DOCUMENTOS DE TRABAJO

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Documento de Trabajo Nro. 215
Agosto, 2017
ISSN 1853-0168

www.cedlas.econo.unlp.edu.ar

Educational Inequality and Intergenerational Mobility in Latin America: A New Database

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6th March 2018

Abstract. The causes and consequences of the intergenerational persistence of inequality are a topic of great interest among various fields in economics. However, until now, issues of data availability have restricted a broader and cross-national perspective on the topic. Based on rich sets of harmonized household survey data, we contribute to filling this gap by computing time series for several indexes of relative and absolute intergenerational education mobility for 18 Latin American countries over 50 years and making them publicly available. We find that intergenerational mobility is, on average, rising in Latin America. This pattern seems to be driven by the high upward mobility of children from low-educated families; at the same time, there is substantial immobility at the top of the distribution. Significant cross-country differences are observed and are associated with income inequality, poverty, economic growth, public educational expenditures, and assortative mating.

JEL D63, I24, J62, O15. ***Keywords*** Inequality, Intergenerational Mobility, Equality of Opportunity, Transition Probabilities, Assortative Mating, Education, Human Capital, Lubotsky-Wittenberg, Latin America.

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1 Introduction

Among the oldest and most debated topics in economics are the causes and consequences of economic inequality. However, while large data sets with multiple and comparable measures of cross-sectional inequality and even historical time series are available for a multitude of countries, this is not the case for the degree of transmission of inequality across generations. Although the subject is extensively analyzed within countries, for instance for the United States (Chetty et al., 2014b,a) and India (Azam and Bhatt, 2015), research on this topic still suffers from the lack of comparable estimates across multiple countries and over longer periods of time. Our study (and the associated database that we provide) contributes to filling this gap by estimating trends of relative and absolute intergenerational mobility for educational attainment in Latin America using novel sets of harmonized household survey data.

The evaluation of intergenerational mobility allows us to address one important question: for a given level of inequality, how likely is it that families persist at the top or bottom of the distribution over the course of time?[1] Analyzing the subject across multiple countries and periods further helps us determine which factors are associated with this likelihood. However, comparing estimates for different countries that are derived from different studies raises the question of whether the uncovered cross-country differences are real or due to differences in data and measurement (Solon, 2002). Therefore, in order to deepen our understanding of the factors associated with the intergenerational transmission of socioeconomic status, it is necessary to study the subject within a harmonized framework.

We provide a panel of comparable summary indicators for intergenerational education mobility over a span of more than 50 years in 18 countries, which we make available for future research. The present study aims to introduce this new data set and provide a comprehensive analysis of the

[1]As scholars point out, measures of intergenerational mobility do not perfectly mirror the notion of equality of opportunity. For instance, Jencks and Tach (2006) argue that, mainly because of the intergenerational transmission of genes, values and preferences, the correlation between the status of parents and children should still be positive even in a totally meritocratic society. Bearing this in mind, mobility measures still give meaningful insights on the stratification of the society and empirically show a substantial association with common indices that measure equality of opportunity Brunori et al. (2013).

observed trends regarding intergenerational mobility in Latin America, as well as their association with macroeconomic and institutional characteristics. It extends and builds upon Hertz et al. (2007)'s influential cross-country analysis on educational mobility as well as the existing evidence on intergenerational mobility in Latin America, as reviewed by Torche (2014).

Our analysis contributes in several dimensions to the literature on intergenerational mobility in developing countries: First, we examine multiple countries over a longer time span and within a harmonized framework. Second, we provide more precise estimates that rely on several survey waves and a greater number of observations. Third, we obtain and compare estimates from two independent sources for nine of the 18 countries in our sample. Fourth, we compute several indexes that fulfill different axioms and measure different dimensions of relative and absolute mobility. Fifth, we calculate estimates for father-son and mother-daughter pairs, as well as for the degree of assortative mating. Sixth, we adopt an approach suggested by Lubotsky and Wittenberg (2006) and provide, for the first time, estimates for the association between overall parental social status and the educational attainment of children in Latin America. Finally, we provide a multi-country panel data set for use in future research.

Our findings highlight interesting new aspects about the intergenerational transmission of inequality in Latin America. Although older cohorts display high rates of intergenerational persistence, as shown in existing studies, we observe a rising average trend in educational mobility. This trend seems to be mainly driven by educational expansions that have particularly benefited children from low-educated families. Hence, the new picture emerging shows Latin America is a region with substantial immobility at the top, but decreasing intergenerational persistence at the bottom of the distribution. The uncovered relationships across and within countries show that higher intergenerational mobility is associated with higher economic performance and more progressive public spending in the educational system. Interestingly, these relationships are substantial for absolute mobility and less relevant for relative educational mobility. Furthermore, our descriptive evidence might suggest that the observed rising intergenerational mobility in Latin America is related to the decline in income inequality experienced by the region since the 2000s.

The paper is structured as follows: Section 2 provides an intuitive framework about the intergenerational persistence of socioeconomic status and its macroeconomic implications. Section 3 shows the estimated mobility indexes. Section 4 describes the data sources and harmonization procedure used to obtain our estimates. Section 5 describes the uncovered cross-country patterns and trends of intergenerational mobility in Latin America. Section 6 examines the association between our intergenerational mobility estimates and economic performance. Section 7 describes the approach proposed by Lubotsky and Wittenberg (2006) and shows the estimates for intergenerational persistence obtained with this application. Section 8 concludes.

2 Theoretical Framework: Intergenerational Persistence and its Macroeconomic Implications

Pioneering works by Becker and Tomes (1979, 1986); Loury (1981) and Solon (1992) conceptualize the mechanisms and transmission channels that explain the observed degree of persistence between the economic outcomes of parents and children. In these models, the transmission of economic inequality from one generation to the next is mainly related to the inheritability of earning abilities and parental investments in the human capital of their children. Thereby, the utility of parents depends on their own consumption and the future utility of their children, as well as on direct "warm-glow" benefits of altruistic behavior toward them. Hence, even if the inheritability of abilities would be of negligible size, in unequal societies some persistence will be observed if parents cannot borrow against investments in the human capital of their children. A major substitute of private parental investment in human capital is argued to be public investment, for instance through the provision of a comprehensive education system. Solon (2004) shows how these structural components are related to the observed reduced-form association between parental and children's outcomes. In his analysis, intergenerational mobility decreases with the inheritability of abilities, the efficacy of human capital investment, and the returns to human capital, while increasing with the progressivity of public investment in children's human capital.

