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DISCUSSION PAPER SERIES

IZA DP No. 17072

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JUNE 2024

ISSN: 2365-9793

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ABSTRACT

Schooling Mobility across Three Generations in Six Latin American Countries*

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 (IGM) measures, finding that (i) the empirical multigenerational persistence in our six countries is twice as high as in developed countries, and 77% higher than what the theoretical model by Becker & Tomes (1986) predicts; (ii) Clark's (2014) theory of high and sticky persistence provides a better approximation for describing mobility across multiple generations in our sample; (iii) Even with high persistence, we uncover significant mobility improvements at the bottom of the distribution by estimating measures of absolute upward mobility (Chetty et al., 2014) and bottom-half mobility (Asher et al., 2022) 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.

JEL Classification: J62, N36, I24, I25, I28

Keywords: developing countries, Latin America, intergenerational mobility, educational policy, multiple generations, compulsory schooling

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* Both authors contributed equally to this manuscript. 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 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 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. This paper is dedicated to the memory of our professor Robert J. Lalonde.

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.

[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.

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 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-generations 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-generations 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}).

[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.

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 ($\beta, r, \rho,$) 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

[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).

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 under-predicts 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 fifty 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.

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.

[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).

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.

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 ten-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

[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).

[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 Table A.15 that the estimates for the other countries in our sample are robust to using these survey percentiles.

six countries when we write LAC, otherwise noted. Grandparents average 2.7 years of completed schooling, which more than doubles to 5.7 years of schooling for parents and then increases to 9.8 years for children, as indicated in Figure 1.[9]

Going beyond averages, Figure 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. Figure A.1 confirms that this is also the case for every country in our analysis and Figure A.2a shows that the average schooling has consistently increased in all countries over three generations.

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.[10]

These results can be directly observed from Figure 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 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. Figure A.2b shows that this pattern of increased dispersion from grandparent to parents is common for all countries in our sample.

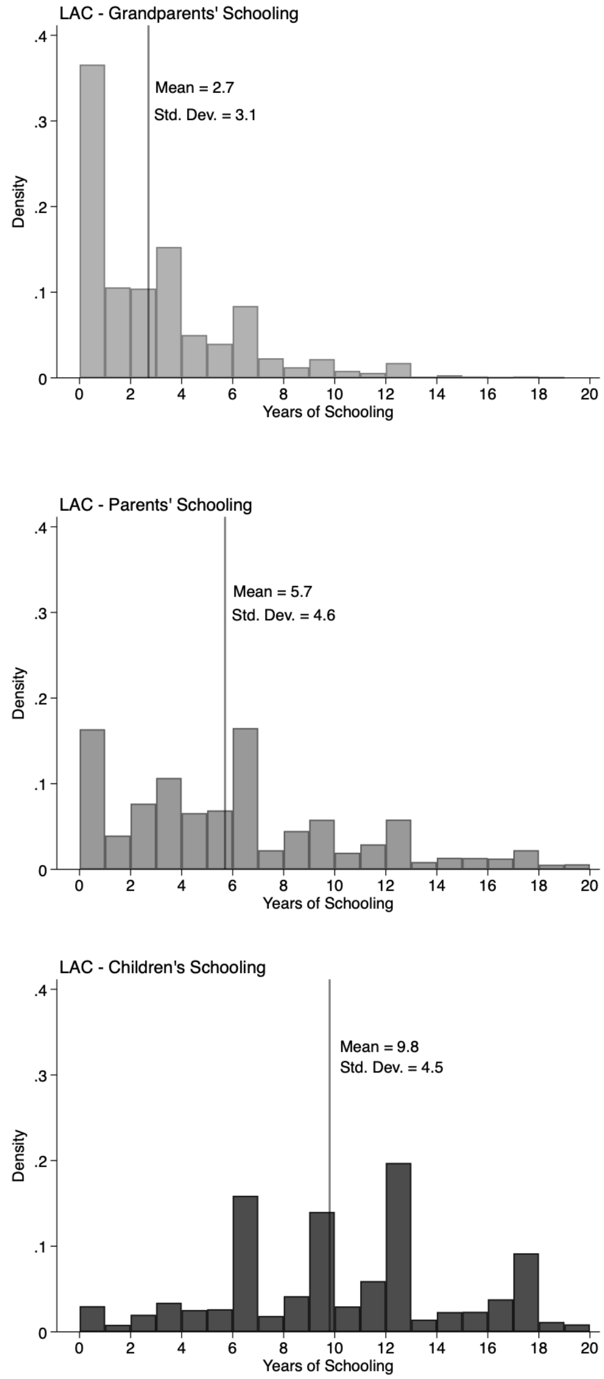
Children's average schooling increases importantly compared to their parents' schooling, but in this case the dispersion remains constant at 4.5 years. While there is some heterogeneity across countries, changes in the dispersion from parents' to children's schooling are markedly smaller than changes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

[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] See Figure A.2b and Figure A.2a in the Appendix for country-specific statistics.

[11] We provide further detail on compulsory schooling laws in subsection 4.3.

Figure 1: Distribution of Schooling Across Three Generations in Six LAC



Notes: Figure 1 plots the distribution of years of schooling for six LAC and for each generation (grandparents, parents and children). Each graph shows a vertical line indicating the mean of the distribution. The data is computed as the simple average across the six countries under study (Chile, Colombia, El Salvador, Mexico, Paraguay and Uruguay). In Figure A.1 we plot the same figures for each country separately.

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. Table A.1 (first column) reports the descriptive statistics supporting this finding. 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). We devote a complete appendix to show that our results are robust to the choice of how to compute grandparental schooling (see Appendix G).

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.

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 Appendix F we describe in detail the exercise of comparing mobility estimates using restricted (co-resident children) and unrestricted

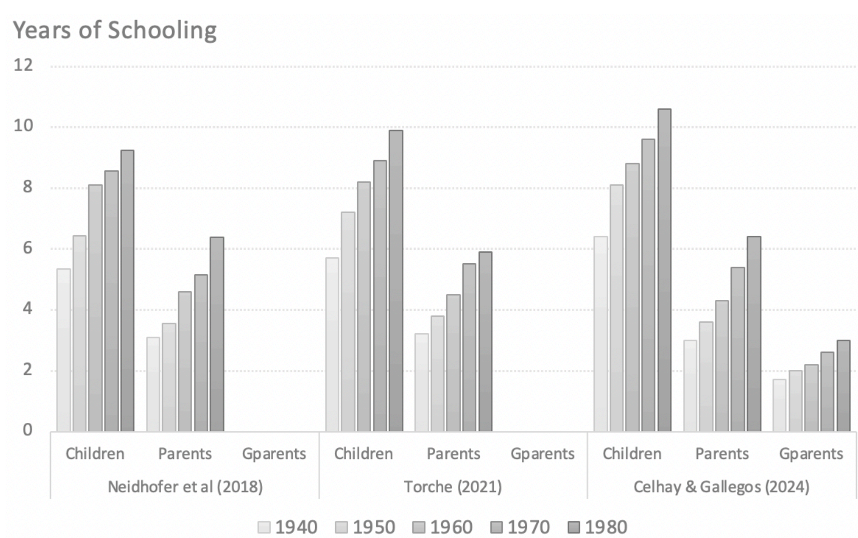
[12] In Hertz et al. (2008), authors report that the respondent's paternal and maternal information on education was available 87 and 92 percent of the time. In our data we have even higher rates, of 88 and 94 percent, respectively.

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 (see Table A.2), 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.

Figure 2: Adding a new generation to the empirical studies



Notes: Figure 2 plots the average schooling by generation, for cohorts born in 1940 to 1980 using data from three studies: Neidhofer et al (2018), Torche (2021b) and our study.

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

[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).

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.

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,

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

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 equation (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 equation (1) above adding the possibility of grandparent contribution in the following reduced form equation:

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

which previous researchers have estimated for developed countries (e.g., Behrman and Taubman, 1985 for the U.S., Lindahl et al., 2015 for Sweden, Braun and Stuhler, 2018 for Germany). In specification (2) we labeled the parameters with a prime ($'$) to differentiate them from parameters in equation (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 (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) estimate it as the expected rank of a child who was born to parent at the 25th percentile

[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 Table A.3 in the Appendix the descriptive statistics on the percentiles of schooling for each generation and country.

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]

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.

[16] Figure A.3 illustrates 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.

3.3.1 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 equation (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 $\alpha_0 = \beta_0 + \beta_1, \ \ \alpha_1 = \beta_1^2$, 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. Following Braun and Stuhler (2018)'s latent factor model (see Appendix D), the correlation of socioeconomic status between generations t

[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.

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.

[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.

To obtain the regression slope coefficients, we directly estimate equation (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 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 eight 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 nine 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 nine 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 nine 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 twelve 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

[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).

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 six-year-old child who turns six 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 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:

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

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.

[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 equation (1).

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-generations 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,b).

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.

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 examines 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 Figure 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.

Table 1: Educational Intergenerational Mobility Measures for Six Latin American Countries

	LAC	Chile	Colombia	El Salvador	Mexico	Paraguay	Uruguay
Panel 1: 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	4,362	2,600	1,175	6,523	1,227	582
Panel 2: 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	3,462	1,499	29,702	1,595	637
Panel 3: 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
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	3,462	1,499	29,702	1,595	637
Panel 4: 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	3,462	1,499	29,702	1,595	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 can be found in Table A.17. 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 exception are the regression slope and correlation estimates for Paraguay in panel 4). †: These estimates are conditioning on children whose parents (G2) are below the 50th percentile of their schooling distribution.

Latin America's high immobility is declining across generations, when measured by regression slope coefficients (βs). The estimated regression slope coefficient for Latin America indicate 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.

Mobility remains constant across generations, when measured by Pearson (r) and Spearman (ρ) 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.

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) reports an average coefficient of 0.79 for LAC, similar to our slope coefficient of 0.77.[22] For younger cohorts, Neidhöfer et al. (2018) finds a regression slope coefficient of 0.60 (and decreasing), resembling the 0.55 regression slope coefficient from our G3 on

[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.

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.

There is higher mobility for the bottom of the distribution, according to the measures of absolute upward (p_{25}) mobility and bottom-half (μ_0^{50}). 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) estimates 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

[23] Note that 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) estimates 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-generations evidence for other countries.

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.

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 equation (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).

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).

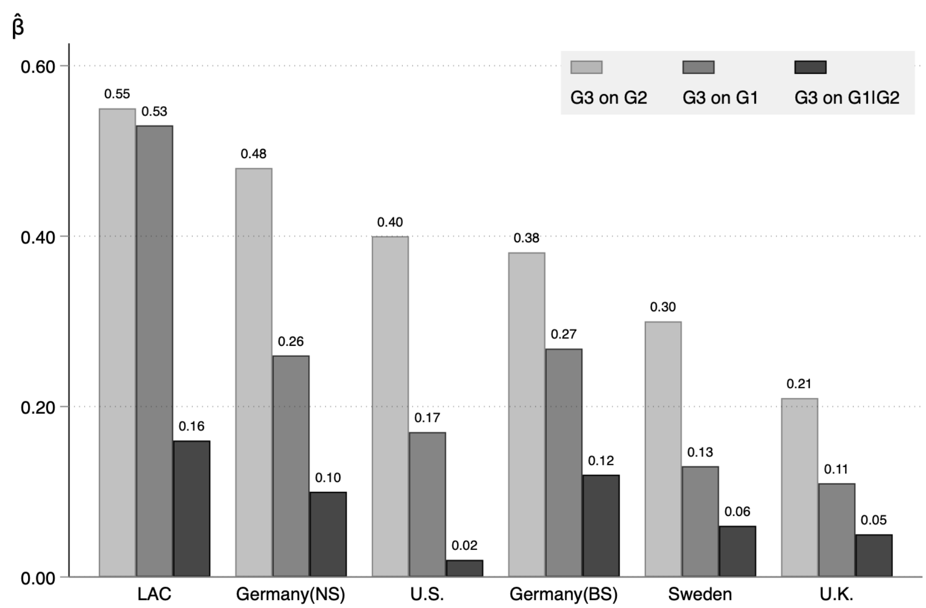
We see this evidence contributing to a deeper understanding of long-term mobility, and expect future work to replicate it in different contexts as more information spanning multiple generations becomes available. Next, we discuss our findings in perspective with results from the available three-generation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

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).

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.[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.

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: Three-generations Estimates in a Comparative Perspective



Notes: Figure 3 plots the regression slope coefficients for for Latin America (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) using the NEPS-2 data. All coefficients are statistically significant at conventional levels.

[24]We present the few available results that are comparable in the Appendix. Also, we are not aware of other evidence implementing μ_0^{50} and p_{25} over three generations.

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.

4.2.1 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) 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.

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.

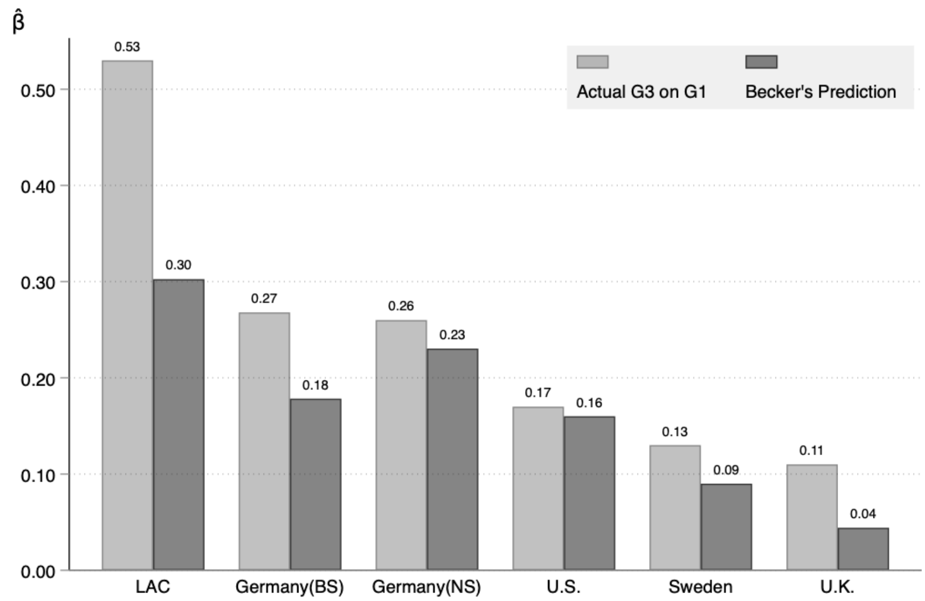
[25] Our LAC conditional estimates are also larger than recent estimates for males in India (0.105) reported by Kundu and Sen (2023) in their Appendix C2, Table C5. We could not include their results in our Figure 3 because they do not report the G3 on G1 coefficient in their paper.

[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.

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 Figure 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]

Figure 4: Actual (βs) Estimates vs Becker's Prediction



Notes: Figure 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 Table A.4 and Table A.5.

Overall, these findings indicate that the iteration of two-generations measures is far from providing a good approximation for mobility across multiple generations in developing countries. The

[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.

