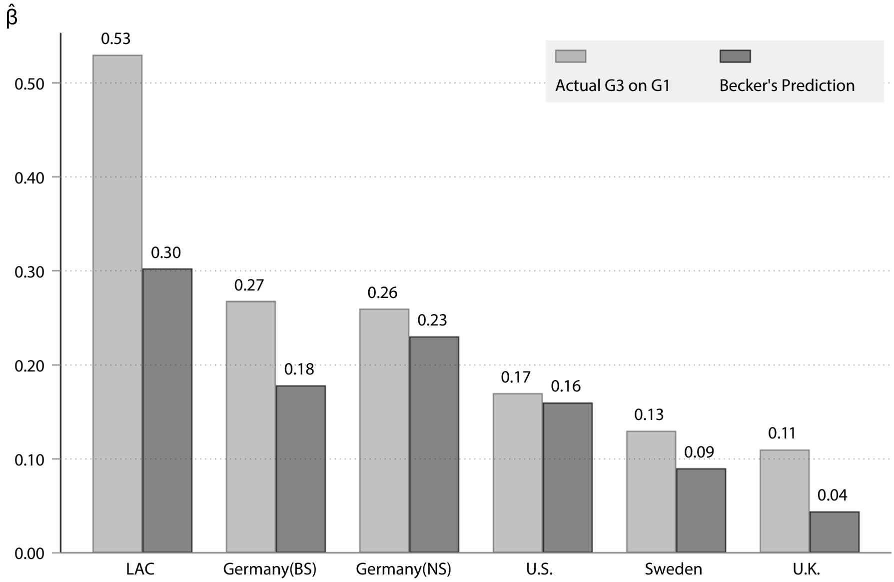

Fig. 4 Actual (βs) estimates vs Becker's prediction. Notes: Fig. 4 plots both the regression slope coefficients for G3 on G1 and the prediction from the Beckerian extrapolation by iteration, for our Latin American countries (LAC) and Sweden, Germany, the U.S., and the U.K. The G3-G1 estimates come from Lindahl et al. (2015) for Sweden and from Neidhöfer and Stockhausen (2019) for Germany(NS), the U.S., and the U.K. We also included Germany(BS), which are estimates from Braun and Stuhler (2018) using the NEPS-2 data. All coefficients are statistically significant at conventional levels. We provide tables with these results for each country and in the Appendix

4.3.2 Clark's universal law

We estimate Clark's measure of immobility (the heritability of unobserved endowments, λ) and compare it with those available for other countries such as Germany, Sweden, United States, and the United Kingdom.

Figure 5 displays the results and helps to assessing (Clark 2014)'s three hypotheses. The findings support the first hypothesis, as the estimated λ is consistently larger than the regression slope coefficient. We also find that Clark's measure of immobility is high for LAC (0.68) compared to developed countries (0.60), as expected. This result indicates that Clark's theory underpredicts mobility but much less than for developed countries. Still, the estimated λ for LAC is lower than the value of 0.75 and therefore provides evidence against Clark's second hypothesis.

The third hypothesis indicates that λ is constant across time and space. Previous studies using data from Europe and the U.S. report significant cross-country variation, thus rejecting this hypothesis (Colagrossi et al. 2020; Braun and Stuhler 2018; Vosters 2018; Torche and Corvalan 2018).

In line with this evidence, we find substantial variation in the latent factor across countries, with values ranging from 0.533 in Paraguay to 0.714 in Chile (see the Appendix for individual country estimates). While some countries show heritability coefficients that are similar to Clark's hypothesis, others do not. Our results are similar