Influential theoretical studies complement this conceptual framework with models of the macroeconomic implications of parental investments. These models show that higher intergenerational mobility promotes growth and economic development, both in the steady state (Owen and Weil, 1998) and when applying a dynamic perspective (Maoz and Moav, 1999). The accumulation and more efficient allocation of human capital in the society are identified as driving mechanisms. Hassler and Mora (2000) argue that technological growth lowers the relative importance of social background while fostering the role of talent and intelligence for the allocation of occupations, finally contributing to higher growth in the future.

Furthermore, the relationship between income inequality and intergenerational mobility is bidirectional. On the one hand, higher income inequality causes greater disparity in human capital investments between rich and poor families (Becker and Tomes, 1979). On the other, upward mobility of low-status families increases the relative supply of high skilled workers, causing lower returns to higher education and, consequently, lower levels of inequality (Hassler et al., 2007).

In what follows, we first describe the estimated mobility indexes formally and then the observed patterns and trends of intergenerational mobility in Latin America. In Section 6, we analyze the relationships hypothesized by economic theory through a stylized analysis using our intergenerational mobility estimates.

3 Measuring Mobility

In cross country comparisons, different indexes measuring intergenerational mobility may yield very different pictures. Therefore, researchers should adopt the measurement that fulfills the needs of the dimension they aim to analyze and the questions they seek to answer.[2] For instance, in the context of educational mobility, some questions might need absolute mobility measures, as would be the case to capture educational expansions (structural mobility). Others might need to neglect this dimension and focus on positional changes of families within the distribution (exchange

[2]For conceptual and methodological reviews on intergenerational mobility, see Black and Devereux (2011); Jäntti and Jenkins (2015); Piketty (2000).

mobility). In this study, and with the creation of the associated database, not only do we try to offer an exhaustive panorama of absolute and relative indexes, but we also try to show the overall picture of intergenerational mobility in Latin America from different perspectives. Future research using our estimates should use the indexes that fit the requirements of the research question regarding two key aspects: i) what is the intuition behind the mechanisms to be analyzed; and ii) which axioms have to be fulfilled.

In what follows, we describe the computed indexes. The key variables are always referring to educational outcomes of parents (y^p) and children (y^c) measured either in completed years of education or the obtainment of a specific educational degree. The indexes are estimated separately for each cohort j and country k.

3.1 Slope coefficient and intergenerational correlations

The most widely used mobility index in the intergenerational mobility literature is the slope coefficient from a linear regression of children's outcomes on parental outcomes.[3] Here, we regress the years of education of the child from family i belonging to cohort j in country k on the years of education of his parents (the exact measurement of these two outcome variables is explained in Section 4):

$$y^c_{ijk} = \alpha_{jk} + \beta_{jk} \cdot y^p_{ijk} + \gamma_{jk} X_{ijk} + \varepsilon_{ijk}. \quad (1)$$

In this equation, α is a constant, X is a vector of control variables for age and sex, while ε is the error term. The slope coefficient can also be standardized to take differences in the variances of children's and parents' outcomes into account:

$$r_{jk} = \beta_{jk} \frac{\sigma^p_{jk}}{\sigma^c_{jk}}. \quad (2)$$

If no control variables are included in the regression, the standardization yields an index equal to Pearson's correlation coefficient.

[3] The specification of the model displayed here simplifies to one child per family.

β and r are measures for positional mobility capturing both structural mobility and exchange mobility. β reflects the degree of regression to the population mean between two generations. Widely used in the literature, it has the advantage of comparability between these and other estimates for the same or other countries. Thereby, r "corrects" β by the changes in inequality in the marginal distributions of the outcome of interest. As there is a lack of consensus regarding which of the two is more suitable for cross-country (and cross-cohort) comparisons, it seems important to report both (Jäntti and Jenkins, 2015).

Further, mobility can be measured by Spearman's rank correlation coefficient. This index, applied to the ranks of y^c and y^p in their respective distributions, captures the pure positional change aspect of mobility:

$$\rho_{jk} = \frac{cov(rank_{y^c_{jk}}, rank_{y^p_{jk}})}{\sigma_{y^c_{jk},rank}\sigma_{y^p_{jk},rank}}. \tag{3}$$

Whether these corrections are necessary or not depends on the research question. As stated before, the intergenerational transmission of inequality could be an important dimension and it may be lost if one measures mobility by (2) and (3). However, if exchange mobility is the only important aspect to be accounted for, then (1) might not be the suitable.

The outcome that is most frequently available for two subsequent generations and that is also comparable across countries is educational attainment measured in completed years of education. Thus, the indexes have one important feature in common: they give a broad and intuitive picture of the overall educational persistence experienced by a certain cohort in a given country.[4]

[4]These measures assume a linear and monotonic relationship of years of education from one generation to the next. Although this method is usually applied in the literature, the validity of the linearity assumption is questioned because the slope might vary with rising parental education. So far, linear and non-linear measures are found to be correlated across countries (see Blanden, 2013), but future research on this topic should investigate this issue in more detail. For completeness, in the Supplemental Material we include an analysis of the correlation between the educational level of parents and children measured in categories using a bivariate ordered probit model. Equation (1) might be also estimated on the logarithm of the outcome of interest, i.e. years of education, hence assuming a log-linear relationship. In this case, the slope coefficient is an elasticity measuring marginal changes in children's education associated with marginal changes in their parent's education. The intuitive difference between the educational persistence explained above and the intergenerational education elasticity (not discussed in this paper but included in the database) lies mainly in the functional form assumed to underlie the intergenerational transmission of education and social status.