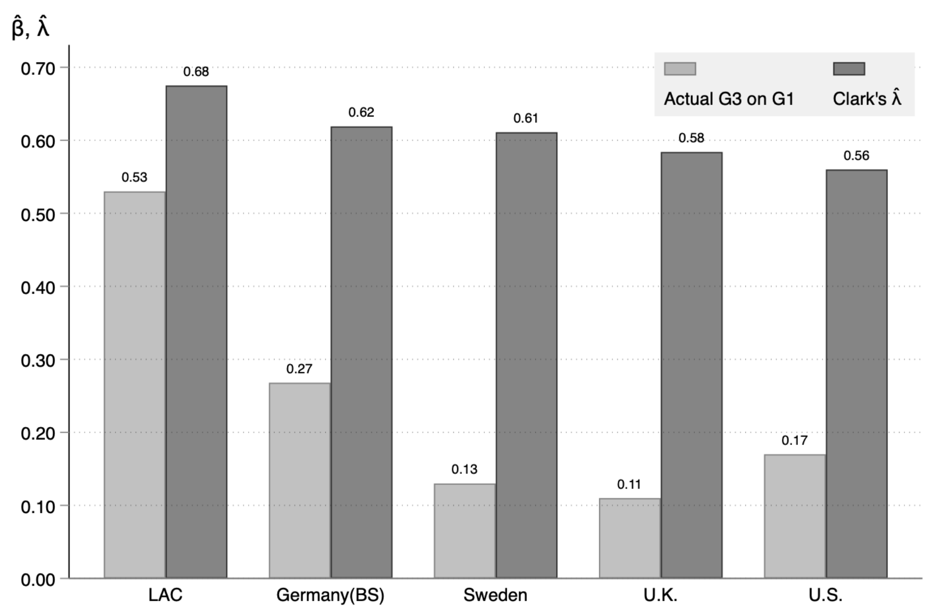
[28]The average over-prediction considering both Germany(BS) and Germany(NS), plus Sweden, the U.S. and the U.K, is 46% still way beyond the 77% for LAC.

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.

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.

Figure 5: Actual (βs) Estimates vs Clark's Heritability Coefficient (λs)



Notes: Figure 5 plots both the regression slope coefficients for G3 on G1 and Clark's heritability coefficient λs for our Latin America (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 Table A.6.

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 Table A.6 for individual country estimates). While some countries show heritability coefficients that are similar to Clark's hypothesis, others do not. Our results are similar 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 fit the data perfectly, but does a better job than the Beckerian theory when describing LAC's long-run immobility.

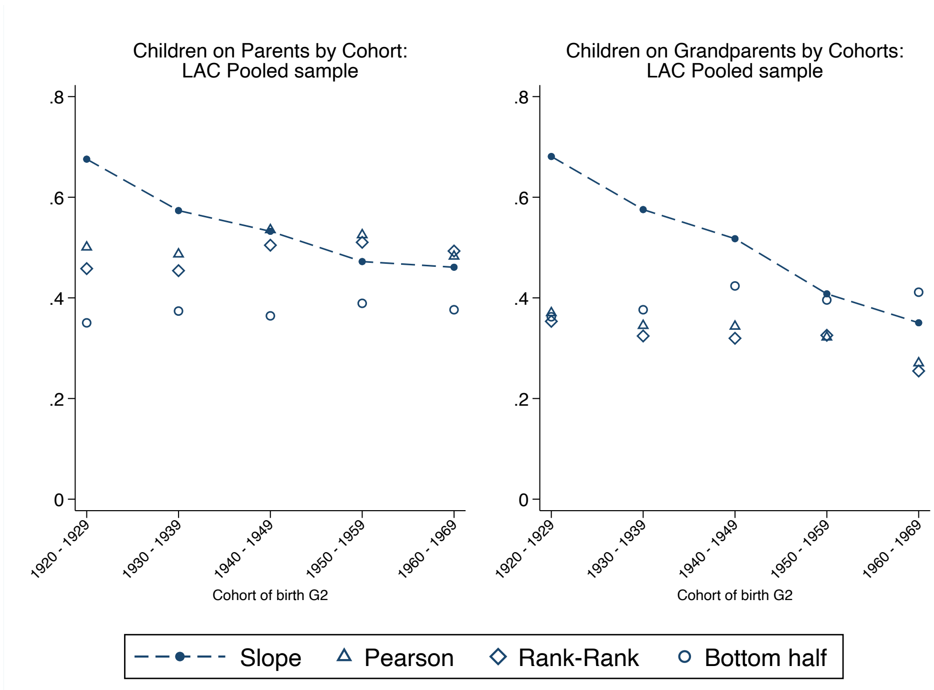
4.3 Trends in Mobility Over Time

The question of whether intergenerational mobility in LAC has improved over time depends on the measures used to evaluate it. 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.

Figure 6 shows the evolution of slope coefficients, Pearson and Spearman correlations, and Bottom-Half mobility for each cohort separately.[29] The results reveal that intergenerational mobility has consistently improved over time as measured by regression slope coefficients (see Panel A), remains relatively stagnant by Pearson and Speaman correlations (see Panel B), and improves according to non-linear for grandparent-children transitions.

[29] We report results for LAC in Table A.7 while Table A.8 to Table A.13 show country specific results.

Figure 6: Trends in Mobility Coefficients across Cohorts of Parents (G2)



Notes: This figure presents the results obtained from estimating equation (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 . The specific coefficients can be found in Table A.7.

Evolution of parent-child mobility. The results in the left panel indicate a decrease in regression slope coefficients over time. For instance, the parent-child coefficient decreases by 0.22 points over 50 years, from 0.68 for the parent generation born in the 1920s to 0.46 for the parent generation born in the 1960s. 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 for non linear measures, which show 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 LAC 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, 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.

4.3.1 Mobility Coefficients and Compulsory Schooling Laws

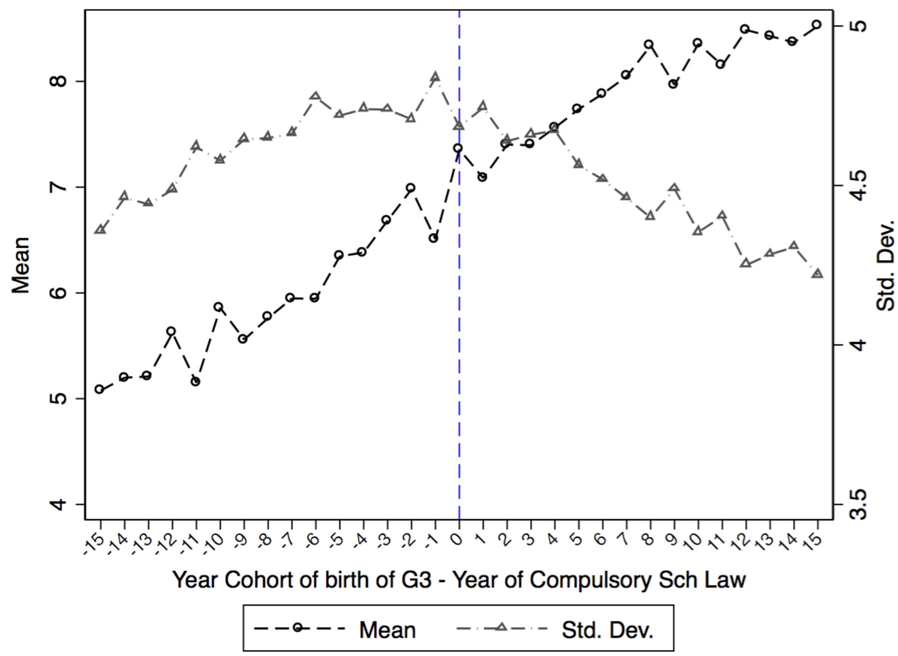
The differences between measures shown in Figure 6 may reflect changes in the distribution of schooling for a particular generation and/or specific groups of the population, as raised by Landersø and Heckman (2017) and Nybom and Stuhler (2021).

We find descriptive evidence that the implementation of compulsory schooling laws led to a significant decrease in the variance of years of schooling among exposed cohorts, while the average schooling remained similar (see Figure 7).

Figure 8 presents the estimated β_cs from equation (4).[30] After the implementation, regression slope coefficients (represented by the connected line) tend to decline rapidly, while Pearson and Spearman correlations remain relatively stable.

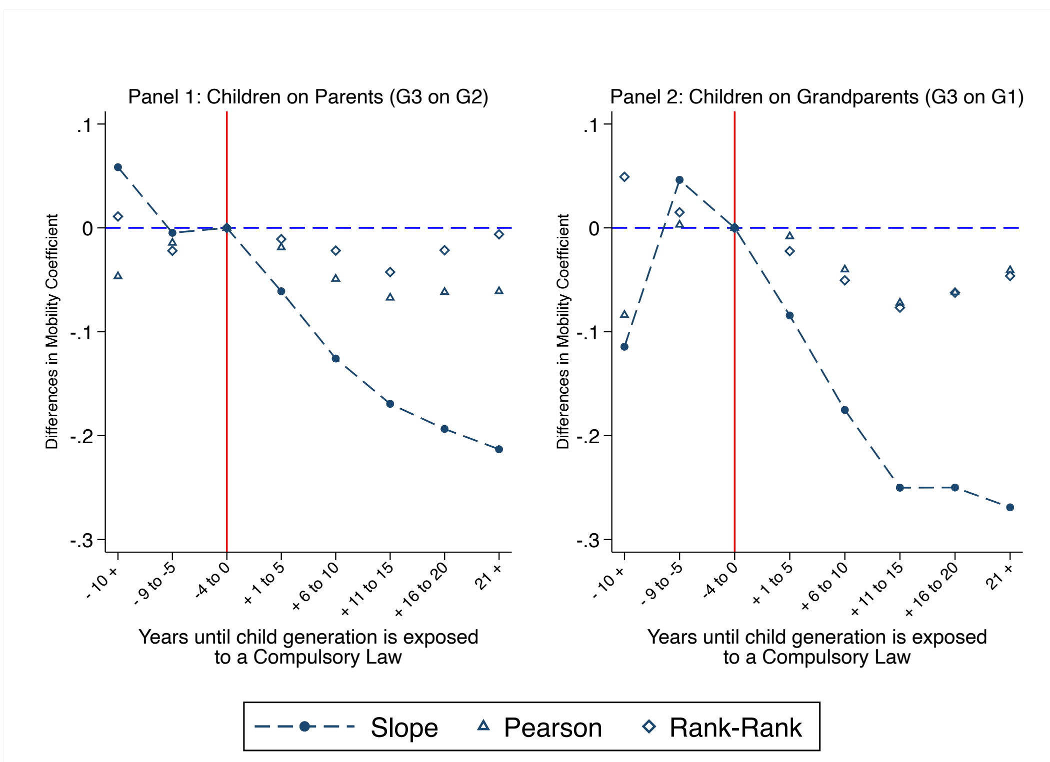
[30] Table A.14 displays the corresponding estimation results.

Figure 7: Schooling Before and After Compulsory Reform



Notes: This figure shows the mean and standard deviations of years of schooling for grandchildren (G3) birth cohorts exposed and unexposed to the reforms. The dashed blue line separates the birth cohorts that were first exposed to compulsory schooling according to their birth year.

Figure 8: Mobility Before and After Compulsory School Reforms



Notes: Panel 1 in Figure 8 shows in 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 in Figure 8 shows in 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. The results are available in Table A.14.

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 cohorts unexposed to the reform (to the left of the 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 (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.

References

Abramitzky, R., Boustan, L., Eriksson, K., Feigenbaum, J., and Pérez, S. (2021). Automated Linking of Historical Data. *Journal of Economic Literature*, 59(3):865–918.

Acciari, P., Polo, A., and Violante, G. L. (2022). "And Yet It Moves": Intergenerational Mobility in Italy. *American Economic Journal: Applied Economics*, 14(3):118–163.

Acemoglu, D., Gallego, F. A., and Robinson, J. A. (2014). Institutions, human capital, and development. *Annu. Rev. Econ.*, 6(1):875–912.

Alesina, A., Hohmann, S., Michalopoulos, S., and Papaioannou, E. (2020). Religion and educational mobility in Africa. Technical report, National Bureau of Economic Research.

Alesina, A., Hohmann, S., Michalopoulos, S., and Papaioannou, E. (2021). Intergenerational Mobility in Africa. *Econometrica*, 89(1):1–35.

Anderson, L. R., Sheppard, P., and Monden, C. W. (2018). Grandparent effects on educational outcomes: a systematic review. *Sociological Science*, 5:114–142.

Asher, S., Novosad, P., and Rafkin, C. (2022). Intergenerational mobility in India: New methods and estimates across time, space, and communities. *Working Paper, September 2022. URL http://paulnovosad. com/pdf/anr-india-mobility. pdf. Conditionally accepted, American Economic Journal: Applied Economics*.

Barone, G. and Mocetti, S. (2021). Intergenerational mobility in the very long run: Florence 1427–2011. *The Review of Economic Studies*, 88(4):1863–1891.

Barro, R. J. (2001). Human capital and growth. *American Economic Review*, 91(2):12â17.

Becker, G. S. and Tomes, N. (1979). An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of Political Economy*, 87(6):1153–1189.

Becker, G. S. and Tomes, N. (1986). Human capital and the rise and fall of families. *Journal of Labor Economics*, 4(3, Part 2):S1–S39.

Behrman, J. and Taubman, P. (1985). Intergenerational earnings mobility in the United States: some estimates and a test of Becker's intergenerational endowments model. *The Review of Economics and Statistics*, pages 144–151.

Behrman, J. R., Gaviria, A., and Székely, M. (2001). Intergenerational mobility in Latin America. *Economia*, 2(1):1–31.

Berman, Y. (2022). The long-run evolution of absolute intergenerational mobility. *American Economic Journal: Applied Economics*, 14(3):61–83.

Biblioteca Nacional de Chile (1965). Reforma Educacional iniciada en 1965. In *El Ministerio de Educación y el Estado docente (1927-2006). Memoria Chilena.* Disponible en http://www.memoriachilena.gob.cl.

Björklund, A. and Salvanes, K. G. (2011). Education and family background: Mechanisms and policies. In *Handbook of the Economics of Education*, volume 3, pages 201–247. Elsevier.

Black, S. and Devereux, P. (2011). Recent developments in intergenerational mobility. *Handbook of Labor Economics*, 4:1487–541.

Braun, S. T. and Stuhler, J. (2018). The transmission of inequality across multiple generations: testing recent theories with evidence from Germany. *The Economic Journal*, 128(609):576–611.

Card, D., Domnisoru, C., and Taylor, L. (2022). The intergenerational transmission of human capital: Evidence from the Golden Age of upward mobility. *Journal of Labor Economics*, 40(S1):S39–S95.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014). Where is the land of opportunity? the geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics*, 129(4):1553–1623.

Clark, G. (2014). *The son also rises: surnames and the history of social mobility*. Princeton University Press.

Colagrossi, M., d'Hombres, B., and Schnepf, S. V. (2020). Like (grand) parent, like child? multigenerational mobility across the EU. *European Economic Review*, 130:103600.

Constitución Política de Colombia (1991). Artículos 27, 67, 69 y 70.

Constitución Política de la República de El Salvador (1983). Sección Tercera: Educación, Ciencia y Cultura.

Corak, M. and Piraino, P. (2011). The intergenerational transmission of employers. *Journal of Labor Economics*, 29(1):37–68.

De los Campos, H. and Ferrando, F. (2013). La universalización de la educación obligatoria en uruguay. avances y desafíos.