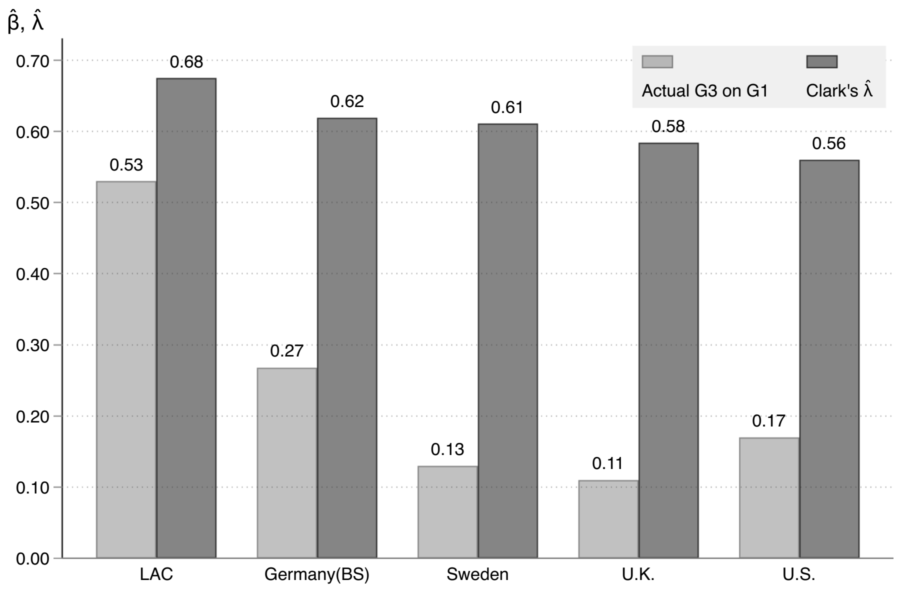

Fig. 5 Actual (βs) estimates vs Clark's heritability coefficient (λs). Notes: Fig. 5 plots both the regression slope coefficients for G3 on G1 and Clark's heritability coefficient λs for our Latin American (LAC) and Sweden, Germany, the U.S., and the U.K. The Swedish estimates come from Lindahl et al. (2015), while the estimates for the U.S. and the U.K. come from Neidhöfer and Stockhausen (2019). We also included Germany(BS), which are estimates from Braun and Stuhler (2018) using the NEPS-2 data. All coefficients are statistically significant at conventional levels. We provide the estimates for each country in the Appendix

to those by Colagrossi et al. (2020), who report large heterogeneity in λ across 28 European countries. This variation across countries suggests that there is no universal law of mobility, highlighting the importance of examining mobility patterns in specific regional contexts.

Overall, our results provide insights to discriminate between competing models of multigenerational mobility in developing countries. Clark's theory does not perfectly match the data, but it aligns better than the Beckerian theory in describing long-term immobility in our Latin American countries

4.4 Trends in mobility over time

The question of whether intergenerational mobility in LAC has improved over time depends on the specific measures used for its assessment. Regression slope coefficients indicate an improvement in intergenerational mobility across multiple generations over time, Pearson and Spearman correlations suggest that mobility is relatively stable, and bottom-half mobility indicates improvements for the lower end of the distribution.

We start by showing the evolution of slope coefficients, Pearson and Spearman correlations, and bottom-half mobility as a function of the parental generation birth cohorts, which is the common practice in the literature. The results, in Fig. 6, reveal that intergenerational mobility has consistently improved over time as measured by

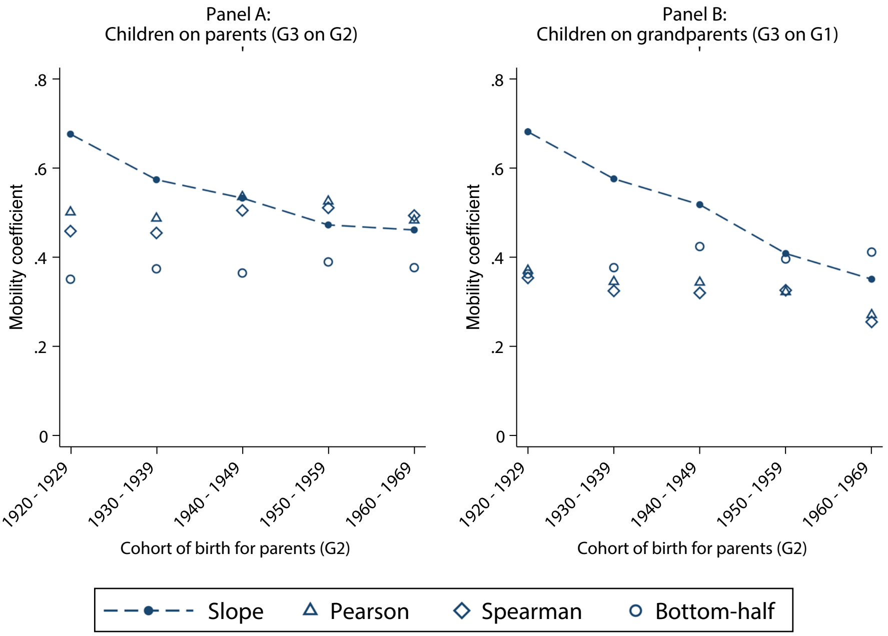

Fig. 6 Trends in mobility coefficients across cohorts of parents (G2). Notes: Fig. 6 presents the results obtained from estimating Eq. 3. The left panel displays the coefficients derived from regressing grandchildren (G3) on parents (G2). Meanwhile, the right panel illustrates the coefficients obtained from regressing grandchildren (G3) on grandparents (G1). The regression slope coefficients are represented by circles connected by lines, Pearson correlation coefficients are denoted by triangles, Spearman rank-rank coefficients are depicted as diamonds, and Asher et al. (2022) μ_0^{50} by empty circles. We provide the specific coefficients in the Appendix

regression slope coefficients, remains relatively stagnant by Pearson and Spearman correlations, and improves according to bottom-half mobility for grandparent–children transitions. We describe these findings in more detail below.