3.2 Transition probabilities

Another insightful measure in terms of intergenerational mobility is the probability of children facing different circumstances, measured by parental educational background, to achieve a certain minimum level of education. We compute two different indicators:

The *probability of bottom upward mobility*

$$BUM_{jk} = Prob(y^{c}_{ijk} \geq s | y^{p}_{ijk} < s), \tag{4}$$

and the *probability of upper class persistence*

$$UCP_{jk} = Prob(y^{c}_{ijk} \geq s | y^{p}_{ijk} \geq s). \tag{5}$$

The indicators yield the probabilities of children to achieve at least the educational degree s, conditional on their parents' education. We define two types of parental education: i) low parental education, i.e. less than s; and ii) high parental education, i.e. at least s. In our estimations, we mainly define s as the obtainment of a secondary school degree. Hence, in terms of social mobility and equality of opportunity, these probabilities measure upward mobility for people at the bottom of the distribution and class persistence at the top, respectively.

3.3 Absolute and directional mobility

The measures described above cover the relative and absolute dimensions of intergenerational mobility, understood as the movement of families within the distribution over time. However, they do not give comparable information about the size of those movements. Therefore, two more indexes – initially developed by Fields and Ok (1996) and mostly applied to measure individual income movements in an intragenerational context – are computed to measure the per capita movements in years of education:

$$M1_{jk} = \frac{1}{N_{jk}} \sum_{i=1}^{N_{jk}} |y^{c}_{ijk} - y^{p}_{ijk}|, \tag{6}$$

$$M2_{jk} = \frac{1}{N_{jk}} \sum_{i=1}^{N_{jk}} (y^{c}_{ijk} - y^{p}_{ijk}). \tag{7}$$

$M1$ shows the average difference between the two generations within the same families, regardless of the direction of the change. Upward and downward movements are summed up to one summary measure. In contrast, $M2$ measures the average directional change between two generations. High values of $M2$ can, for example, be a sign of educational expansion. Together, $M1$ and $M2$ also give insightful information on the degree of downward movements: the smaller is the difference between the two, the lower is the amount, or average degree, of downward mobility.

4 Data

4.1 Description of Data Sources

The sources of information used to obtain our estimates are derived from two sets of representative harmonized household survey data. We used the availability of information on the parental educational background of adult individuals as a selection criteria for our surveys, focusing on surveys that include retrospective questions about parental education. To avoid *co-residency bias*, we did not use surveys in which information on parental characteristics could only be retrieved because parents and children resided in the same household.[5] The first harmonized survey data set is derived from the annual opinion survey, *Latinobarómetro*. The second data set is retrieved through the harmonization of selected representative national household surveys that are mainly conducted by national statistical offices (henceforth National Household Surveys). All surveys used in our analysis are listed and described in more detail in the Supplemental Material.

The main advantage of Latinobarómetro is that it is specifically developed to be used in cross-country studies and, hence, uses the same questionnaire and codification of survey answers in all

[5] For an analysis of co-residency bias in intergenerational mobility estimates, see Emran et al. (2017).

years and countries. The survey includes 18 Latin American countries.[6] The other household surveys are not uniform across Latin American countries. Therefore, not only do we make all possible efforts to make statistics comparable across countries and over time by using similar definitions of variables in each country and survey year, but we also apply consistent methods when processing the data. In particular, the inclusion of retrospective questions is not a universal characteristic found in all household surveys. Thus, while we estimate the indexes for 18 countries with the Latinobarómetro sample, estimates are only obtained for 9 countries using National Household Surveys. The advantage of many of the National Household Surveys is that they offer a substantially larger number of observations. Furthermore, the survey structure allows us to estimate father-son and mother-daughter associations, while Latinobarómetro only includes information on the parent with the highest educational degree.

We draw the same sample for each country and survey. The sample comprises individuals born between 1940 and 1990, who were at least 23 years old when surveyed. The age limit ensures that individuals have a higher likelihood to have completed their educational career, thus avoiding biased estimates. Since parental education is retrieved trough retrospective questions, whether individuals and their parents reside together in the same household is not relevant for inclusion in our sample. Thus, the main restriction criteria is the availability of information on own and parental education.[7] Our final samples, including all countries and cohorts, is comprised of 194,202 individuals from the Latinobarómetro survey and 1,181,229 individuals from the National Household Surveys. Estimates based on both data sets are obtained by weighting each observation by the inverse probability of selection, normalizing the weights over the different survey waves.

[6] The representativeness of the survey has varied over time, reaching 100% of the total population in all countries around 2000.

[7] A separate section in the Supplemental Material is dedicated to the issue of sample selection. Essentially, we observe that the share of missing information on parental education in the single surveys varies between 2 and 26 % of the respondents. Some sensitivity analyses show that although individuals with higher education are slightly overrepresented in the restricted sample – i.e. among individuals with available information on parental education – the mean and variance of years of education are not affected by sample selectivity in the surveys. This pattern is observed in all surveys and, hence, should not affect the interpretation of cross-country differences.

4.2 Measurement of educational attainment

In Latinobarómetro the information recorded regarding parental education refers only to the parent with the highest education. In the National Household Surveys, the education of both parents, mother and father, is provided. In that case, we use the parent with the highest educational degree, as is commonly done in the literature (Black and Devereux, 2011), to obtain our baseline estimates. In Section 7, we show how our estimates change if we use instead the average years of education over both parents and discuss the properties of both measures as proxies for parental educational background.

Our main measure, completed years of education, measures the regular years of education associated with the degree obtained by parents and children. In order to improve the comparability of these measures, we use the same coding used by Latinobarómetro to process the National Household Surveys. That is, we truncate the years of education at the university level because the degree of heterogeneity is greater at that level. Thus, the completed years of education of parents and children are metric variables that range from 0 to 15. [8]

Figure 1 shows the mean and coefficient of variation of completed years of education in our samples, comparing the statistics obtained from Latinobarómetro and the National Household Surveys. The cohorts always refer to the children's generation. It is evident than in most countries the two harmonized survey sets yield very similar statistics in trends and levels. Throughout the cohorts, educational attainment of individuals in Latin America increased steadily, while there is certain heterogeneity in the levels of schooling among countries. In the youngest cohort, we find Guatemala, Honduras, and Nicaragua,with around six years of education on average; at the other end of the spectrum, we find Argentina, Chile, and Colombia, with around 12 years.