Derenoncourt, E. (2022). Can you move to opportunity? Evidence from the Great Migration. *American Economic Review*, 112(2):369–408.

Deutscher, N. and Mazumder, B. (2021). Measuring intergenerational income mobility: A synthesis of approaches. *Journal of Economic Literature*.

Elías, R. (2014). Análisis de la reforma educativa en paraguay: discursos, prácticas y resultados. Technical report, Buenos Aires, CLACSO.

Emran, M. S., Greene, W., and Shilpi, F. (2018). When measure matters coresidency, truncation bias, and intergenerational mobility in developing countries. *Journal of Human Resources*, 53(3):589–607.

Enamorado, T., Fifield, B., and Imai, K. (2019). Using a probabilistic model to assist merging of large-scale administrative records. *American Political Science Review*, 113(2):353–371.

Feigenbaum, J. J. (2018). Multiple measures of historical intergenerational mobility: Iowa 1915 to 1940. *The Economic Journal*, 128(612):F446–F481.

Ferrie, J., Massey, C., and Rothbaum, J. (2021). Do grandparents matter? Multigenerational mobility in the United States, 1940–2015. *Journal of Labor Economics*, 39(3):597–637.

Fields, G. S. and Ok, E. A. (1996). The meaning and measurement of income mobility. *Journal of Economic Theory*, 71(2):349–377.

Francesconi, M. and Nicoletti, C. (2006). Intergenerational mobility and sample selection in short panels. *Journal of Applied Econometrics*, 21(8):1265–1293.

Hertz, T., Jayasundera, T., Piraino, P., Selcuk, S., Smith, N., Verashchagina, A., et al. (2008). The inheritance of educational inequality: International comparisons and fifty-year trends. *The BE Journal of Economic Analysis & Policy*, 7(2):1–46.

Hilger, N. G. (2015). The great escape: Intergenerational mobility in the United States since 1940. Technical report, National Bureau of Economic Research.

IADB (2016). Harmonized LSPS (Longitudinal Social Protection Survey) Database. Technical report, Inter-American Development Bank. Labor Markets Division. Washington, DC. Link to website here.

Kundu, A. and Sen, K. (2023). Multigenerational mobility among males in india. *Review of Income and Wealth*, 69(2):395–418.

Landersø, R. and Heckman, J. J. (2017). The Scandinavian fantasy: The sources of intergenerational mobility in Denmark and the United States. *The Scandinavian Journal of Economics*, 119(1):178–230.

Lee, C.-I. and Solon, G. (2009). Trends in intergenerational income mobility. *The Review of Economics and Statistics*, 91(4):766–772.

Lindahl, M., Palme, M., Massih, S. S., and Sjögren, A. (2015). Long-term intergenerational persistence of human capital an empirical analysis of four generations. *Journal of Human Resources*, 50(1):1–33.

Lindahl, M., Palme, M., Sandgren-Massih, S., and Sjögren, A. (2014). A test of the Becker-Tomes model of human capital transmission using microdata on four generations. *Journal of Human Capital*, 8(1):80–96.

Lu, F. and Vogl, T. (2023). Intergenerational persistence in child mortality. *American Economic Review: Insights*, 5(1):93–110.

Machin, S. (2007). Education expansion and intergenerational mobility in Britain. *Schools and the Equal Opportunity Problem. The MIT Press: Cambridge*, 7:1–63.

Machin, S., Salvanes, K. G., and Pelkonen, P. (2012). Education and mobility. *Journal of the European Economic Association*, 10(2):417–450.

Mazumder, B. (2005). Fortunate sons: New estimates of intergenerational mobility in the United States using social security earnings data. *Review of Economics and Statistics*, 87(2):235–255.

Modalsli, J. (2023). Multigenerational Persistence: Evidence from 146 years of Administrative Data. *Journal of Human Resources*, 58(3):929–961.

MPC (2020). Integrated Public Use Microdata Series, International: Version 7.3 [dataset]. Technical report, Minnesota Population Center, Minneapolis, MN: IPUMS.

Munoz, E. and Siravegna, M. (2021). When measure matters: Coresidence bias and intergenerational mobility revisited. *Available at SSRN 3969270*.

Narayan, A., Van der Weide, R., Cojocaru, A., Lakner, C., Redaelli, S., Mahler, D. G., Ramasubbaiah, R. G. N., and Thewissen, S. (2018). *Fair progress?: Economic mobility across generations around the world*. World Bank Publications.

Neidhöfer, G., Serrano, J., and Gasparini, L. (2018). Educational inequality and intergenerational mobility in Latin America: A new database. *Journal of Development Economics*, 134:329–349.

Neidhöfer, G. and Stockhausen, M. (2019). Dynastic inequality compared: Multigenerational mobility in the United States, the United Kingdom, and Germany. *Review of Income and Wealth*, 65(2):383–414.

Nybom, M. and Stuhler, J. (2016). Heterogeneous income profiles and lifecycle bias in intergenerational mobility estimation. *Journal of Human Resources*, 51(1):239–268.

Nybom, M. and Stuhler, J. (2017). Biases in standard measures of intergenerational income dependence. *Journal of Human Resources*, 52(3):800–825.

Nybom, M. and Stuhler, J. (2021). Interpreting trends in intergenerational mobility. Technical report, Swedish Institute for Social Research working paper.

Olivera Campirán, M. (2011). Evolución histórica de la educación básica a través de los proyectos nacionales: 1921 - 1999. Technical report, Universidad de Guadalajara, México.

Olivetti, C., Paserman, M. D., and Salisbury, L. (2018). Three-generation mobility in the United States, 1850–1940: The role of maternal and paternal grandparents. *Explorations in Economic History*, 70:73–90.

Oreopoulos, P., Page, M. E., and Stevens, A. H. (2006). The intergenerational effects of compulsory schooling. *Journal of Labor Economics*, 24(4):729–760.

Piopiunik, M. (2014). Intergenerational transmission of education and mediating channels: Evidence from a compulsory schooling reform in Germany. *The Scandinavian Journal of Economics*, 116(3):878–907.

Razzu, G. and Wambile, A. (2020). Three-generation educational mobility in six African countries. Technical report, University of Reading Discussion Paper No. 2020-23.

Sheppard, P. and Monden, C. (2018). The additive advantage of having educated grandfathers for children's education: Evidence from a cross-national sample in europe. *European Sociological Review*, 34(4):365–380.

Solon, G. (1992). Intergenerational income mobility in the United States. *The American Economic Review*, pages 393–408.

Solon, G. (2018). What do we know so far about multigenerational mobility? *The Economic Journal*, 128(612):F340–F352.

Stuhler, J. (2012). Mobility across multiple generations: The iterated regression fallacy. Technical report, IZA Discussion Paper.

Stuhler, J. (2023). Multigenerational inequality. *Research Handbook on Intergenerational Inequality (forthcoming)*.

Torche, F. (2015). Analyses of intergenerational mobility: An interdisciplinary review. *The ANNALS of the American Academy of Political and Social Science*, 657(1):37–62.

Torche, F. (2021a). Education Mobility in the Developing World. In Vegard, I., Anirudh, K., and Kunal, S., editors, *Social Mobility in Developing Countries: Concepts, Methods, and Determinants*, chapter 7, pages 139–171. Oxford University Press, United Nations University World Institute for Development Economics Research (UNU-WIDER).

Torche, F. (2021b). Intergenerational mobility in Latin America in comparative perspective. Technical report, Working Paper 2, UNDP LAC.Background Paper for the UNDP LAC 2021 Regional Human Development Report.

Torche, F. and Corvalan, A. (2018). Estimating intergenerational mobility with grouped data: A critique of Clark's the Son also Rises. *Sociological Methods & Research*, 47(4):787–811.

Van der Weide, R., Lakner, C., Mahler, D. G., Narayan, A., and Ramasubbaiah, R. (2021). Intergenerational mobility around the world. *Available at SSRN 3981372*.

Vosters, K. (2018). Is the Simple Law of Mobility Really a Law? Testing Clark's Hypothesis. *The Economic Journal*, 128(612):F404–F421.

A Additional Tables

Table A.1: Descriptive Statistics by Generation and Country

Sample:	LAC			Chile			Colombia			El Salvador		
	Mean	Std	N	Mean	Std	N	Mean	Std	N	Mean	Std	N
Grandparents												
G1 Schooling Average	2.65	3.13	16469	4.43	4.05	4362	2.62	2.79	2600	1.59	2.86	1175
G1 Schooling Grandfather	3.05	3.61	14481	5.18	4.63	3646	3.15	3.43	2122	1.88	3.23	1147
G1 Schooling Grandmother	2.52	3.15	15463	4.11	4.01	4076	2.87	2.98	2249	1.53	3.13	1159
Parents												
G2 Schooling	5.64	4.63	16469	8.10	4.69	4362	5.94	4.75	2600	4.85	5.03	1175
G2 Schooling Mother	5.32	4.49	9146	8.05	4.64	2047	5.76	4.70	1324	4.31	4.72	690
G2 Schooling Father	6.04	4.77	7323	8.14	4.73	2315	6.12	4.78	1276	5.51	5.32	485
G2 Age	61.42	10.08	16469	58.71	10.33	4362	61.66	10.82	2600	62.62	11.19	1175
G2 Age at birth of G3	25.41	6.66	16469	23.84	5.36	4362	27.90	6.84	2600	28.77	7.40	1175
G2 Sex (Male=1)	0.44	0.50	16469	0.52	0.50	4362	0.50	0.50	2600	0.45	0.50	1175
Grandchildren												
G3 Schooling	9.78	4.52	48899	11.48	3.66	12004	10.37	4.85	3462	9.52	5.19	1499
G3 Schooling Daughter	9.80	4.53	24026	11.50	3.57	5894	11.16	4.75	1654	9.66	5.33	791
G3 Schooling Son	9.76	4.52	24873	11.46	3.75	6110	9.77	4.84	1808	9.36	5.02	708
G3 Age	34.70	8.38	48899	34.82	8.39	12004	33.59	9.38	3462	32.99	8.80	1499
G3 Sex (Male=1)	0.51	0.50	48899	0.51	0.50	12004	0.57	0.50	3462	0.48	0.50	1499

Sample:	Mexico			Paraguay			Uruguay		
	Mean	Std	N	Mean	Std	N	Mean	Std	N
Grandparents									
G1 Schooling Average	1.65	2.28	6523	3.04	3.29	1227	3.93	3.17	582
G1 Schooling Grandfather	1.95	2.65	6158	3.80	3.77	924	4.11	3.63	484
G1 Schooling Grandmother	1.53	2.34	6327	2.67	3.29	1139	3.79	2.93	513
Parents									
G2 Schooling	3.86	4.06	6523	6.43	4.25	1227	6.79	4.03	582
G2 Schooling Mother	3.54	3.77	3887	6.39	4.41	775	6.89	3.96	423
G2 Schooling Father	4.32	4.39	2636	6.48	4.06	452	6.54	4.22	159
G2 Age	61.95	8.43	6523	60.06	9.69	1227	69.64	11.51	582
G2 Age at birth of G3	23.49	5.66	6523	28.87	6.71	1227	28.29	7.89	582
G2 Sex (Male=1)	0.42	0.49	6523	0.45	0.50	1227	0.28	0.45	582
Grandchildren									
G3 Schooling	8.47	4.57	29702	11.21	4.73	1595	9.62	3.59	637
G3 Schooling Daughter	8.29	4.61	14763	12.19	4.84	647	10.14	3.52	277
G3 Schooling Son	8.64	4.52	14939	10.50	4.52	948	9.23	3.59	360
G3 Age	34.87	8.13	29702	30.16	7.32	1595	41.58	8.85	637
G3 Sex (Male=1)	0.51	0.50	29702	0.58	0.49	1595	0.57	0.50	637

Notes: Table A.1 reports descriptive statistics of the main variables used in our analysis. The survey respondent in each survey is the family member of generation 2 (G2). He or she provides information about the grandparent generation (G1) and the children generation (G3). To compute statistics for LAC we pool all countries together and compute the simple mean and standard deviation of the pooled sample without using survey weights. For each individual country we compute the mean and standard deviation using the corresponding sample weights provided by each survey. G2 Age at birth of G3 is computed by taking the difference between the age of the parent and the age of the eldest son/daughter in the sample.

Table A.2: Descriptive Statistics of Schooling by Country and Data Source for the Respondent Generation (G2)

Sample:	**LAC**			**Chile**			**Colombia**			**El Salvador**		
	Mean	Std	N	Mean	Std	N	Mean	Std	N	Mean	Std	N
Survey	5.640	4.632	16,469	8.097	4.686	4,362	5.942	4.745	2,600	4.850	5.026	1,175
Census	5.542	4.842	3,779,052	8.956	4.602	667,916	5.208	4.679	1,309,252	4.867	5.137	160,117
Sample:				**Mexico**			**Paraguay**			**Uruguay**		
				Mean	Std	N	Mean	Std	N	Mean	Std	N
Survey				3.864	4.055	6,523	6.432	4.253	1,227	6.791	4.030	582
Census				4.025	4.274	1,369,658	6.307	4.451	156,046	7.475	3.908	116,063

Notes: Table A.2 reports descriptive statistics of years of schooling for the generation of respondents comparing our sample to census data using IPUMS international. To compute statistics for LAC we pool all countries together and compute the simple mean and standard deviation of the pooled sample without using survey weights. For each individual country we compute the mean and standard deviation using the corresponding sample weights provided by each survey.

Table A.3: Descriptive Statistics on Percentiles of Schooling by Country and Generation

Sample:	**Chile**			**Colombia**			**El Salvador**		
	Mean	Std	N	Mean	Std	N	Mean	Std	N
G1 Percentile	0.25	0.28	4362	0.35	0.27	2600	0.29	0.32	1175
G2 Percentile	0.38	0.34	4362	0.41	0.31	2600	0.36	0.31	1175
G3 Percentile	0.46	0.28	12004	0.50	0.29	3462	0.50	0.33	1499
Sample:	**Mexico**			**Paraguay**			**Uruguay**		
	Mean	Std	N	Mean	Std	N	Mean	Std	N
G1 Percentile	0.29	0.32	6523	0.29	0.32	1227	0.27	0.28	582
G2 Percentile	0.34	0.30	6523	0.49	0.37	1227	0.31	0.29	582
G3 Percentile	0.41	0.29	29702	0.45	0.29	1595	0.36	0.30	637

Notes: Table A.3 reports descriptive statistics on the percentiles of schooling for each generation and country.

Table A.4: (Over) Prediction of long run mobility from iteration of **Regression Slope Coefficients**

Country	G3 on G2 Estimate	Prediction for G3 on G1	Actual estimate for G3 on G1	Overprediction
LAC	0.551	0.304	0.534	77%
Chile	0.453	0.205	0.376	83%
Colombia	0.521	0.271	0.579	113%
El Salvador	0.553	0.306	0.675	121%
Mexico	0.672	0.452	0.842	86%
Paraguay	0.459	0.211	0.331	57%
Uruguay	0.351	0.123	0.343	178%

Notes: This table presents the results of estimating equation (1) and equation (2) for each country. Column (1) reports the coefficient of estimating equation (1) using the children and parents generation. Column (2) reports the prediction of the the association of education between children and grand parents, resulting from squaring column 1. Column (3) reports the actual estimate obtained from the data. Column (4) computes the percent of overprediction following Braun and Stuhler (2018) as the actual estimate minus the prediction, over the prediction.