Evolution of parent–child mobility. The results in the left panel indicate a decrease in regression slope coefficients over time. The parent–child coefficient decreases by 0.22 points over 50 years, starting from 0.68 for the parent generation born in the 1920 s to 0.46 for the parent generation born in the 1960 s. However, when examining the Pearson or Spearman correlations, there is a pattern of no improvements over the same 50-year period. This is also the case when using bottom-half mobility, which shows no improvements across cohorts in the expected ranking of parents born to grandparents at the bottom half. These findings align with the research conducted by Neidhöfer et al. (2018) and Hertz et al. (2008) for similar cohorts in Latin American countries.

Evolution of grandparent–children mobility. The regression slope coefficients for the association between grandparents and children also show a declining trend over time. It decreases by 0.33 points over a span of 50 years, starting again from 0.68 for older cohorts to 0.35 for younger cohorts. The decrease in regression slope coefficients is more pronounced for G3-G1 compared to G3-G2, suggesting that the association between grandparents-children schooling tends to diminish more rapidly than that of parents-children. However, it is important to note that this observation may be influenced by the sensitivity of coefficients to shifts in the distribution of schooling over time. The bottom line is that, even after 50 years, the G3-G1 regression coefficient persists and remains statistically distinguishable from zero.

When examining the Pearson and Spearman correlations, we once again observe a pattern of stagnant mobility. However, unlike the parent–child coefficients, they show a slight improvement for this period. Finally, bottom-half mobility measures show a consistent improvement in mobility from grandparents to children. The expected ranking of a child who descends from grandparents at the bottom half improves by approximately 10 percentage points over 50 years.

4.4.1 Mobility coefficients and compulsory schooling laws

The differences between measures shown in Fig. 6 may reflect changes in the distribution of schooling for a particular generation or specific groups of the population, as raised by Landersø and Heckman (2017) and Nybom and Stuhler (2021). We find descriptive evidence along these lines, as displayed in Fig. 7. The implementation of compulsory schooling laws increased the average schooling, but also led to a significant decrease in the dispersion of years of schooling among exposed cohorts.

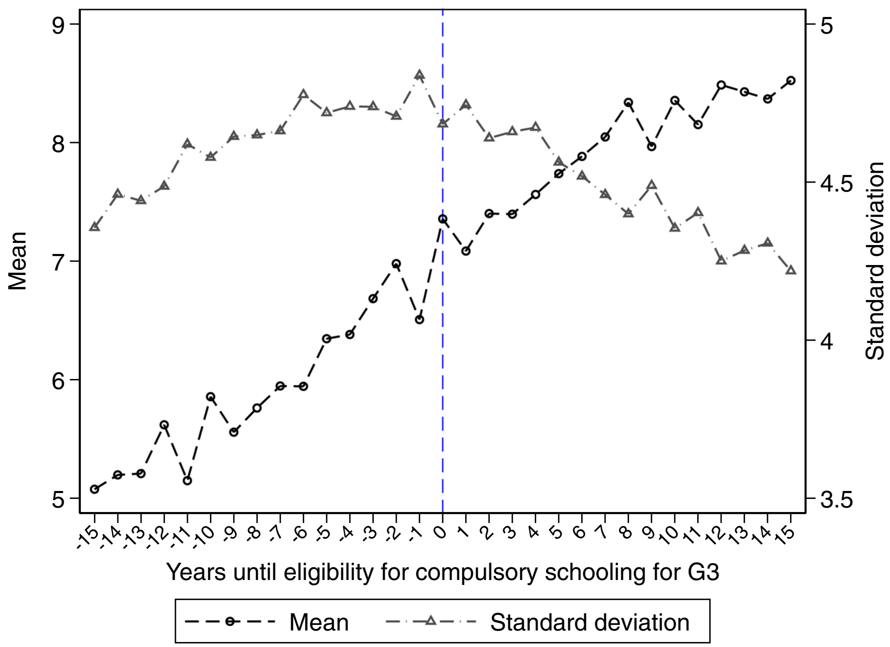

Fig. 7 Schooling before and after eligibility for compulsory reforms. Notes: Fig. 7 displays the mean and standard deviations of schooling (in the vertical axes) versus years until eligibility for compulsory schooling reforms (horizontal axis) for children (G3). The vertical dashed blue line is drawn at zero, meaning that it separates children cohorts that were first exposed to compulsory schooling by birth year