Measuring intergenerational mobility using educational attainment of parents and children has a double function. On the one hand, education and educational mobility are important measures in

[8] Latinobarómetro uses the same codification to measure the education of individuals and their parents. The other surveys include either information on completed years of education or on the highest obtained degree of respondents and their parents. In those cases, we impute the years of education required to complete the obtained degree and follow the same scheme used in the Latinobarómetro survey. Detailed information on the codification of educational attainment for parents and children in each country is available in the Supplemental Material.

their role as drivers of human development. On the other, education is a meaningful proxy measure of social status. As pointed out by Hertz et al. (2007, page 6):

> Education-, income-, and occupational status-based measures all perform similar descriptive functions: they quantify the intergenerational association between conceptually and empirically distinct, but closely related, scalar measures of long-run socioeconomic status.

Indeed, as shown by Blanden (2013), there is a meaningful correlation between estimates of intergenerational income mobility and educational mobility across countries. Furthermore, education has some practical advantages with respect to income when the aim is to investigate intergenerational mobility using household survey data. First, educational attainment is usually fixed and time-invariant in adulthood. Hence, a single cross-section is sufficient to obtain consistent estimates while, because of the volatility of income over the lifecycle, income mobility measures require panel data with several observations (see e.g. Nybom and Stuhler, 2016). Second, retrospective information on parental education are more reliable and of higher quality than on income or other social status measures.

In order to give an idea of how educational attainment is related to economic well-being in Latin America, Figure 2 shows average income levels for six broad educational categories. Furthermore, returns to education – measured by the ratio of incomes achieved by high and low educated people – are displayed for a younger (Y) and an older (O) cohort in each Latin American country. We see that, although substantial differences between countries exist, higher educational degrees are clearly associated with higher levels of income. Furthermore, despite the educational expansions experienced in all countries, returns to education are rather similar for people of different ages. Thus, at least for the Latin American context, educational mobility measures should also be meaningful indicators for intergenerational mobility of (material) well-being. In Section 7 we adopt the methodology suggested by Lubotsky and Wittenberg (2006), which allows including multiple measures of parental social status to measure intergenerational mobility, and verify this claim in more detail.

5 Intergenerational Mobility in Latin America

5.1 Cross-Country Patterns

Before reporting the intergenerational mobility trends through the summary measures described in Section 3, we describe the cross-country differences in mobility patterns for the entire sample. First, Figure 3 illustrates absolute (or structural) mobility patterns, and, then, Figure 4 illustrates relative (or exchange) mobility; both using Latinobarómetro as data source.

Figure 3 ranks countries in Latin America according to the percentage of people who have more education than their parents, measured in completed years of schooling. We see that more than 50% of people born between 1940 and 1990 in all countries in the region have achieved higher educational attainment than their parents. Venezuela and Paraguay lead the group of countries with high absolute mobility, while Guatemala, Nicaragua, and Honduras are at the bottom end of the ranking. Although this evidence is illustrative of the differences between countries in terms of mobility, it is far from complete because it does not take into account the position of individuals in the distribution and the size of the change between generations.

Figure 4 is more informative about the movement of families within the distribution. In the upper part, we show the composition of the educational classes by parental educational background. Here, individuals and their parents are ranked according to their relative educational position, measured in standard deviations from the country's average years of education and grouped in three different classes: high, middle, and low levels of education. The cells of the matrix contain the percentage of individuals in the children's generation associated with the respective parental educational class.

Focusing on the three most meaningful cells – the ones that display persistence at the top and at the bottom of the distribution, as well as the degree of bottom-up mobility – Latin America appears to be a region with low intergenerational mobility, on average. Almost 60% of children with high and low education, respectively, have parents in the same educational class. Moreover, only 14% of the individuals in the high education class come from low-education families. The lower part of Figure 4 ranks the countries by this last indicator for bottom-up mobility. We see that the share ranges from less than 10% in Chile to about 20 % in Nicaragua and the Dominican Republic. To give a benchmark for these estimates, we estimate the same indicators for the U.S. and Germany using the same sample restriction criteria and comparable household surveys (PSID and SOEP, respectively). It turns out that in these two countries persistence at the bottom is higher than the Latin American average (USA 61.5 %, Germany 56.5 %). In contrast, persistence at the top is lower (USA 51.2 %, Germany 55.8 %) and bottom-up mobility higher (USA 21.5 %, Germany 17.8 %) than in most Latin American countries.[9]

It is worth noting that the country rankings change considerably depending on the adopted concept of mobility (relative or absolute). For example, it is particularly striking that Nicaragua is both one of the countries with the highest relative mobility and the lowest absolute mobility. What explains this seemingly controversial finding is that Nicaragua is one of the countries with the lowest and most unequally distributed educational attainments on average. Hence, while the opportunities of children from low educated families to improve their educational level are high, the chances that this improvement translates into a considerable jump within the distribution are quite modest. This finding confirms the importance of i) evaluating intergenerational mobility using multiple measures; and ii) measuring the mobility of people born in different years separately.

5.2 Trends

Figures 5, 7, and 9 show the trends and geography of intergenerational mobility in Latin America measured by the indexes explained in Section 3 with the Latinobarómetro survey. Figures 6, 8, and 10 show the corresponding averages for the nine countries where we have National Household Surveys available to perform the analysis. Since the trends and levels obtained with the National Household Surveys basically mirror the results obtained with Latinobarómetro for all the estimated indexes, we focus the descriptive analysis in this section on the results obtained with Latinobaróme-

[9] A matrix showing educational transitions within families from the perspective of the parental generation is included in the Supplemental Material.

tro data. Furthermore, we exclude point estimates if these were obtained from samples of less than 200 individual observations. Charts for each country are included in the Supplemental Material.

Figure 5 and 6 show intergenerational mobility measured by the regression coefficient (β), the standardized coefficient (r), and the Spearman's rank correlation coefficient (ρ). Aggregate results for Latin America are constructed as the unweighted average of the 18 or 9 countries analyzed, depending which survey was used. β changes substantially and significantly over the observed period. For people born in the 1940s, an additional year of parental education is associated with an average increase of about 0.6 years of education, while for people born in the 1980s the same measure is around 0.4.[10] The results for the older cohorts are consistent with past estimates for Latin America, e.g. by Hertz et al. (2007).