Table A.5: (Over) Prediction of long run mobility from iteration of **Pearson Correlation Coefficients**

Country	G3 on G2 Estimate	Prediction for G3 on G1	Actual estimate for G3 on G1	Overprediction
LAC	0.519	0.269	0.340	26%
Chile	0.576	0.332	0.409	23%
Colombia	0.504	0.254	0.321	26%
El Salvador	0.545	0.297	0.377	27%
Mexico	0.528	0.279	0.385	38%
Paraguay	0.419	0.176	0.240	37%
Uruguay	0.393	0.154	0.301	95%

Notes: This table presents the results of estimating equation (1) and equation (2) for each country. Column (1) reports the coefficient of estimating equation (1) using the children and parents generation. Column (2) reports the prediction of the association of schooling between children and grandparents resulting from squaring column 1. Column (3) reports the actual estimate obtained from the data. Column (4) computes the percent of overprediction following Braun and Stuhler (2018) as the actual estimate minus the prediction, over the prediction.

Table A.6: Clark's Latent factor model parameters

	β_{-1} (1)	β_{-2} (2)	λ (3)	ρ (4)	λ_A (5)
LAC	0.562	0.379	0.675	0.913	0.705
	(0.006)	(0.009)	(0.013)	(0.009)	(0.014)
Chile	0.595	0.425	0.714	0.913	0.732
	(0.012)	(0.021)	(0.026)	(0.016)	(0.029)
Colombia	0.515	0.341	0.663	0.882	0.640
	(0.018)	(0.023)	(0.034)	(0.025)	(0.037)
El Salvador	0.566	0.384	0.678	0.913	0.702
	(0.032)	(0.038)	(0.033)	(0.024)	(0.046)
Mexico	0.559	0.393	0.702	0.892	0.731
	(0.013)	(0.020)	(0.024)	(0.016)	(0.029)
Paraguay	0.523	0.279	0.533	0.990	0.600
	(0.031)	(0.067)	(0.111)	(0.188)	(0.107)
Uruguay	0.439	0.298	0.678	0.805	0.754
	(0.044)	(0.063)	(0.120)	(0.082)	(0.136)

Notes: Table A.6 reports the estimated values of β_{-1}, β_{-2}, λ, ρ and λ_A for LAC and each country along with bootstrapped standard errors in parentheses. We follow exactly the method used by Braun and Stuhler (2018) to compute estimates for β_{-1} and β_{-2}, and then produce estimates for Clark's λ (with bootstrapped standard errors). We estimate β_{-2} by computing the Pearson correlation 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). To keep comparability with Braun and Stuhler's (2018) 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. Column (3) and (4) report estimates for λ and ρ based on these intergenerational correlations, and column (5) reports λ_A estimates which are based on the intergenerational correlation between G1 and G2 only, as in Braun and Stuhler (2018). The estimates for LAC are computed by pooling all six surveys.

Table A.7: Regression Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients of Figure 6

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.676	0.501	0.458			
	(0.023)					
G1 Schooling				0.681	0.370	0.353
				(0.038)		
G2 Sch. x Chrt: 1930 - 39	-0.102	0.487	0.454			
	(0.027)					
G2 Sch. x Chrt: 1940 - 49	-0.143	0.535	0.505			
	(0.025)					
G2 Sch. x Chrt: 1950 - 59	-0.204	0.525	0.510			
	(0.026)					
G2 Sch. x Chrt: 1960 - 69	-0.215	0.483	0.493			
	(0.032)					
G1 Sch. x Chrt: 1930 - 39				-0.106	0.345	0.324
				(0.046)		
G1 Sch. x Chrt: 1940 - 49				-0.163	0.343	0.320
				(0.041)		
G1 Sch. x Chrt: 1950 - 59				-0.273	0.322	0.326
				(0.042)		
G1 Sch. x Chrt: 1960 - 69				-0.330	0.271	0.255
				(0.051)		
Observations	48,899	48,899	48,899	48,899	48,899	48,899

Notes: This table presents the results obtained from estimating equation (3) by pooling all countries using country fixed effects. In this regression we do not include survey weights. The first three columns display the regression slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. Standard errors are reported in parentheses.

Table A.8: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients: Chile sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.538	0.589	0.549			
	(0.029)					
G1 Schooling				0.482	0.463	0.355
				(0.039)		
G2 Sch. x Chrt: 1930 - 39	-0.067	0.567	0.513			
	(0.036)					
G2 Sch. x Chrt: 1940 - 49	-0.124	0.550	0.544			
	(0.034)					
G2 Sch. x Chrt: 1950 - 59	-0.139	0.550	0.632			
	(0.034)					
G2 Sch. x Chrt: 1960 - 69	-0.050	0.585	0.625			
	(0.063)					
G1 Sch. x Chrt: 1930 - 39				-0.070	0.430	0.427
				(0.052)		
G1 Sch. x Chrt: 1940 - 49				-0.161	0.377	0.394
				(0.044)		
G1 Sch. x Chrt: 1950 - 59				-0.170	0.384	0.368
				(0.044)		
G1 Sch. x Chrt: 1960 - 69				-0.162	0.446	0.368
				(0.073)		
Observations	12,004	12,004	12,004	12,004	12,004	12,004

Notes: This table presents the results obtained from estimating equation (3) for Chile using weights provided by the survey. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. Standard errors are reported in parentheses.

Table A.9: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients: Colombia sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.763 (0.105)	0.533	0.586			
G1 Schooling				0.963 (0.190)	0.285	0.290
G2 Sch. x Chrt: 1930 - 39	-0.128 (0.122)	0.427	0.297			
G2 Sch. x Chrt: 1940 - 49	-0.264 (0.111)	0.484	0.424			
G2 Sch. x Chrt: 1950 - 59	-0.271 (0.109)	0.535	0.517			
G2 Sch. x Chrt: 1960 - 69	-0.246 (0.113)	0.537	0.506			
G1 Sch. x Chrt: 1930 - 39				-0.333 (0.227)	0.313	0.192
G1 Sch. x Chrt: 1940 - 49				-0.260 (0.201)	0.375	0.221
G1 Sch. x Chrt: 1950 - 59				-0.442 (0.198)	0.310	0.204
G1 Sch. x Chrt: 1960 - 69				-0.501 (0.198)	0.322	0.198
Observations	3,462	3,462	3,462	3,462	3,462	3,462

Notes: This table presents the results obtained from estimating equation (3) for Colombia using weights provided by the survey. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. Standard errors are reported in parentheses.

Table A.10: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients: El Salvador sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.748	0.637	0.504			
	(0.151)					
G1 Schooling				1.107	0.544	0.419
				(0.156)		
G2 Sch. x Chrt: 1930 - 39	-0.273	0.409	0.368			
	(0.188)					
G2 Sch. x Chrt: 1940 - 49	-0.165	0.512	0.454			
	(0.165)					
G2 Sch. x Chrt: 1950 - 59	-0.152	0.579	0.556			
	(0.159)					
G2 Sch. x Chrt: 1960 - 69	-0.269	0.627	0.692			
	(0.158)					
G1 Sch. x Chrt: 1930 - 39				-0.388	0.338	0.173
				(0.191)		
G1 Sch. x Chrt: 1940 - 49				-0.296	0.353	0.125
				(0.200)		
G1 Sch. x Chrt: 1950 - 59				-0.110	0.407	0.136
				(0.219)		
G1 Sch. x Chrt: 1960 - 69				-0.645	0.474	0.322
				(0.165)		
Observations	1,499	1,499	1,499	1,499	1,499	1,499

Notes: This table presents the results obtained from estimating equation (3) for El Salvador using weights provided by the survey. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. Standard errors are reported in parentheses.

Table A.11: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients: Mexico sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.818	0.552	0.528			
	(0.063)					
G1 Schooling				1.017	0.414	0.411
				(0.114)		
G2 Sch. x Chrt: 1930 - 39	-0.132	0.510	0.363			
	(0.075)					
G2 Sch. x Chrt: 1940 - 49	-0.215	0.533	0.476			
	(0.067)					
G2 Sch. x Chrt: 1950 - 59	-0.163	0.565	0.585			
	(0.083)					
G2 Sch. x Chrt: 1960 - 69	0.000	.	.			
	(0.000)					
G1 Sch. x Chrt: 1930 - 39				-0.150	0.377	0.134
				(0.129)		
G1 Sch. x Chrt: 1940 - 49				-0.245	0.397	0.183
				(0.123)		
G1 Sch. x Chrt: 1950 - 59				-0.383	0.329	0.177
				(0.184)		
G1 Sch. x Chrt: 1960 - 69				0.000	.	.
				(0.000)		
Observations	29,702	29,702	29,702	29,702	29,702	29,702

Notes: This table presents the results obtained from estimating equation (3) for Mexico using weights provided by the survey. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. Standard errors are reported in parentheses.

Table A.12: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients: Paraguay sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	1.407	0.734	0.582			
	(0.238)					
G1 Schooling				0.837	0.387	0.510
				(0.207)		
G2 Sch. x Chrt: 1930 - 39	-0.674	0.477	0.445			
	(0.272)					
G2 Sch. x Chrt: 1940 - 49	-0.775	0.505	0.500			
	(0.244)					
G2 Sch. x Chrt: 1950 - 59	-1.009	0.413	0.422			
	(0.242)					
G2 Sch. x Chrt: 1960 - 69	-1.070	0.321	0.376			
	(0.255)					
G1 Sch. x Chrt: 1930 - 39				-0.115	0.374	0.333
				(0.248)		
G1 Sch. x Chrt: 1940 - 49				-0.394	0.262	0.305
				(0.253)		
G1 Sch. x Chrt: 1950 - 59				-0.521	0.265	0.329
				(0.217)		
G1 Sch. x Chrt: 1960 - 69				-0.646	0.155	0.206
				(0.257)		
Observations	1,595	1,595	1,595	1,595	1,595	1,595

Notes: This table presents the results obtained from estimating equation (3) for Paraguay using weights provided by the survey. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. Standard errors are reported in parentheses.

Table A.13: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients: Uruguay sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.364	0.360	0.282			
	(0.096)					
G1 Schooling				0.533	0.460	0.426
				(0.104)		
G2 Sch. x Chrt: 1930 - 39	0.000	.	.			
	(0.000)					
G2 Sch. x Chrt: 1940 - 49	-0.082	0.342	0.447			
	(0.110)					
G2 Sch. x Chrt: 1950 - 59	0.034	0.431	0.583			
	(0.123)					
G2 Sch. x Chrt: 1960 - 69	-0.001	0.373	0.356			
	(0.130)					
G1 Sch. x Chrt: 1930 - 39				0.000	.	.
				(0.000)		
G1 Sch. x Chrt: 1940 - 49				-0.142	0.373	0.324
				(0.124)		
G1 Sch. x Chrt: 1950 - 59				-0.258	0.240	0.231
				(0.146)		
G1 Sch. x Chrt: 1960 - 69				-0.354	0.129	0.129
				(0.179)		
Observations	637	637	637	637	637	637

Notes: This table presents the results obtained from estimating equation (3) for Uruguay using weights provided by the survey. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. Standard errors are reported in parentheses.

Table A.14: Regression of Mobility Coefficients in Figure 8

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.712	0.598	0.477			
	(0.027)	(0.024)	(0.019)			
G1 Schooling				0.749	0.417	0.363
				(0.047)	(0.026)	(0.021)
G2 Sch. $\times$ $\mathbf{1}$(- 10 + years)	0.058	-0.047	0.011			
	(0.060)	(0.045)	(0.035)			
G2 Sch. $\times$ $\mathbf{1}$(- 9 to - 5 years)	-0.005	-0.014	-0.022			
	(0.045)	(0.037)	(0.032)			
G2 Sch. $\times$ $\mathbf{1}$(+ 1 to 5 years)	-0.061	-0.019	-0.011			
	(0.028)	(0.025)	(0.020)			
G2 Sch. $\times$ $\mathbf{1}$(+ 6 to 10 years)	-0.126	-0.049	-0.022			
	(0.028)	(0.025)	(0.020)			
G2 Sch. $\times$ $\mathbf{1}$(+ 11 to 15 years)	-0.169	-0.067	-0.043			
	(0.028)	(0.026)	(0.020)			
G2 Sch. $\times$ $\mathbf{1}$(+ 16 to 20 years)	-0.194	-0.062	-0.021			
	(0.028)	(0.026)	(0.021)			
G2 Sch. $\times$ $\mathbf{1}$(21 + years)	-0.213	-0.061	-0.006			
	(0.028)	(0.026)	(0.020)			
G1 Sch. $\times$ $\mathbf{1}$(- 10 + years)				-0.114	-0.084	0.049
				(0.094)	(0.043)	(0.041)
G1 Sch. $\times$ $\mathbf{1}$((- 9 to - 5 years)				0.046	0.003	0.015
				(0.073)	(0.036)	(0.034)
G1 Sch. $\times$ $\mathbf{1}$(+ 1 to 5 years)				-0.084	-0.008	-0.022
				(0.049)	(0.027)	(0.022)
G1 Sch. $\times$ $\mathbf{1}$(+ 6 to 10 years)				-0.175	-0.040	-0.050
				(0.049)	(0.027)	(0.022)
G1 Sch. $\times$ $\mathbf{1}$(+ 11 to 15 years)				-0.250	-0.072	-0.077
				(0.049)	(0.028)	(0.023)
G1 Sch. $\times$ $\mathbf{1}$(+ 16 to 20 years)				-0.250	-0.062	-0.062
				(0.049)	(0.028)	(0.023)
G1 Sch. $\times$ $\mathbf{1}$(21 + years)				-0.269	-0.041	-0.046
				(0.049)	(0.028)	(0.024)
Observations	48262	48262	48262	48262	48262	48262

Notes: This table presents the results obtained from estimating equation (4) for by pooling all countries using country fixed effects. In this regression we do not include survey weights. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. Standard errors are reported in parentheses.