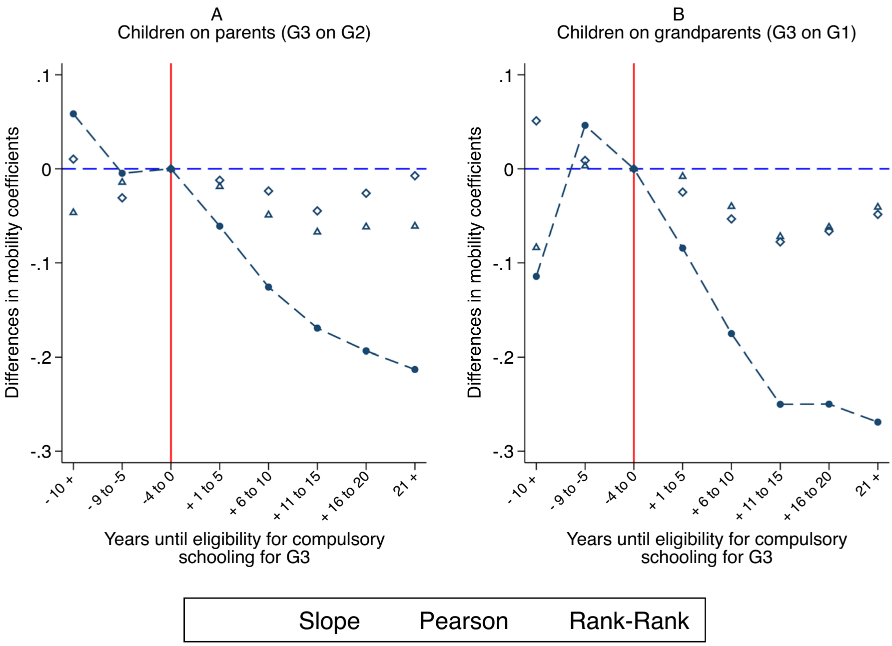

Fig. 8 Mobility before and after compulsory school reforms. Notes: Panel 1 shows on the y-axis the coefficients between a regression of G3 years of schooling against G2 years of schooling (in circles), and against G1 years of schooling (in triangles), for each birth cohort pooling all countries. Panel 2 shows on the y-axis the coefficients between a regression of G3 years of schooling against G2 years of schooling (in circles), and against G1 years of schooling (in triangles), for each birth cohort pooling all countries

This fact is consistent with the changes in mobility estimated before and after the compulsory laws. Figure 8 presents the estimated β_cs from Eq. 4. After the implementation, regression slope coefficients (represented by the connected line) tend to decline rapidly, while Pearson and Spearman correlations remain relatively stable.

The left panel displays the mobility coefficients from a regression model that examines the relationship between child and parental education among cohorts exposed and unexposed to compulsory schooling reforms within each country. The reference cohort is the one that was not exposed to the compulsory schooling reform. The figure indicates that cohorts unexposed to the reform (to the left of the vertical red line) are quite similar in terms of mobility. However, once the reform is implemented, the coefficients consistently decrease in comparison to the reference cohort.

The right panel shows a similar pattern for children and grandparents. It plots the coefficients from a regression model that investigates the relationship between child and grandparental education and the child's birth cohort. Prior to the compulsory schooling laws, the mobility coefficients remain stable across cohorts. After the implementation of the reforms, there is a significant increase in mobility (i.e., a decrease in coefficients) compared to the reference cohort.

In both analyses, the Pearson and Spearman correlations exhibit a stable pattern across cohorts. The estimated coefficients before and after the reforms suggest that compulsory schooling laws have a lesser impact on mobility when accounting for changes in the distribution of education across generations.

Overall, these results suggest that compulsory schooling laws are strongly associated with increases in educational attainment, but more weakly associated with changes in the relative position within the distribution of schooling.

5 Conclusions

This paper provides new evidence on intergenerational mobility across three generations in developing countries, focusing on six diverse Latin American countries (LAC). We build a novel dataset that combines survey information with national census data, covering about 50,000 triads of grandparents-parents-children born between 1890 and 1990. Examining a century of data, we study a period in which significant political reforms and socioeconomic changes occurred in the region.

We replicate and extend previous two-generation studies, contextualizing our findings within the literature for LAC and studies conducted in more mobile, developed nations. Estimating a host of five mobility measures, our results contribute to providing a deeper understanding of long-run mobility patterns.