Comparing these trends with those observed for other countries, we see that, while Latin America has historically been perceived as a region with low social mobility, the educational mobility of the youngest cohorts is similar to that of developed countries like the U.S. (see Hertz et al., 2007; Neidhöfer and Stockhausen, 2018). The map shows that the increase in mobility is recorded for almost all Latin American countries over time. In contrast, r and ρ are relatively stable, at around 0.5 throughout the entire period. This shows that the type of mobility experienced in Latin America has mainly been structural. However, in the two countries where the rise in intergenerational mobility has been the strongest, the Dominican Republic and Venezuela, both structural as well as exchange mobility increased significantly. Guatemala and Honduras are the only countries where structural as well as exchange mobility did not rise over the observation period.

Note, that our estimates are obtained using years of education of the parent with the highest degree as proxy for parental educational background, while Hertz et al. (2007) use the average years of education among both parents. Section 7 discusses the implications of these methodological

[10] Because of surviving bias associated with own and parental education, the sample of older individuals who participate in household surveys might be selective. Hence, intergenerational persistence estimates of the cohorts 1940 to 1950 might be upwardly biased by differential mortality rates among low and highly educated people. Furthermore, the strength of this bias might depend on cross-country characteristics like the extensiveness and quality of the health system.

choices and shows comparable estimates. The interpretation of our findings does not change if we adopt the average years of education of parents as a proxy for parental background.

Figures 7 and 8 illustrate the extent and differences across cohorts of the probability of upward mobility for people at the bottom of the distribution, as well as the probability of class persistence at the top. On average, the predicted probability of upper class persistence is high and oscillates around 0.7. By contrast, the predicted probability that individuals who were born in the 1980s to low-educated parents attain a secondary school degree is more than twice as high as the same probability for individuals born in the 1940s. However, not all countries show the same pattern. Although bottom-up mobility increased in most of the countries – up to a 300 % increase in Brazil and Mexico – it is on low levels and almost unchanged over time in Uruguay and the Central American countries Guatemala, Honduras, and Nicaragua.[11] Very high bottom-up mobility rates in the youngest cohorts (higher than 0.5) are observed in Argentina, Mexico, Peru, and Venezuela. One striking finding is that, in Nicaragua, the youngest cohorts of individuals show a surprisingly low probability of attaining a secondary school degree. This applies even to people with a high parental educational background. One possible explanation for this finding could be the violent wars suffered by the country from 1978 to 1990, which affected the people born during this era.

Figures 9 and 10 show absolute and directional mobility trends. These measures show the magnitude and pattern of the change between the educational attainment of parents and children, on average. As is evident, since the outcome measure – completed years of education – is bounded, rising parental education also reduces the margins and possibilities for the children to experience an improvement. This fact explains the inverted U-shape pattern of the time series for these two indexes. In the sixties, the distance between parental and child education reaches a maximum and later decreases as parental education rises. Interestingly, the gap between M1 and M2 does not change significantly across cohorts, showing that downward mobility is almost stable at around one year of schooling on average.

[11] The spatial dimension of this phenomenon is a striking finding that might deserve special attention in future studies.

5.3 Persistence at the Tails

Research on intergenerational income mobility in developed countries indicates that the degree of persistence may depend on the position of families in the income distribution. Palomino et al. (2017) find, for instance, that in the US, income persistence is stronger at the tails of the distribution than for middle class families. Furthermore, their evidence shows that education is a relevant factor that influences economic mobility at both tails of the income distribution. Checchi et al. (2013) show that, in Italy, the strongest educational persistence is observed for children born to uneducated and tertiary educated fathers. A similar picture is also shown by Neidhöfer and Stockhausen (2018) for educational persistence in Germany, the UK, and the US, extending over three generations, i.e. from grandparents to grandchildren. Our computed transition probabilities hint at a similar scenario for educational persistence at the top in Latin America, but are not conclusive about the lower end of the distribution. Hence, we test if this hypothesis holds for Latin America, subdividing the lower educational class into two separate categories – low and very low educated parents; i.e. parents with completed primary education but incomplete secondary and parents with no educational degree or no schooling at all, respectively – and estimate, for each class, the probability that children stay in the same class as their parents.

Figure 11 shows the average trends of these probabilities for Latin America; country-wise estimates are included in the Supplemental Material. On average, we observe lower mobility at both tails of the distribution for older cohorts of individuals. For people born between 1940 and 1947 the degree of persistence is around 65 % for individuals with high and very low educated parents, and around 50 % for families in the middle of the distribution. In contrast, younger cohorts show a different pattern: while persistence at the top is very high (up to 80 %), persistence at the bottom of the distribution is substantially lower and similar to the degree of persistence of 'middle-class' families. The estimates for every single country show that the hypothesis of higher persistence at the tails of the distribution is confirmed for older cohorts in almost all Latin American countries and for younger cohorts in Bolivia, Brazil, El Salvador, and Guatemala.

6 Intergenerational Mobility, Institutions and Economic Performance

The aim of this part of the analysis is to show the association between intergenerational mobility with macroeconomic and institutional characteristics as hypothesized by economic theory (see Section 4). The first part of this stylized analysis focuses on the evidence about steady-state relationships, while the second part takes a more dynamic perspective showing estimates that control for cross-country heterogeneity. Although these correlations cannot be interpreted as causal effects, they might be seen as a first step to understand the potential underlying mechanisms.