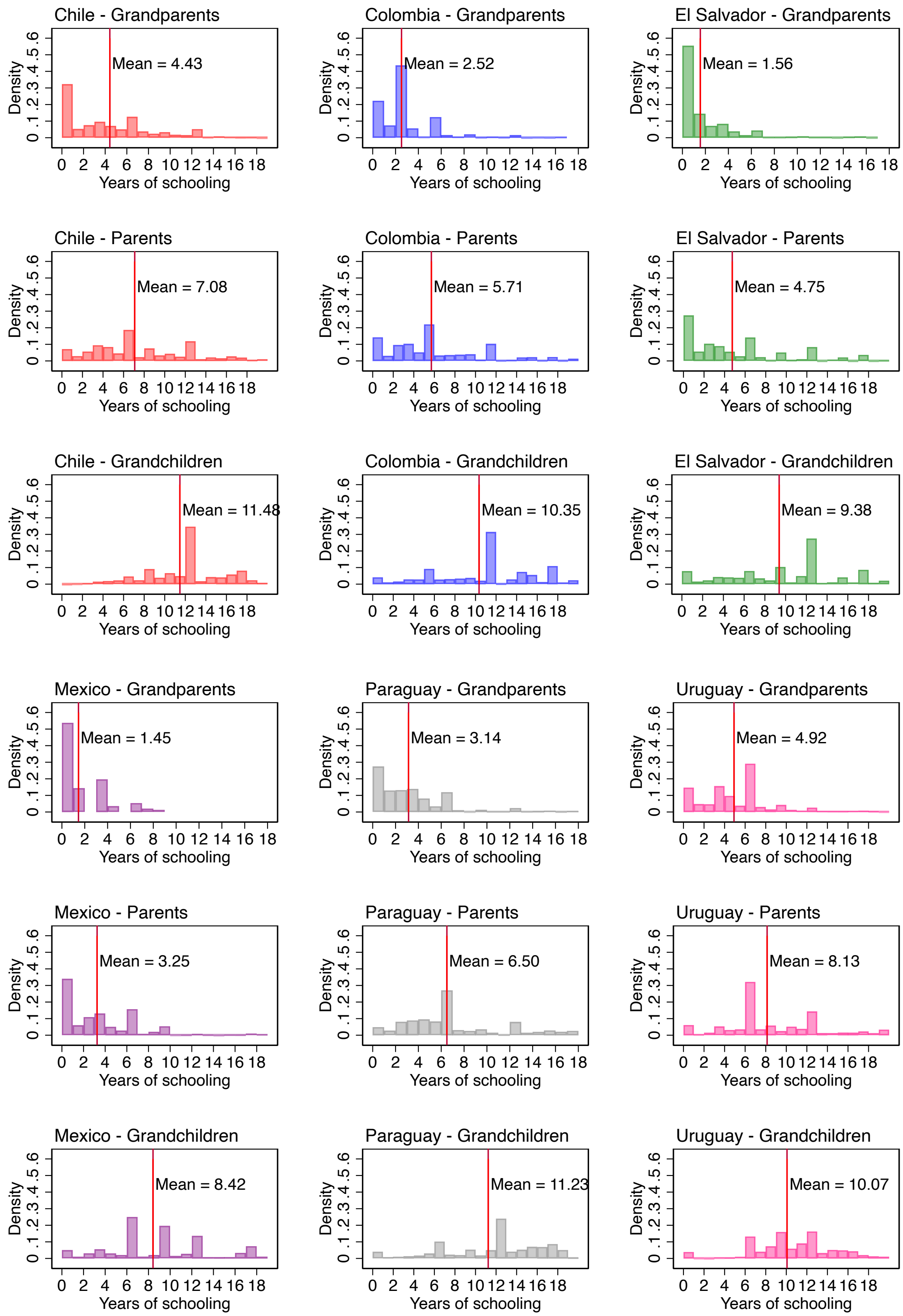
Table A.15: Educational Intergenerational Mobility Measures for Six Latin American Countries (using survey percentiles)

	LAC	Chile	Colombia	El Salvador	Mexico	Paraguay	Uruguay
Panel 1: 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)	0.523	0.600	0.496	0.514	0.523	0.571	0.460
Bottom-Half Mobility (μ_0^{50})	31.38	28.22	39.77	34.10	24.23	28.75	33.22
Absolute Upward Mobility (p_{25})	0.357	0.347	0.380	0.371	0.407	0.311	0.334
Observations	16,469	4,362	2,600	1,175	6,523	1,227	582
Panel 2: 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)	0.529	0.574	0.514	0.556	0.569	0.509	0.406
Bottom-Half Mobility (μ_0^{50})	32.41	32.37	32.45	32.53	35.97	31.98	29.16
Absolute Upward Mobility (p_{25})	0.364	0.354	0.358	0.345	0.410	0.321	0.372
Observations	48,899	12,004	3,462	1,499	29,702	1,595	637
Panel 3: 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)	0.370	0.418	0.359	0.380	0.409	0.334	0.302
Bottom-Half Mobility (μ_0^{50})	33.88	32.77	38.00	37.46	26.19	34.81	34.08
Absolute Upward Mobility (p_{25})	0.404	0.398	0.412	0.395	0.476	0.349	0.386
Observations	48,899	12,004	3,462	1,499	29,702	1,595	637
Panel 4: 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	0.092	0.144	-0.007	0.156
Spearman's rank correlation (ρ)	0.128	0.116	0.139	0.128	0.154	0.065	0.147
Bottom-Half Mobility (μ_0^{50})†	28.00	29.48	31.84	31.63	26.22	27.09	21.76
Absolute Upward Mobility (p_{25})	0.247	0.226	0.252	0.253	0.301	0.189	0.269
Observations	48,899	12,004	3,462	1,499	29,702	1,595	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 can be found in Table A.17. 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 exception are the regression slope and correlation estimates for Paraguay in panel 4). †: These estimates are conditioning on children whose parents (G2) are below the 50th percentile of their schooling distribution.

B Additional Figures

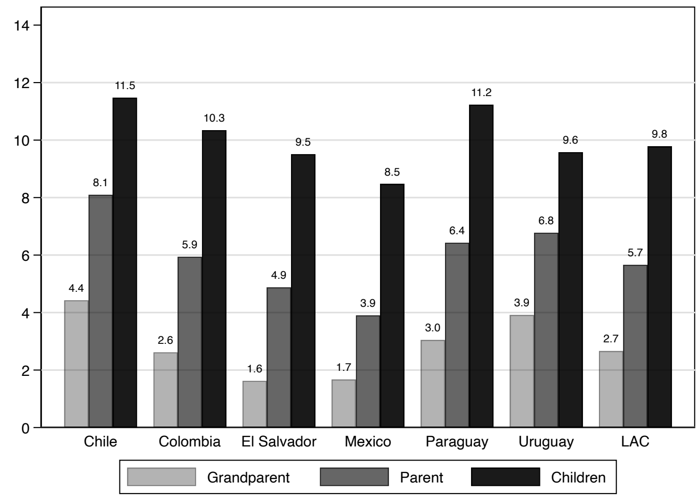
Figure A.1: Distribution of Schooling by Country and Generation



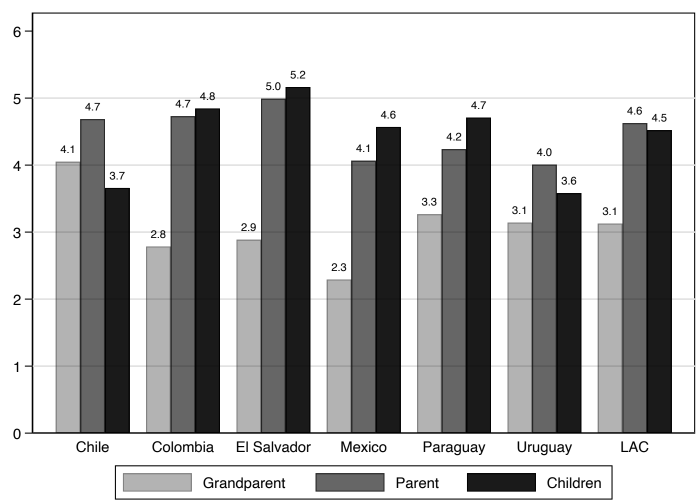
Notes: Figure A.1 plots the distribution of years of schooling for the six countries under study (Chile, Colombia, El Salvador, Mexico, Paraguay and Uruguay) and for each generation (grandparents, parents and children). Each graph shows a vertical line indicating the mean of the distribution.

Figure A.2: Descriptive Statistics of Schooling Across Countries and Generations

(a) Mean Years of Schooling



(b) Standard Deviation of Years of Schooling



Notes: Figure A.2a and Figure A.2b plot the mean and the standard deviation of schooling (measured in years of completed education) for each country and generation in our sample, respectively. The bars to the right in each graph display the results for Latin America, computed as the simple average across countries.

Figure A.3: Mean Child Percentile against Parent Percentile for six countries: Non parametric fit

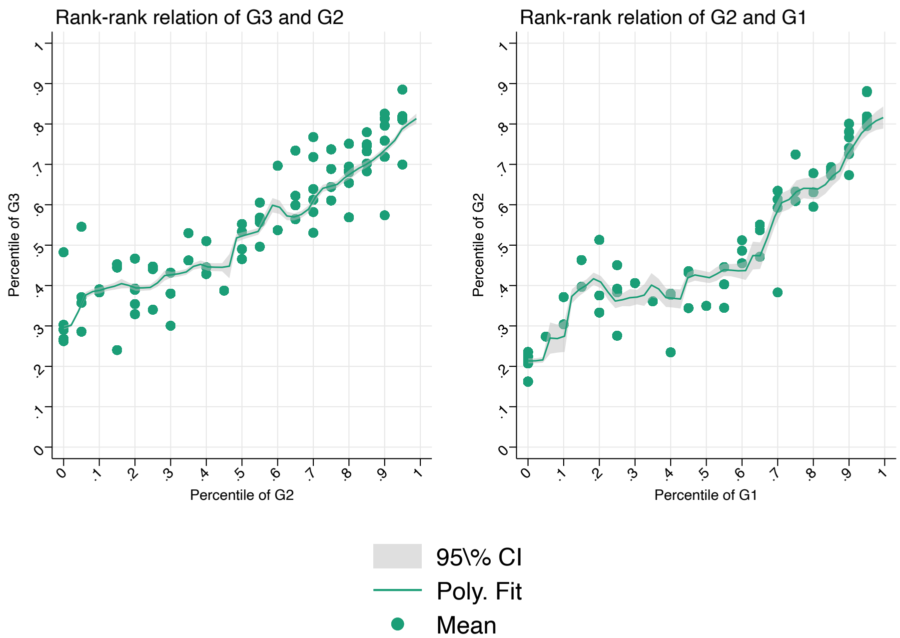
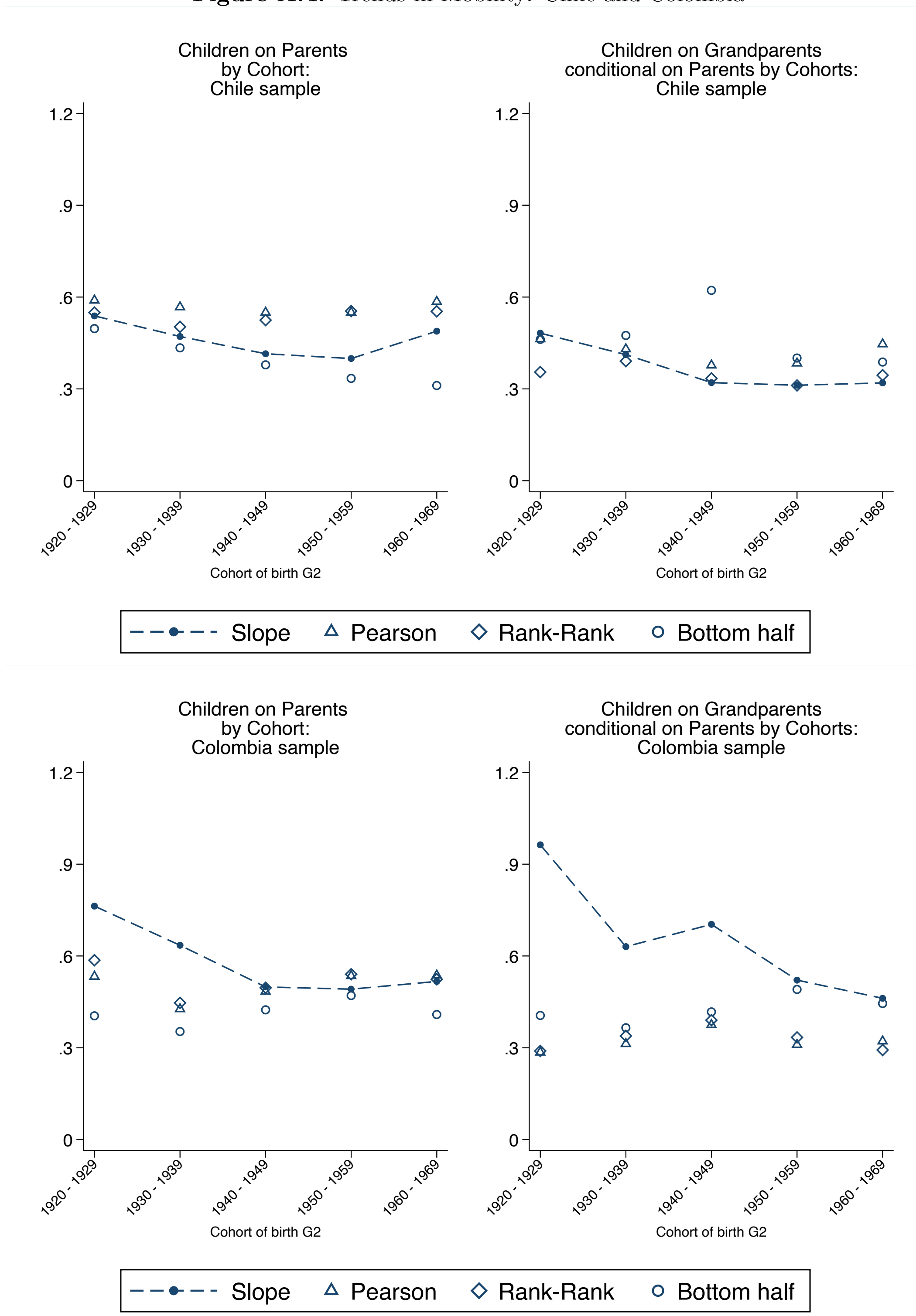
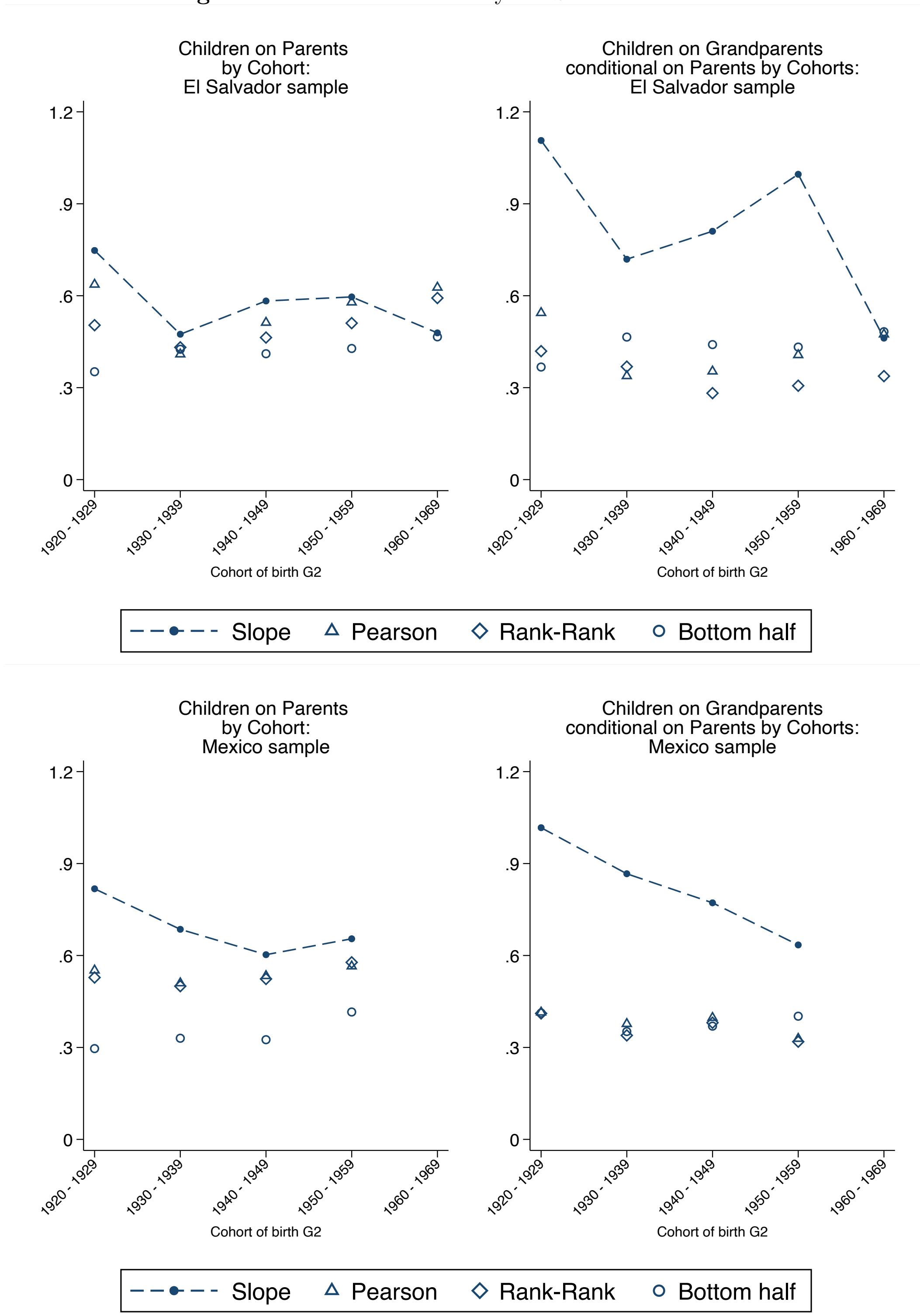