Our results indicate that the set of LAC we examined exhibits a high degree of immobility across generations within the same families. Whether we consider mobility from grandparents to parents, from parents to children, or from grandparents to children, the region shows limited mobility compared to high-income countries considered in previous research (Lindahl et al. 2015; Braun and Stuhler 2018; Neidhöfer and Stockhausen 2019).

Younger generations consistently attain more years of schooling than previous generations which translates into higher mobility according to regression slope coefficients. However, we find a stagnancy in mobility when we account for changes in the distribution of schooling across generations. One reason behind this result is that there is a limit to the amount of education individuals can attain, resulting in capped schooling distributions. This limitation creates a ceiling effect that can be partially alleviated when using measures that focus at the bottom of the distribution.

We thus implement recently developed measures of mobility, finding notable improvement gains from the lower end of the distribution. This result is natural given the important educational upgrade experienced at the bottom of the schooling distribution in LAC, especially for the transition from the grandparental to the parental generation.

Our results beyond two generations are also important to contrast theories of intergenerational mobility, uncovering two novel findings. First, the Beckerian exponentiation procedure markedly overpredicts mobility for the six LAC under study, at a much larger rate than the overestimation reported for developed countries. Second, we find that Clark's theory underpredicts mobility but much less than for developed countries. Clark's measure of immobility is substantially higher for our six LAC than the available estimates for developed countries.

Put together, our empirical evidence does not support Becker's widely used prediction of low multigenerational persistence. The Beckerian theory appears to fit the empirical results only for world's most mobile countries. Clark's theory of high and sticky persistence provides a better approximation for describing mobility across multiple generations in our six developing countries.

We also document that three-generation mobility has improved over time according to regression slope and bottom-half measures, but not by Pearson and Spearman measures. We show that educational reforms can explain differences across measures of multigenerational mobility, because they affect both the mean and the dispersion of schooling.

Our findings are robust across a wide range of empirical exercises, but it is important to acknowledge some of the limitations of our analysis. First, we do not test whether grandparents have an independent causal effect on their grandchildren's educational outcomes. Identifying the precise causal channels driving these associations is beyond the scope of this work. Second, we cannot explain the observed pattern of multigenerational persistence, as we lack instruments to identify these effects, e.g., data on grandparents' deaths. Third, our dataset is sparse in the sense that besides education, we do not have much information on grandparents or children in the data. This restriction prevents us from further analyses, such as exploring specific channels or documenting heterogeneity across many different groups.

Overall, we see our work as contributing to a deeper understanding of long-term mobility and expect future research to replicate it in different contexts, as better data and more information spanning multiple generations becomes available.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00148-025-01066-7.

Acknowledgements We thank Jan Stuhler, Klaus Zimmerman, Elisa Jacome, Tom Vogl, Leah Boustan, Alex Eble, Susan Mayer, Ercio Munoz, Guido Neidhöfer, Elisabetta Aurino, Carolina Lopez, Dolores De la Mata, Maria Berniell, Ernesto Schargrodsky and seminar participants at the AEFP Education in Developing Countries Group Workshop, the LACEA-LAMES Annual Meeting, the London School of Economics and Centre for Social Conflict and Cohesion Studies Inequalities Conference, the Conference of Social Mobility and Intergenerational Transmission of Opportunities OPINBI-CM at the University of Alcala, and the SCHPP Annual Conference for helpful comments and suggestions. Ela Diaz provided excellent research assistance. We also thank editor Alfonso Flores-Lagunes and three reviewers for helpful comments. Gallegos thanks the Center for Studies of Conflict and Social Cohesion (ANID/FONDAP/15130009 and ANID/FONDAP/1523A0005) and support from ANID (FONDECYT/Iniciación/11220263). Celhay acknowledges financial support from ANID (FONDECYT/Regular/1221461) and support from ANID (PIA/PUENTE AFB230002). This paper was awarded the https://www.caf.com/en/currently/calls/2020/12/intergenerational-mobility-in-latinamerica/ CAF Development Bank's competitive grant "Intergenerational Mobility in Latin America." The views expressed in this paper are those of the authors and should not be attributed to the CAF Development Bank or any other institution.

Data availability The datasets analyzed during the current study are public. For more information see the Harmonized LSPS (Longitudinal Social Protection Survey) Database. Technical report, Inter-American Development Bank. Labor Markets Division. Washington, DC, 2016. The data is available here https://mydata.iadb.org/Labor/Harmonized-LSPS-Longitudinal-Social-Protection-Sur/ck3a-ui6v and here https://www.mhasweb.org/Home/index.aspx.

Declarations

Conflict of interest The authors declare no competing interests.

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