Figure 12 shows scatter-plots, linear fits, and correlation coefficients of the cross-country relationships. This analysis is focused on the regression coefficient as an indicator of intergenerational persistence because this indicator comprises both structural as well as exchange mobility. We find that higher degrees of intergenerational mobility are associated with: i) High levels of GDP per capita; ii) Lower levels of income inequality and poverty; iii) Lower returns to education, as measured by the ratio of hourly wages of people with high and low education; and iv) Higher amounts of public expenditure in education and, in particular, the share of expenditure devoted to primary and secondary education with respect to expenditures in tertiary education. These findings confirm the predictions of the influential theoretical models summarized in Section 4 and the patterns uncovered in existing empirical findings. For instance, the negative relationship between inequality and intergenerational mobility is shown to hold across countries (Corak, 2013), as well as within the U.S. (Chetty et al., 2014a) and China (Fan et al., 2015). Güell et al. (2015) find that intergenerational mobility within Italy is positively correlated with economic performance. Mayer (2008) show that across and within US-states, higher per child public spending is associated with higher intergenerational mobility.

To go deeper into these relationships, we regress a series of macroeconomic outcomes separately on our intergenerational mobility estimates. To make full use of the available data, we analyze the association between the degree of intergenerational mobility of people born in a particular year and the economic performance of their country of residence years later. These associations are purely descriptive and the exact identification of causal channels are beyond the scope of this work. However, they are indicative about how equality of opportunity, measured by social intergenerational mobility, might affect economic performance; a topic receiving special attention (among others, Ferreira et al., 2017; Marrero and Rodríguez, 2013).[12]

We estimate the following equation

$$Y_{i,t} = \alpha + \theta M_{i,t-s} + \vartheta_i + \varepsilon_{i,t}, \tag{8}$$

where Y is the outcome of interest measured in country i and year t, M is the degree of intergenerational mobility of the population born in year $t-s$, ϑ a country fixed effect, α the constant, and ε the error term. θ is the coefficient of interest that captures the within-country proportion of variance in $Y_{i,t}$ explained by the average degree of intergenerational mobility of the population born s years before. Several issues challenge the causal interpretation of θ; for instance, variables related to Y and correlated with M that are omitted from the regression. Hence θ should not be interpreted in structural terms but merely as a descriptive parameter showing the direction of the relationship between Y and M.

Table 1 shows the estimates of θ for different outcome variables Y – displayed in different sub-tables – and specifications of M – displayed in different columns of the tables. The dependent and independent variables are standardized to have mean zero and standard deviation of one. We chose a suitable time lag s to measure Y when the individuals of the cohort $t-s$ were old enough to contribute substantially to the economic performance of the country; $s = 50$ is our main specification.[13]

[12] A suitable way to analyze the opposite direction of the relationship – i.e. the driving forces of intergenerational mobility – would be to relate a cohort's level of mobility with indicators of its initial conditions, like the macroeconomic and institutional circumstances experienced by people in their childhood (e.g., see Neidhöfer, 2016). However, macroeconomic indicators for Latin America are available from the 90s onward while the last cohort for which we computed intergenerational mobility indexes are people born in 1990.

[13] Other specifications of s (e.g. $s = 30$ and $s = 40$) yield qualitatively similar results and are included in the Supplemental Material. The only significant differences arise hereby measuring mobility by $M1$ and $M2$. This is related to the inverted U-shaped pattern of these estimates (by construction) with rising average educational attainments of the population, as shown in Section 5.

Generally, the analysis controlling for cross-country heterogeneity confirms the general patterns shown in Figure 12. Interestingly, the mobility indicators that capture the structural mobility component, for instance educational mobility $(1-\beta)$ and bottom upward mobility (BUM), are positively and significantly associated with economic performance, while the coefficients of the standardized persistence – measured by the rank correlation, an index that reacts only to positional changes of families within the distribution of educational attainments $(1-\rho)$ – show no statistically significant associations. A possible interpretation of these findings is that what positively influences economic performance is not the amount of exchange mobility – the rise of some families that is necessarily accompanied by the fall of other families – but the opportunities for children from the lower bottom of the distribution to improve their human capital as compared to their parents.

These preliminary analyses using our database open up interesting avenues for future research on the causal mechanisms behind the highlighted relationships. For instance, the fall in inequality and poverty experienced in Latin American could be related to the increase in intergenerational mobility in the region. The decline in returns to education, a factor related to the inequality decline in Latin America (Gasparini and Lustig, 2011), driven by the higher supply of educated people coming from families with low educational background, could be a channel of this relationship. Another interesting finding is the positive relationship between social mobility and the progressiveness of public educational expenditures. While the reverse causality is extensively studied – i.e. public educational expenditures as a driver of higher mobility (e.g. Ichino et al., 2011) – the direction highlighted here is not yet examined extensively in the literature. A possible channel driving this relationship might operate through preferences for redistribution that are argued to be influenced by the perceptions about social mobility and individual experiences of mobility (see Alesina et al., 2017; Piketty, 1995). Following this argumentation, we expect cohorts that experienced higher mobility to be more optimistic about social mobility and, hence, to favor less redistributive policies, like public expenditures in education. However, we find the inverse relationship: the mobility experienced by a cohort is positively related to the amount and progressiveness of educational expenditures when this cohort reaches the age of 30, 40, and 50. The dataset created here makes it possible for these aspects to be analyzed in greater detail in the future.

7 Family Background and Intergenerational Persistence

In the literature on educational mobility, the usually adopted proxy for parental educational background is the education of the parent with the higher degree. In sociology, this procedure is known as the *dominance principle* (Erikson, 1984). The assumptions behind this procedure are mainly that this proxy is suitable to capture family human capital in the parental generation and, in the context of education, that the informational advantage of one parent is sufficient for educational decisions. Hence, in some surveys, like Latinobarometro, parental education is codified according to the parent with the highest level of education.

Instead, some studies use the average years of education of father and mother as the independent variable to measure intergenerational mobility (e.g. Hertz et al., 2007). Indeed, the education of both parents are valid, although imperfect, proxies for family educational background. Depending on the degree of assortative mating – i.e. the likelihood of people with similar educational attainment to marry each another – the two procedures yield different coefficient estimates.[14] Hence, we would like to understand how the measurement of intergenerational persistence changes when the information on both parents is available, if cross-country comparisons are affected and what to take into account when comparing our estimates with others that use the average education of both parents.

From a theoretical point of view it is debatable what best approximates the human capital advantage transmitted by parents. As stated by Erikson (1984, page 503):

> There are several possible ways to get from the work positions of the individual members of the primary generation to a class position for the family. We could try to find some average of the individual positions. ... To find an average code is problematic because work positions differ in several dimensions. But even if we disregard this

[14] Obviously, with perfect assortative mating the two measures are equal.