Figure A.4: Trends in Mobility: Chile and Colombia



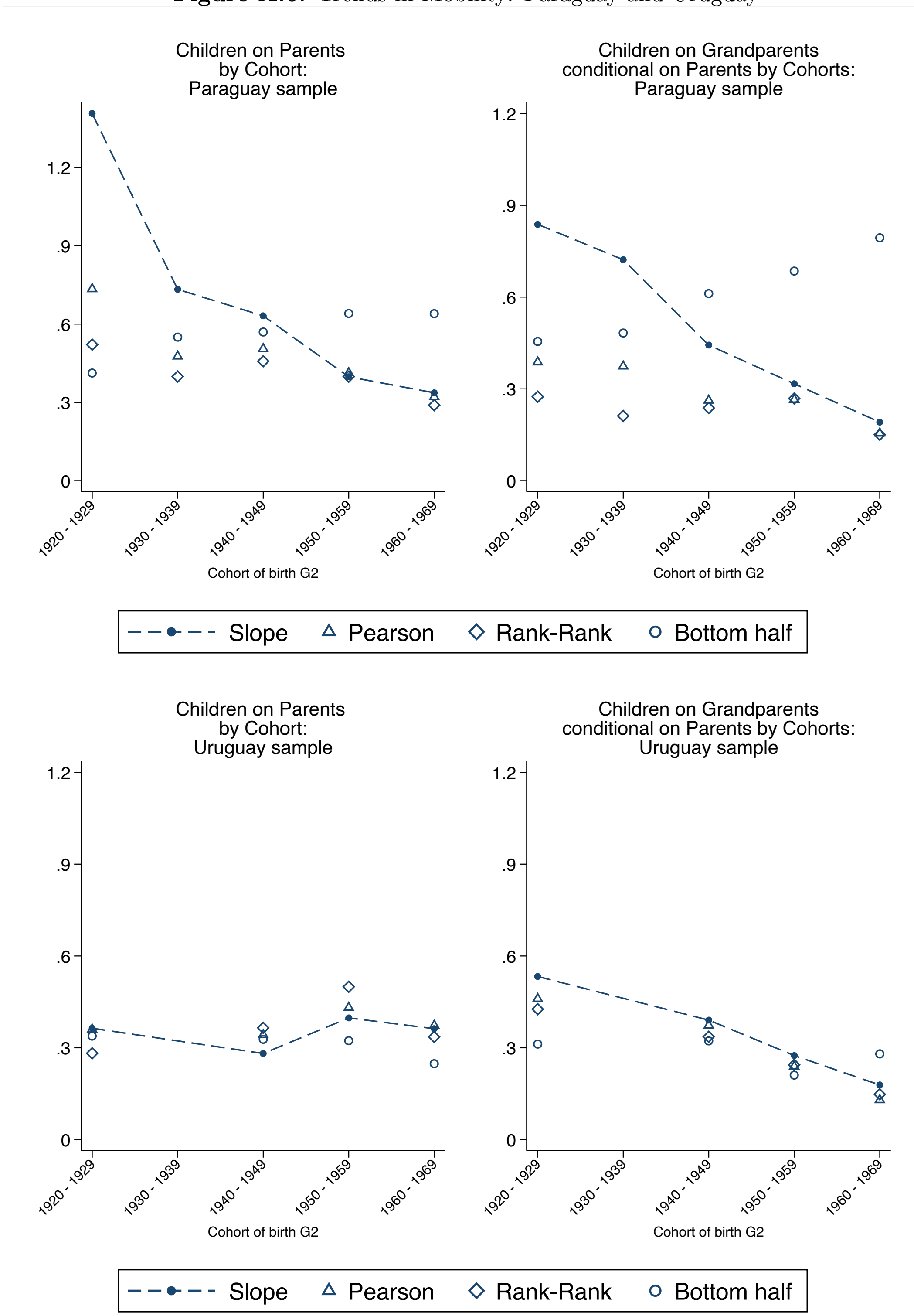
Notes: This figure presents the results obtained from estimating equation (3) for countries separately. The left panel displays the coefficients derived from regressing grandchildren (G3) on parents (G2). Meanwhile, the right panel illustrates the coefficients obtained from regressing grandchildren (G3) on grandparents (G1). The slope coefficients are represented by circles connected by lines, Pearson correlation coefficients are denoted by triangles, and Spearman rank-rank coefficients are depicted as diamonds. The specific coefficients can be found in Tables A.8 to Tables A.13.

Figure A.5: Trends in Mobility: El Salvador and Mexico



Notes: This figure presents the results obtained from estimating equation (3) for countries separately. 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 slope coefficients are represented by circles connected by lines, Pearson correlation coefficients are denoted by triangles, and Spearman rank-rank coefficients are depicted as diamonds. The specific coefficients can be found in Tables A.8 to Tables A.13.

Figure A.6: Trends in Mobility: Paraguay and Uruguay



Notes: This figure presents the results obtained from estimating equation (3) for countries separately. 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 slope coefficients are represented by circles connected by lines, Pearson correlation coefficients are denoted by triangles, and Spearman rank-rank coefficients are depicted as diamonds. The specific coefficients can be found in Tables A.8 to Tables A.13.

C Gender Lineages in Multigenerational Persistence

In this section we document intergenerational mobility measures by gender lineages within families. We take advantage of the structure of our data to run different analysis considering when the respondent is male and when the respondent is female. See Figure A.7 below.

Figure A.7: Gender Lineage Structure of the Data

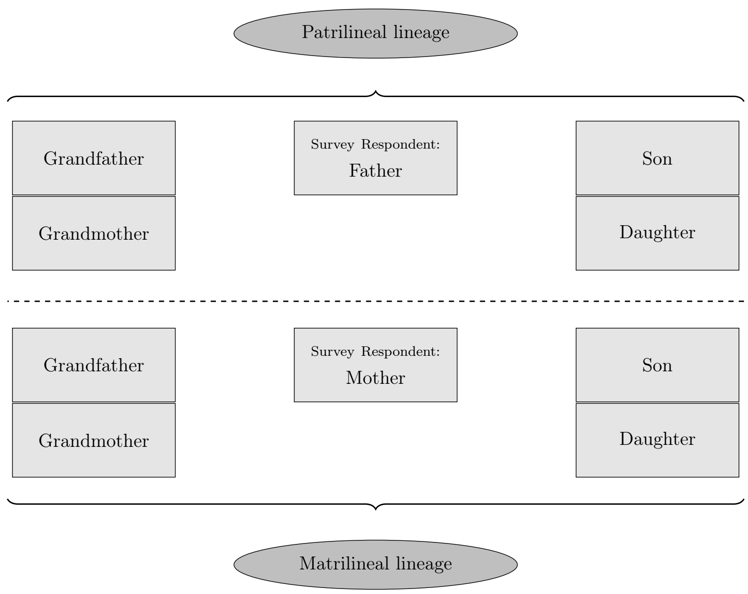


Table A.16 reports the estimates for patrilineal and matrilineal estimations, respectively. The initial findings, presented in Column (1), display slope coefficients using the son's educational attainment as the dependent variable. The father's, grandfather's, and grandmother's education are considered as explanatory variables, exploring the patrilineal lineage for sons. The key observation points to a statistically significant association between the educational levels of both grandparents. Notably, no discernible differences are evident between the contributions of paternal grandfathers and grandmothers.

In Column (2), a parallel examination is conducted for granddaughters. An additional year of schooling for grandfathers corresponds to a modest 0.044 increase in educational years for granddaughters. In contrast, an additional year of grandmother's schooling is associated with a more substantial 0.115 increase in educational years for granddaughters. Significantly, only the coefficient for grandmother's schooling attains statistical significance. This suggests that, while both patrilineal grandparents influence the educational outcomes of grandsons, the educational trajectories of granddaughters are predominantly linked to their grandmother's education.

An analogous examination is carried out for matrilineal lineages in Columns (3) and (4), replicating these analyses for the matrilineal lineage using female respondents. Our results indicate that grandfathers' education is more relevant than grandmothers' on the mother's side for both sons and daughters.

These findings align with evidence in other contexts that lacks a clear pattern on how parental lineages impact (Anderson et al., 2018;Sheppard and Monden, 2018). The variability observed is likely influenced by assortative mating, contributing to multicollinearity in measures of grandparental schooling and the proximity of grandchildren to their grandparents across diverse contexts. Additionally, constructing an ideal dataset for gender lineages necessitates the inclusion of grandparents for both parents, a data point that is often unavailable. To address this, survey producers could enhance the autobiographical modules, typically containing relevant questions, by adding more details on ancestry. This modification would enable the construction of a more comprehensive family tree, facilitating a deeper understanding of lineages.

Table A.16: Educational Intergenerational Mobility and Parental Lineages

	Patrilineal G2: Father		**Matrilineal** G2: Mother	
	G3: Son (1)	G3: Daughter (2)	G3: Son (3)	G3: Daughter (4)
Slope coefficients (β):				
G2	0.485	0.477	0.502	0.518
	(0.014)	(0.014)	(0.015)	(0.015)
G1: Father	0.083	0.044	0.170	0.142
	(0.020)	(0.023)	(0.021)	(0.020)
G1: Mother	0.071	0.115	0.037	0.035
	(0.024)	(0.028)	(0.025)	(0.023)
Pearson correlations (r):				
G2	0.497	0.477	0.443	0.461
G1: Father	0.063	0.032	0.119	0.100
G1: Mother	0.046	0.074	0.023	0.022
Spearman's rank correlations (ρ):				
G2	0.439	0.425	0.396	0.410
G1: Father	0.081	0.075	0.129	0.123
G1: Mother	0.069	0.091	0.037	0.044
Observations	9,221	8,720	11,938	11,814

Notes: Table A.16 presents a range of intergenerational mobility (IGM) metrics for Latin America. The estimates for the LAC region are derived from combining data from six surveys, utilizing country fixed effects, and employing robust standard errors (in parentheses) clustered at the family level. The regression models use the schooling of the child generation (G3) as the dependent variable, with regressors including the schooling of the parent generation, the schooling of the grandfather, and the schooling of the grandmother. Additionally, the regressions control for the age and age squared of sons/daughters and fathers. Notice that the sample size differs from that used in Table 1 due to the specific requirements of this analysis. Each panel in Table A.16 reports three intergenerational mobility measures: regression slope coefficients, Pearson's and Spearman's correlations. Standard errors (in parentheses) are provided exclusively for the regression slope coefficients.

D Latent Factor Model

Braun and Stuhler (2018) provide the following latent factor model that allows to directly test Clark's hypothesis. The observed socioeconomic status for a given generation, denoted as S_{it} (in this case, measured by years of schooling), is determined by the following equation:

$$S_{it} = \rho e_{it} + \mu_{it}, \tag{A.1}$$

In this equation, e_{it} represents unobserved endowments, such as abilities, that are transformed into socioeconomic status, and μ_{it} is random noise. These endowments are inherited from one generation to the next through:

$$e_{it} = \lambda e_{it-1} + \varepsilon_{it}, \tag{A.2}$$

where ε_{it} is random noise and assumed to be independent of μ_{it}. The coefficient that measures the association between the socioeconomic status of children and that of any of their predecessors $(-s)$ can be written as:

$$\begin{aligned}
\beta_1^{-s} &= Cov(S_{it}, S_{it-s}) \\
&= \rho^2 Cov(e_{it}, e_{it-s}) \\
&= \rho^2 \lambda^s
\end{aligned}$$

After normalizing the variance of S_{it} and e_{it} to one, we can see that the association of socioeconomic status across generations within the same family is determined by two factors: the current generation's ability to transform endowments into socioeconomic status (ρ) and the heritability of unobserved endowments (λ). Therefore, the coefficient β_1^{-s} not only measures the extent to which a person's current status is influenced by the status of their ancestors s generations ago, but also reflects the extent to which the endowments that contribute to this status are inherited across generations.

Moreover, the heritability of endowments becomes increasingly important in explaining long-term mobility, as its relative weight to ρ increases when linking the socioeconomic status of the current generation to older generations. This indicates that the influence of inherited factors may become more dominant as we consider longer chains of intergenerational transmission, which may limit the degree to which individuals can move up or down the socioeconomic ladder over time.

One of the most significant implications of this framework is that standard studies of mobility that analyze the association between the status of two generations cannot fully account for long-term mobility patterns. This is because studies that only focus on parent-child associations are limited to capturing differences in ρ (as noted by Braun and Stuhler, 2018), and hence, the influence of the heritability factor is mostly underestimated by such models.

Clark (2014) suggests that λ is large and approximately equal to 0.75, and persistent in magnitude over time, across countries, or within countries across different developmental stages. To estimate ρ and λ in our data, we follow exactly Braun and Stuhler, 2018's approach. Let β_{-1} denote the average of the Pearson correlations between G1 and G2 and between G2 and G3, and β_{-2} denote the Pearson correlation between children and grandparent. The ratio of these two coefficients allows us to identify λ and ρ as follows:

$$\lambda = \frac{\beta_{-2}}{\beta_{-1}} \tag{A.3}$$

$$\rho = \sqrt{\frac{\beta_{-1}^2}{\beta_{-2}}} \tag{A.4}$$

We estimate β_{-1} and β_{-2} with no covariates as in Braun and Stuhler (2018), and compute bootstrapped standard errors of these parameters.

E Measures of Intergenerational Mobility

A growing body of literature on intergenerational mobility uses different measures to analyze how individuals improve their welfare across generations (see Munoz and Siravegna (2021) for a summary). In particular, Asher et al. (2022) develop a measure of upward mobility that is useful for developing countries where data is usually obtained from surveys, reported in levels, and where schooling distributions tend to concentrate a large population at the lowest levels of schooling.

Ideally, we would like to have a measure that is not affected by changes in the distribution and growth of welfare across different generations, in the spirit of using rank-rank correlations or a transformation of it. In fact, Asher et al. (2022) build on Chetty et al. (2014) who construct a measure of absolute upward mobility as the expected income rank of a child who was born to someone at the 25th percentile of their distribution of reference. Using ranks allows for controlling changes in the distribution of the measure that a researcher uses as a proxy of welfare (e.g., education or income). Asher et al. (2022) adapt the measures in Chetty et al. (2014) to educational data, which is usually reported in bins or levels. In short, they introduce a new measure which they call "bottom half mobility" which corresponds to the expected educational rank of a child whose parent was at the 50th percentile of their distribution of reference.

This measure is particularly useful in our case. Consider Figure 1, which shows the distribution of years of schooling by generation. For grandparents there is a concentration of 40% at the lowest level of schooling (i.e., no schooling at all), and it then peaks at four years of schooling. The parental generation concentrates 20% of the sample in the lowest level, while it peaks at six years of schooling. Years of schooling for the children generation peaks at six years of schooling, but also at 12 years of schooling, which corresponds to completing high school.

Additionally, most measures of intergenerational mobility are linear, while non-linear patterns can provide a lot of information about how mobility behaves across generations, especially at the bottom. To address this issue, we transform the years of schooling data into bins of "No education", "Incomplete primary", "Complete primary", "Incomplete high school", "Complete high school", and "Some college or more". We do this because milestones of completion are more important than an additional year of schooling for welfare interpretation.

Using these data, we estimate "bottom half mobility", which, in Asher et al. (2022) notation, corresponds to $\mu_0^{50} = E(y|x \in [0, 50])$, where y is child rank and x is parent rank. Another main advantage of this measure is that it is comparable across different contexts as it is unaffected by changes in inequality and growth. As the authors put it, a similar change in points of ranking can be interpreted similarly across two different countries, even though a one-point change in El Salvador is different from a one-point change in Mexico or Denmark. For estimation, we use the code made publicly available by Asher et al. (2022) in their *Replication and Data Repository for "Intergenerational Mobility in India: New Measures and Estimates Across Time and Social groups"* (see https://github.com/devdatalab/paper-anr-mobility-india). We thank the authors for sharing their programs.

We use methods from Asher et al. (2022) to estimate two measures of intergenerational mobility in Latin America: bottom half mobility and absolute upward mobility, across three generations of the same family. Bottom half mobility measures the expected educational rank of a child born to someone at the 50th percentile of their reference distribution, while absolute upward mobility measures the expected educational rank of a child born to someone at the 25th percentile of their reference distribution.

We exclude Uruguay and Paraguay from the analysis as we are unable to obtain informative bounds for their data. For Chile, we obtain wide bounds when analyzing mobility from grandparents to parents but we leave this country in the Table for the reader to discern. The estimates for Latin America are computed using all countries together without sampling weights. Table A.17 shows the results for the computation of bottom half mobility measures and absolute upward mobility.

The results indicate that if a parent (G2) is born to a grandparent (G1) who falls in the bottom half of the education distribution, they can expect to be situated in the 33rd percentile when the median of the first interval is computed. However, in the subsequent transition (G2-G3) for LAC, we observe greater mobility, with children born to parents in the lower half of the education distribution expected to be situated at the 42nd percentile (median of the interval). This corresponds to a mobility increase of over nine points with respect to the analysis of parents and grandparents.

As a benchmark, Asher et al. (2022) estimate an interval of [36.6; 39.0] for similar cohorts in India and, using data from Chetty et al. (2014), estimate this number for the USA with a mobility indicator of 41.7, which is considered a country with the lowest level of mobility among OECD countries.

This finding contrasts with our previous results using standardized measures such as the Pearson correlation or Spearman's rank, which showed limited mobility across generations within families. Specifically, the measures in Table A.17 reveal mobility across generations when focusing on the bottom of the schooling distribution. The differences across measures are partly due to changes in the distribution of schooling over time, as documented for each country in Figure A.1. Notably, schooling distributions have consistently improved educational outcomes for those in the bottom of the distribution. Consequently, by concentrating on this segment of the distribution, the measures provide a different perspective than when analyzing mobility across generations using the entire distribution.

Table A.17: Estimates of Bottom-Half mobility and absolute upward mobility

		Bottom Half Mobility (μ_0^{50})				Absolute Upward Mobility (p_{25})			
		G1-G2	G2-G3	G1-G3	G1-G3|G2	G1-G2	G2-G3	G1-G3	G1-G3|G2
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LAC	Midpoint	33.62	41.01	46.76	37.05	42.65	42.00	49.40	40.58
	Interval	[30.85; 36.39]	[40.41; 41.60]	[44.15; 49.36]	[35.15; 38.95]	[33.19; 52.11]	[37.48; 46.52]	[42.66; 56.14]	[36.55; 44.61]
Chile	Midpoint	31.40	35.04	43.96	36.19	42.62	34.01	46.84	39.24
	Interval	[31.14; 31.66]	[34.62; 35.46]	[42.89; 45.02]	[35.26; 37.11]	[33.58; 51.65]	[30.98; 37.03]	[44.86; 48.81]	[37.53; 40.95]
Colombia	Midpoint	32.72	44.20	43.20	35.97	33.40	44.69	42.88	35.72
	Interval	[32.62; 32.81]	[43.99; 44.41]	[42.27; 44.13]	[35.36; 36.58]	[32.76; 34.03]	[39.14; 50.24]	[33.37; 52.38]	[29.17; 42.26]
El Salvador	Midpoint	39.72	45.21	59.78	49.47	65.03	48.33	69.07	57.53
	Interval	[29.13; 50.30]	[42.89; 47.52]	[50.98; 68.58]	[42.19; 56.74]	[45.37; 84.69]	[43.96; 52.69]	[52.72; 85.42]	[44.01; 71.04]
Mexico	Midpoint	31.44	36.06	44.34	26.14	46.36	34.93	48.18	36.39
	Interval	[30.17; 32.57]	[35.74; 36.38]	[43.24; 45.44]	[25.14; 27.13]	[40.64; 52.08]	[34.20; 35.66]	[42.86; 53.50]	[35.62; 37.15]
Paraguay	Midpoint	39.49	56.66	61.04	49.94	42.78	63.49	60.66	49.85
	Interval	[36.28; 42.69]	[56.65; 56.67]	[58.47; 63.61]	[49.53; 50.34]	[21.87; 63.69]	[55.58; 71.40]	[53.51; 67.80]	[48.83; 50.86]
Uruguay	Midpoint	26.98	28.85	28.20	24.61	25.74	26.58	28.77	24.76
	Interval	[25.71; 28.24]	[28.55; 29.14]	[27.04; 29.36]	[23.43; 25.78]	[24.94; 26.54]	[21.03; 32.12]	[28.62; 28.91]	[24.13; 25.39]
					Estimates from Asher et al. (2022)				
India	Midpoint		37.80				43.50		
	Interval		[36.6; 39.0]				[39.90; 47.10]		

Notes: Table A.17 reports the results for the computation of bottom half mobility measures and absolute upward mobility for LAC and each country in particular. We report both the midpoint and the interval of the estimates, as in Asher et al. (2022).

F Robustness to cohabitation bias

Most studies in the vast literature on intergenerational mobility suffer from cohabitation, and provide different solutions to their use of co-resident samples. Examples of such studies include Alesina et al. (2020), Alesina et al. (2021), Asher et al. (2022), Card et al. (2022), Derenoncourt (2022), Feigenbaum (2018), Hilger (2015), and Van der Weide et al. (2021). The magnitude of the problem resides in whether children who live with their parents have different characteristics compared to those who do not. Few studies have directly addressed this issue, highlighting the need to consider a broader sample to obtain more accurate estimates of intergenerational mobility.

For example, Francesconi and Nicoletti (2006) used panel data from the UK to explore co-residence bias and found that intergenerational mobility elasticities in income were underestimated by 12% to 39% when using only the sample of co-resident children. This indicates that intergenerational mobility estimates that rely solely on co-resident samples may be significantly biased downwards.

Similarly, Emran et al. (2018) used survey data from Bangladesh and India to compare estimates using the subsample of co-resident children with the full sample of children. They found that the intergenerational regression coefficient was biased downward by 17.6% to 29.7%, while the measure of intergenerational correlation (Pearson correlation) was biased downward by 8.7% to 10.7%. These findings suggest that using only co-resident samples can significantly underestimate intergenerational mobility estimates.

Finally, Munoz and Siravegna (2021) provide further evidence of co-residence bias for a large set of indicators used in studies of intergenerational mobility in education. They find that regression coefficients and Pearson correlations are biased downwards, but the bias is small. They also compare estimates using Census Data and Latinobarometro data and find that the magnitude of the bias for absolute measures of mobility is small, while relative intergenerational mobility indicators are less robust to co-residency. Overall, their results indicate that while co-residence bias may have a small impact on some measures of intergenerational mobility, it is still important to account for it in order to obtain more accurate estimates.

To our knowledge, no other studies have directly addressed this issue, and no study on multi-generational mobility has examined the bias from co-residency when analyzing intergenerational mobility beyond two generations.

In our data, the surveys conducted in Chile and Mexico provide an opportunity to examine co-resident bias. Both surveys record information on education for children who reside with and without the household head at the time of the survey.

To address concerns regarding the use of co-resident children's data, we take several steps. First, we compare our estimates using co-resident data to those from other studies (e.g., Torche (2021b), Hertz et al. (2008), Neidhöfer et al. (2018)) that do not suffer from this problem. We find that our estimates, using similar birth cohorts and different measures of intergenerational mobility in education, are very close.

Next we use our data from Chile and Mexico to compare estimates using restricted (co-resident children) and unrestricted data. Our results suggest that standardized measures of mobility in education are less susceptible to bias than regression slope coefficients.[31] We find a downward bias ranging from 11.1% to 15.6% for slope coefficients and 5.3% to 11.9% for Pearson correlation, while Spearman's rank correlation is not subject to significant bias. These results suggest that our estimates using standardized measures of mobility are not significantly biased by co-residency. Our results also indicate a lower bound of immobility, suggesting that our main results showing high levels of immobility could be even larger when using the full sample of children.

In this section, we estimate the analysis for Chile and Mexico using two different samples: the sample of co-resident children and the unrestricted sample using all children. We do this to document the potential co-residence bias in previous estimates and to extrapolate the results to our data to determine the bounds of our estimates and in which direction they may be biased.

Table A.18 presents the results for Chile and Mexico using the full sample and the co-resident sample of children. One main finding is that using the co-resident sample consistently estimates a lower regression slope coefficient and Pearson correlation, except for Panel 3 for Chile where the regression of grandchildren on grandparents shows a larger coefficient than the one using the full sample.

Moreover, the results show that standardized measures of mobility in education are less susceptible to bias than regression slope coefficients. This is consistent with Emran et al. (2018) who suggest

[31] This is consistent with Emran et al. (2018), who suggest focusing on the intergenerational correlation as it is subject to smaller biases from co-residency.

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Overall, our findings suggest a downward bias ranging from 11.1% to 15.6% for regression slope coefficients and 5.3% to 11.9% for Pearson correlation, while Spearman's rank correlation is not subject to significant bias. This is reassuring that our estimates using standardized measures of mobility are not subject to severe bias from co-residency. Our results also indicate a lower bound of immobility, suggesting that our main results showing high levels of immobility could be even larger when using the full sample of children.

Table A.18: Relative Mobility Measures by Country and Generational Analysis using Coresident Sample

Panel 1: Children on Parents (G3 on G2)

Country:	Chile		Mexico	
Sample:	Full Sample	Coresident Sample	Full Sample	Coresident Sample
Slope coefficient	0.453***	0.396***	0.672***	0.587***
	(0.010)	(0.014)	(0.020)	(0.031)
Pearson Correlation	0.576	0.539	0.528	0.481
Spearman's rank correlation	0.522	0.501	0.456	0.431

Panel 2: Children on Grandparents (G3 on G1)

Country:	Chile		Mexico	
Sample:	Full Sample	Coresident Sample	Full Sample	Coresident Sample
Slope coefficient	0.376***	0.334***	0.842***	0.711***
	(0.015)	(0.016)	(0.037)	(0.054)
Pearson Correlation	0.409	0.387	0.385	0.339
Spearman's rank correlation	0.352	0.354	0.331	0.306

Panel 3: Children on Grandparents conditional on Parents (G3 on G1|G2)

Country:	Chile		Mexico	
Sample:	Full Sample	Coresident Sample	Full Sample	Coresident Sample
Slope coefficient	0.103***	0.122***	0.316***	0.244***
	(0.015)	(0.017)	(0.039)	(0.065)
Pearson Correlation	0.112	0.142	0.144	0.116
Spearman's rank correlation	0.118	0.148	0.172	0.146
Observations	12,004	3,565	29,702	5,494
Mean of G1 Schooling	4.429	4.770	1.670	1.822
Mean of G2 Schooling	8.097	8.757	3.909	4.676
Mean of G3 Schooling	11.477	12.041	8.470	9.396

Notes: Table A.18 reports slope coefficients from regressions using raw measures of years of schooling as the dependent variable (Slope Coefficients), using standardized years of schooling as the dependent variable (Pearson correlation), and using the Rank of years of schooling as the dependent variable (Spearman's rank correlation). Panel 1 estimates regressions (1) using children schooling measures as the dependent variable and parent schooling as the independent variables. Panel 2 estimates regression (1) using children schooling measures as the dependent variable and grandparent schooling as the independent variables. Panel 3 estimates regression (2) using children schooling measures as the dependent variable and grandparent schooling as the independent variables conditioning on schooling of the parent generation. All regressions control for age and gender of the parental and children generation. The numbers of the first column are computed by pooling all six surveys and running a regression using country fixed effects without sampling weights. Standard errors in parenthesis are clustered at the family level.

G Robustness to computing G1 schooling

Our results are generally robust to different ways of computing grandparental schooling. We provide below tables with our main estimates when using the maximum education between both grandparents (G1) instead of their average (as we present in the main text).