> and assign numbers to the categories to make it possible to calculate averages, this method seems dubious. At least I would be hesitant to claim that the class position of a managing director married to a shop assistant would be on a par with, say, the class positions of two elementary school teachers married to each other.

Although the citation above applies to the occupation of fathers and mothers, it seems reasonably translatable to education as well. Moreover, if the formal education of women is constrained, for instance by cultural aspects, the educational attainment of mothers do not reflect their actual level of human capital. This issue is particularly clear in the case of earnings, where some studies use the earnings of the husband as a proxy to measure the intergenerational mobility of women (Chadwick and Solon, 2002).

However, from a statistical point of view, taking only the information of the parent with the highest degree excludes information that contributes to the variation of the dependent variable, i.e. children's education. If there are multiple proxies for one latent variable (in this case parental educational background or parental human capital), taking the average of all available proxies is one possible way to measure the correlation with less attenuation bias than by including only one proxy. However, this method gives equal weights to the contribution of each proxy variable and might not be the optimal solution if, for instance, one variable is a much better proxy than the other one. An extended approach, developed by Lubotsky and Wittenberg (2006, henceforth LW), is to compute the weights of each proxy such that the relative contribution of the variables to explain the variation in the dependent variable is taken into account. LW show that this approach is superior to estimates obtained with the average over the proxies and leads to a significant reduction in attenuation bias in comparison to the inclusion of only one proxy.

We adopt this method to have a further benchmark for our estimates and compare educational persistence with respect to the parent with the higher education, the average education of both parents, or a weighted sum of the education of both parents. We perform this analysis with the National Household Survey Data where we have information on both paternal and maternal educational attainment. With this data we also estimate time trends for the degree of assortative mating in each country and disentangle our estimates by father-son and mother-daughter lineages; results and a discussion are included in the Supplemental Material.

To illustrate the LW procedure, we present a formal discussion, departing from a structural equation showing the intergenerational relationship between children's educational attainment (y_{it}) and the latent educational background of the family in the parental generation (h^*_{it-1}):

$$y_{it} = \beta^* h^*_{it-1} + \varepsilon_{it}. \tag{9}$$

Each available proxy measure j is a linear projection of parental educational background:

$$y_{jit-1} = \rho_j h^*_{it-1} + u_{jit-1}. \tag{10}$$

All variables are hereby demeaned and, hence, the equations do not include the constant. It is typically assumed that $Cov(u_{jit-1}, \varepsilon_{it}) = 0$ and $Cov(u_{1it}, u_{jit-1}) = 0$ for all j, i.e. that each proxy affects the education of children only through h^*_{it-1}. In contrast to other methods, in this set up the strong assumption that $Cov(u_{jit-1}, u_{kit-1}) = 0$ for all $j \neq k$ is not made. Furthermore, a normalization is applied that sets the scale of the latent variable on the scale of one of the proxies by normalizing the ρ-coefficient of this variable to be equal to one. Then, for $\rho_1 = 1$ all other ρ_j can be defined as

$$\rho_j = \frac{Cov(y_{it}, y_{jit-1})}{Cov(y_{it}, y_{1it-1})}. \tag{11}$$

These ρ_j can be easily estimated by IV estimation, instrumenting y_{1it-1} with y_{it} in a regression where y_{jit-1} is the dependent variable. Following this procedure, the LW estimator is then defined by

$$\hat{\beta^*} = \sum_{j=1}^{J} \hat{\rho}_j \hat{\phi}_j, \tag{12}$$

where the $\hat{\phi}_j$ are the estimated coefficients of an auxiliary joint linear regression of children's education on all the proxy measures for parental background:

$$y_{it} = \phi_1 y_{1it-1} + \phi_2 y_{2it-1} + \ldots + \phi_J y_{Jit-1} + v_{it}. \tag{13}$$

7.1 Approximations for Parental Educational Background

In the context of the parental educational background analyzed here, the two natural proxies are the educational attainment of both parents. The two procedures described above that are usually applied to obtain intergenerational persistence estimates – the *dominance principle* and taking the average over both parents – are equivalent to the construction of an index measure for the latent variable. Assume that y_{1t-1} is the education of the parent with the higher and y_{2it-1} the education of the parent with the lower education among the two. Both procedures somehow assume that the underlying latent variable is a weighted average of both proxies: $h^*_{it} = w_1 y_{1it-1} + w_2 y_{2it-1}$, with both procedures arbitrarily setting the weights w_1 and w_2: the dominance principle gives all weight to the parent with the higher education and sets $w_2 = 0$; the other procedure sets $w_1 = w_2 = 1/2$. The LW procedure is equivalent to constructing the weights from the coefficient estimates of equation (13) such that $w_j = \phi_j/(\phi_1 + \phi_2\rho_2)$ for $j\varepsilon(1,2)$.[15]

The left panel of Figure 13 shows the distinct estimates averaged over all cohorts for each country: (i) Our baseline estimate, obtained regressing children's education on the years of education of the parent with the higher degree (henceforth dominance-coefficient); (ii) the estimates using the average over both parents (henceforth average-coefficient); and (iii) the LW-type estimate.[16] The latter is displayed on the x-axis. Controls for age and sex are included as dummy variables in all regressions. The difference between average-coefficient and dominance-coefficient shows the effect of gradually increasing the weight of the other parent in the intergenerational relationships

[15] As shown by Lubotsky and Wittenberg (2006), the best, but unfeasible, solution would be to weight the proxies prior to the regression with the optimal weights, which are however only obtainable knowing the variances and covariances between the error components in the proxies (u_{1it-1} and u_{2it-1}).

[16] Tables and graphs showing the LW-estimates for each country and cohort are included in the Supplemental Material.

up to giving both parents equal weights. We observe that this difference is, on average, around 15 percent of the size of the estimate and, obviously, is lower for higher degrees of assortative mating.