Table A.19: Mobility Measures by Country and Generational Analysis with the maximum of G1

	LAC	Chile	Colombia	El Salvador	Mexico	Paraguay	Uruguay
Panel 1: Parents on Grandparents (G2 on G1)							
Slope coefficient	0.632***	0.568***	0.662***	0.778***	0.803***	0.629***	0.517***
	(0.009)	(0.015)	(0.028)	(0.050)	(0.033)	(0.037)	(0.046)
Pearson correlation	0.498	0.558	0.473	0.548	0.540	0.549	0.459
Spearman's rank correlation	0.453	0.515	0.463	0.438	0.499	0.449	0.420
Observations	16,364	4,362	2,600	1,175	6,443	1,227	557
Panel 2: Children on Parents (G3 on G2)							
Slope coefficient	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	0.519	0.576	0.504	0.545	0.528	0.419	0.393
Spearman's rank correlation	0.437	0.522	0.514	0.499	0.456	0.311	0.398
Panel 3: Children on Grandparents (G3 on G1)							
Slope coefficient	0.438***	0.312***	0.461***	0.543***	0.680***	0.282***	0.286***
	(0.010)	(0.013)	(0.027)	(0.042)	(0.031)	(0.048)	(0.048)
Pearson correlation	0.328	0.390	0.312	0.373	0.376	0.230	0.282
Spearman's rank correlation	0.311	0.368	0.337	0.321	0.356	0.206	0.285
Panel 4: Children on Grandparents conditional on Parents (G3 on G1|G2)							
Slope coefficient	0.132***	0.081***	0.136***	0.137***	0.268***	-0.021	0.138***
	(0.010)	(0.013)	(0.026)	(0.044)	(0.033)	(0.053)	(0.047)
Pearson correlation	0.099	0.101	0.092	0.094	0.148	-0.017	0.136
Spearman's rank correlation	0.148	0.133	0.121	0.120	0.187	0.072	0.151
Observations	48,899	12,004	3,462	1,499	29,702	1,595	637

Notes: Table 1 displays a host of intergenerational mobility (IGM) measures for Latin America and the six countries under study, organized in four panels. Each panel reports three intergenerational mobility measures: slope coefficients, Pearson's correlations, and Spearman's rank correlations of schooling using different pairs of generations, computed as described in section 3. The estimates for 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. This analysis uses the maximum schooling between both grandparents (G1). Standard errors in parentheses.

Table A.20: Clark's Latent factor model parameters with the maximum of G1

	β_{-1} (1)	β_{-2} (2)	λ (3)	ρ (4)	λ_A (5)
LAC	0.552	0.369	0.668	0.909	0.685
	(0.006)	(0.009)	(0.014)	(0.010)	(0.015)
Chile	0.580	0.406	0.700	0.911	0.699
	(0.013)	(0.021)	(0.027)	(0.017)	(0.030)
Colombia	0.514	0.334	0.651	0.889	0.627
	(0.018)	(0.024)	(0.035)	(0.026)	(0.037)
Colombia	0.559	0.384	0.687	0.902	0.703
	(0.033)	(0.039)	(0.034)	(0.024)	(0.044)
Mexico	0.547	0.383	0.701	0.883	0.713
	(0.013)	(0.021)	(0.028)	(0.018)	(0.033)
Paraguay	0.521	0.271	0.520	1.001	0.584
	(0.031)	(0.060)	(0.100)	(0.114)	(0.094)
Uruguay	0.435	0.276	0.634	0.829	0.697
	(0.044)	(0.063)	(0.119)	(0.091)	(0.137)

Notes: This table reports the estimated values of λ and ρ for each country along with their bootstrap standard errors in parentheses. The numbers for the LAC row are computed by pooling all six surveys and computing correlations without sampling weights. Standard errors for the LAC row are also computed using bootstrapping. The estimates for each country and the pooled estimate for LAC are based on regressing children's schooling to parents' schooling and grandparents' schooling separately using Equation (1). The estimates are based on the sample used in each country and may not be directly comparable due to differences in sample size and composition. This analysis uses the maximum schooling between both grandparents (G1).

Table A.21: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients of Figure 6 with the maximum of G1

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.676 (0.023)	0.501	0.431			
G1 Schooling				0.547 (0.030)	0.353	0.346
G2 Sch. x Chrt: 1930 - 39	-0.102 (0.027)	0.487	0.411			
G2 Sch. x Chrt: 1940 - 49	-0.143 (-0.143)	0.535	0.499			
G2 Sch. x Chrt: 1950 - 59	-0.204 (-0.204)	0.525	0.503			
G2 Sch. x Chrt: 1960 - 69	-0.215 (-0.215)	0.483	0.420			
G1 Sch. x Chrt: 1930 - 39				-0.072 (0.038)	0.334	0.346
G1 Sch. x Chrt: 1940 - 49				-0.123 (0.034)	0.329	0.245
G1 Sch. x Chrt: 1950 - 59				-0.215 (0.034)	0.306	0.272
G1 Sch. x Chrt: 1960 - 69				-0.242 (0.043)	0.269	0.214
Observations	48,899	48,899	48,899	48,899	48,899	48,899

Notes: This table presents the results obtained from estimating equation (3) by pooling all countries using country fixed effects. In this regression we do not include survey weights. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. This analysis uses the maximum schooling between both grandparents (G1). Standard errors are reported in parentheses.

Table A.22: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients with the maximum of G1: Chile sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.538	0.589	0.549			
	(0.029)					
G1 Schooling				0.409	0.456	0.430
				(0.032)		
G2 Sch. x Chrt: 1930 - 39	-0.067	0.567	0.513			
	(0.036)					
G2 Sch. x Chrt: 1940 - 49	-0.124	0.550	0.544			
	(-0.124)					
G2 Sch. x Chrt: 1950 - 59	-0.139	0.550	0.632			
	(-0.139)					
G2 Sch. x Chrt: 1960 - 69	-0.050	0.585	0.625			
	(-0.050)					
G1 Sch. x Chrt: 1930 - 39				-0.073	0.404	0.430
				(0.044)		
G1 Sch. x Chrt: 1940 - 49				-0.144	0.359	0.379
				(0.037)		
G1 Sch. x Chrt: 1950 - 59				-0.159	0.351	0.348
				(0.037)		
G1 Sch. x Chrt: 1960 - 69				-0.119	0.444	0.385
				(0.073)		
Observations	12,004	12,004	12,004	12,004	12,004	12,004

Notes: This table presents the results obtained from estimating equation (3) or Chile using weights provided by the survey. In this regression we do not include survey weights. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. This analysis uses the maximum schooling between both grandparents (G1). Standard errors are reported in parentheses.

Table A.23: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients with the maximum of G1: Colombia sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.763	0.533	0.586			
	(0.105)					
G1 Schooling				0.619	0.275	0.273
				(0.121)		
G2 Sch. x Chrt: 1930 - 39	-0.128	0.427	0.297			
	(0.122)					
G2 Sch. x Chrt: 1940 - 49	-0.264	0.484	0.424			
	(-0.264)					
G2 Sch. x Chrt: 1950 - 59	-0.271	0.535	0.517			
	(-0.271)					
G2 Sch. x Chrt: 1960 - 69	-0.246	0.537	0.506			
	(-0.246)					
G1 Sch. x Chrt: 1930 - 39				-0.076	0.313	0.273
				(0.151)		
G1 Sch. x Chrt: 1940 - 49				-0.093	0.347	0.251
				(0.134)		
G1 Sch. x Chrt: 1950 - 59				-0.222	0.294	0.233
				(0.129)		
G1 Sch. x Chrt: 1960 - 69				-0.199	0.340	0.261
				(0.128)		
Observations	3,462	3,462	3,462	3,462	3,462	3,462

Notes: This table presents the results obtained from estimating equation (3) or Colombia using weights provided by the survey. In this regression we do not include survey weights. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. This analysis uses the maximum schooling between both grandparents (G1). Standard errors are reported in parentheses.

Table A.24: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients with the maximum of G1: El Salvador sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.748	0.637	0.504			
	(0.151)					
G1 Schooling				0.767	0.495	0.365
				(0.199)		
G2 Sch. x Chrt: 1930 - 39	-0.273	0.409	0.368			
	(0.188)					
G2 Sch. x Chrt: 1940 - 49	-0.165	0.512	0.454			
	(-0.165)					
G2 Sch. x Chrt: 1950 - 59	-0.152	0.579	0.556			
	(-0.152)					
G2 Sch. x Chrt: 1960 - 69	-0.269	0.627	0.692			
	(-0.269)					
G1 Sch. x Chrt: 1930 - 39				-0.232	0.350	0.365
				(0.216)		
G1 Sch. x Chrt: 1940 - 49				-0.127	0.364	0.157
				(0.223)		
G1 Sch. x Chrt: 1950 - 59				-0.116	0.366	0.176
				(0.233)		
G1 Sch. x Chrt: 1960 - 69				-0.356	0.461	0.345
				(0.210)		
Observations	1,499	1,499	1,499	1,499	1,499	1,499

Notes: This table presents the results obtained from estimating equation (3) or El Salvador using weights provided by the survey. In this regression we do not include survey weights. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. This analysis uses the maximum schooling between both grandparents (G1). Standard errors are reported in parentheses.

Table A.25: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients with the maximum of G1: Mexico sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.818	0.552	0.475			
	(0.063)					
G1 Schooling				0.807	0.416	0.408
				(0.086)		
G2 Sch. x Chrt: 1930 - 39	-0.132	0.510	0.435			
	(0.075)					
G2 Sch. x Chrt: 1940 - 49	-0.215	0.533	0.535			
	(-0.215)					
G2 Sch. x Chrt: 1950 - 59	-0.163	0.565	0.571			
	(-0.163)					
G2 Sch. x Chrt: 1960 - 69	0.000	.	.			
	(0.000)					
G1 Sch. x Chrt: 1930 - 39				-0.106	0.363	0.408
				(0.100)		
G1 Sch. x Chrt: 1940 - 49				-0.192	0.381	0.236
				(0.095)		
G1 Sch. x Chrt: 1950 - 59				-0.242	0.341	0.237
				(0.148)		
G1 Sch. x Chrt: 1960 - 69				0.000	.	.
				(0.000)		
Observations	29,702	29,702	29,702	29,702	29,702	29,702

Notes: This table presents the results obtained from estimating equation (3) or Mexico using weights provided by the survey. In this regression we do not include survey weights. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. This analysis uses the maximum schooling between both grandparents (G1). Standard errors are reported in parentheses.

Table A.26: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients with the maximum of G1: Paraguay sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	1.407	0.734	0.464			
	(0.238)					
G1 Schooling				0.821	0.381	0.302
				(0.214)		
G2 Sch. x Chrt: 1930 - 39	-0.674	0.477	0.288			
	(0.272)					
G2 Sch. x Chrt: 1940 - 49	-0.775	0.505	0.379			
	(-0.775)					
G2 Sch. x Chrt: 1950 - 59	-1.009	0.413	0.313			
	(-1.009)					
G2 Sch. x Chrt: 1960 - 69	-1.070	0.321	0.162			
	(-1.070)					
G1 Sch. x Chrt: 1930 - 39				-0.268	0.330	0.302
				(0.242)		
G1 Sch. x Chrt: 1940 - 49				-0.425	0.275	0.305
				(0.241)		
G1 Sch. x Chrt: 1950 - 59				-0.546	0.259	0.278
				(0.221)		
G1 Sch. x Chrt: 1960 - 69				-0.674	0.132	0.100
				(0.243)		
Observations	1,595	1,595	1,595	1,595	1,595	1,595

Notes: This table presents the results obtained from estimating equation (3) or Paraguay using weights provided by the survey. In this regression we do not include survey weights. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. This analysis uses the maximum schooling between both grandparents (G1). Standard errors are reported in parentheses.

Table A.27: Slope Coefficients, Pearson Correlation, and Rank-Rank Regression coefficients with the maximum of G1: Uruguay sample

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope	Pearson	Spearman	Slope	Pearson	Spearman
	(1)	(2)	(3)	(4)	(5)	(6)
G2 Schooling	0.364	0.360	0.324			
	(0.096)					
G1 Schooling				0.353	0.356	0.299
				(0.128)		
G2 Sch. x Chrt: 1930 - 39	0.000	.	.			
	(0.000)					
G2 Sch. x Chrt: 1940 - 49	-0.082	0.342	0.425			
	(-0.082)					
G2 Sch. x Chrt: 1950 - 59	0.034	0.431	0.601			
	(0.034)					
G2 Sch. x Chrt: 1960 - 69	-0.001	0.373	0.387			
	(-0.001)					
G1 Sch. x Chrt: 1930 - 39				0.000	.	0.299
				(0.000)		
G1 Sch. x Chrt: 1940 - 49				-0.007	0.359	0.443
				(0.143)		
G1 Sch. x Chrt: 1950 - 59				-0.122	0.227	0.386
				(0.152)		
G1 Sch. x Chrt: 1960 - 69				-0.122	0.181	0.205
				(0.194)		
Observations	637	637	637	637	637	637

Notes: This table presents the results obtained from estimating equation (3) or Uruguay using weights provided by the survey. In this regression we do not include survey weights. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. This analysis uses the maximum schooling between both grandparents (G1). Standard errors are reported in parentheses.

Table A.28: Regression of Mobility Coefficients in Figure 8 with the maximum of G1

	Children on Parents (G3 on G2)			Children on Grandparents (G3 on G1)		
	Slope (1)	Pearson (2)	Spearman (3)	Slope (4)	Pearson (5)	Spearman (6)
G2 Schooling	0.712	0.598	0.539			
	(0.027)	(0.024)	(0.021)			
G1 Schooling				0.586	0.417	0.366
				(0.038)	(0.026)	(0.023)
G2 Sch. $\times$ **1**(- 10 + years)	0.058	-0.047	0.002			
	(0.060)	(0.045)	(0.039)			
G2 Sch. $\times$ **1**(- 9 to - 5 years)	-0.005	-0.014	-0.006			
	(0.045)	(0.037)	(0.034)			
G2 Sch. $\times$ **1**(+ 1 to 5 years)	-0.061	-0.019	-0.019			
	(0.028)	(0.025)	(0.022)			
G2 Sch. $\times$ **1**(+ 6 to 10 years)	-0.126	-0.049	-0.044			
	(0.028)	(0.025)	(0.023)			
G2 Sch. $\times$ **1**(+ 11 to 15 years)	-0.169	-0.067	-0.074			
	(0.028)	(0.026)	(0.023)			
G2 Sch. $\times$ **1**(+ 16 to 20 years)	-0.194	-0.062	-0.050			
	(0.028)	(0.026)	(0.023)			
G2 Sch. $\times$ **1**(21 + years)	-0.213	-0.061	-0.056			
	(0.028)	(0.026)	(0.023)			
G1 Sch. $\times$ **1**(- 10 + years)				-0.031	-0.084	0.054
				(0.073)	(0.043)	(0.044)
G1 Sch. $\times$ **1**((- 9 to - 5 years)				0.034	0.003	0.013
				(0.060)	(0.036)	(0.036)
G1 Sch. $\times$ **1**(+ 1 to 5 years)				-0.063	-0.008	-0.025
				(0.039)	(0.027)	(0.024)
G1 Sch. $\times$ **1**(+ 6 to 10 years)				-0.119	-0.040	-0.045
				(0.039)	(0.027)	(0.025)
G1 Sch. $\times$ **1**(+ 11 to 15 years)				-0.174	-0.072	-0.075
				(0.039)	(0.028)	(0.025)
G1 Sch. $\times$ **1**(+ 16 to 20 years)				-0.177	-0.062	-0.060
				(0.039)	(0.028)	(0.025)
G1 Sch. $\times$ **1**(21 + years)				-0.186	-0.041	-0.060
				(0.039)	(0.028)	(0.025)
Observations	48262	48262	48262	48262	48262	48134

Notes: This table presents the results from equation (4) for by pooling all countries using country fixed effects. In this regression we do not include survey weights. The first three columns display the slope coefficients, Pearson correlation coefficients, and Spearman's rank-rank correlation for a regression of children's schooling on parents' schooling. The last three columns show the same results for a regression of children's schooling on grandparents' schooling. This analysis uses the maximum schooling between both grandparents (G1). Standard errors are reported in parentheses.