The distance between the regression coefficients and the 45 degree line shows the difference with respect to the LW-type coefficient. Taking the LW estimate as a benchmark, the dominance-coefficient is constantly lower and the average-coefficient constantly higher. The bias is, on average, around nine percent for both estimates, with the correlation between the three estimates lying between 0.95 and 0.98. Country rankings and time trends do not change significantly applying either measurement. This is not surprising given the high correlation between maternal and paternal educational attainment that we observe in Latin America: around 0.7, with countries ranging between 0.6 and 0.8.[17] Hence, the measurement of parental education does not change the interpretation of cross-country comparisons and trends in our application.

Nevertheless, it is interesting to note that both measures do not take optimally into account the role of the parent with lower education. While the average-coefficient overestimates the role, the dominance-coefficient underestimates it. This might be particularly relevant for countries and regions with lower degrees of assortative mating and future research should address this point. In our application, we observe rising educational attainment of women, higher degrees of mother-daughter mobility rates, and lower assortative mating in Latin American countries. In addition, we find an inverse relationship between assortative mating and intergenerational mobility, confirming the findings of the scant existing evidence on the issue (e.g. Chadwick and Solon, 2002; Ermisch et al., 2006; Guell et al., 2015). If these trends persist, this issue might be of crucial importance for the measurement of intergenerational persistence in future studies of Latin America.

7.2 Education and Social Status

The method proposed by LW is used in the intergenerational mobility literature to test whether attenuation bias decreases as multiple proxies for latent status are included in the estimations (Adermon et al., 2016; Nybom and Vosters, 2016; Vosters, 2015). As mentioned above, the LW approach

[17] Our estimates and a more detailed discussion on intergenerational persistence by gender and assortative mating in Latin America are included in the Supplemental Material.

is chosen over other methodologies, like using instrumental variables, because it allows obtaining estimates without making restrictive assumptions on the cross-correlations of error terms that are likely to occur between different proxy measures of parental socioeconomic status (Nybom and Vosters, 2016). Following this literature, we apply the LW procedure to get a sense of how much educational mobility explains about the association between the social status of families and children's educational attainment in Latin America. For this application we use the few surveys that include also retrospective questions about the occupation of parents.

Following the notation used above, h^*_{it-1} now expresses the social status of parents. y_{1it-1} and y_{2it-1} still define the education of the parent with higher and lower education, respectively. Now the equations include also $y_{3it-1},...,y_{Jit-1}$ dummy variables for the $J-2$ parental occupational categories. Since the information included in the surveys for different countries have different levels of detail, we adopt the categorization of the survey with the lowest level of detail. Following Nybom and Vosters (2016), we include the missing values as a separate category and aggregate them with military occupations because of the low numbers of observations and difficult categorization of these occupations. The other three categories are i) executive, managers, professionals and self-employed; ii) worker; and iii) elementary occupations.

The right panel of Figure 13 shows graphically how the coefficient changes when the occupation of both parents is included in a LW-type estimation of the regression coefficients.[18] We observe that when including the occupation of father and mother, the LW regression coefficient rises on average by four percent, ranging from two percent in Chile to seven percent in Mexico. Further, the country ranking does not change in this case. Unfortunately, income is not observed retrospectively in the surveys for parents of adult respondents. Hence, a very important proxy variable for parental socioeconomic status cannot be included in the estimation of the coefficients. However, with the available data sources, these estimates are the most consistent approximation for the bundled association between parental social status and educational attainment of children in Latin America.

[18]Tables showing the LW-estimates and their bootstrapped standard errors are included in the Supplemental Material.

8 Conclusions

In this paper, we introduce a new panel data set of intergenerational mobility estimates for Latin America and provided a comprehensive descriptive analysis of observed trends and patterns. The strength of our analysis is that it provides highly comparable estimates of educational mobility for people born over a span of over 50 years and in multiple countries, extending the influential work of Hertz et al. (2007). Furthermore, we find intergenerational mobility to be positively associated with economic growth and progressive public expenditure in education, but negatively associated with income inequality, poverty, returns to education, and the degree of assortative mating. The positive relationship between intergenerational mobility and economic performance is also found in estimations controlling for cross-country heterogeneity by fixed effects.

A new picture emerges comparing our findings with other studies that focus on international comparisons of economic mobility. Existing studies consistently show that Latin America is historically one of the regions with strong intergenerational persistence (see e.g. the review by Torche, 2014). Our findings confirm this picture for older cohorts. However, we find also that the intergenerational mobility of educational attainment is on the rise in Latin America, driven by the educational expansions that have particularly benefited children from the bottom of the distribution. Younger generations in most Latin American countries display levels of mobility that are rather similar to their peers in the developed world, for instance in the US. Hence, in a world of rising income inequality and decreasing or stagnating social mobility, Latin America stands out. First, because of the exceptional decline in income inequality (Alvaredo and Gasparini, 2015), and, second, as shown by our analysis, because of the increasing rates of social mobility experienced by individuals born in the 1970s and 80s. The connection between the two phenomena is a topic of great interest for future research.

In the future, our estimates can be used to analyze the characteristics that influence or are influenced by educational persistence. For instance, in the context of developing countries, key aspects include: the intergenerational transmission of poverty, the impact of educational expansions and social programs on equality of opportunity, as well as the role played by institutions. In our view, the data set is useful for at least one important reason: equality of opportunity and social mobility seem to be common goals for policy makers, as well as among egalitarians and utilitarians. Hence, our panel provides an essential tool for discussions and future research on the topic, at both the cross country and within country levels.

Acknowledgements *We thank Christian Ambrosius, Fabrizio Bernardi, Shahe Emran, Stephan Klasen, Martin Nybom, Heike Solga, Viktor Steiner, and Oliver Winkler for their fruitful remarks, as well as participants of conferences and seminars in Bariloche, Berlin, Buenos Aires, Florence, Göttingen, La Plata, Kiel, New York, Oxford, and Santa Fe. Guido Neidhöfer acknowledges funding through the Jacobs Foundation and the Hans Böckler Foundation.*

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9 Tables

Table 1: Intergenerational mobility and economic performance.

(a) Economic growth

	(1) M = $1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	0.100*** (0.0194)	-0.025 (0.0185)	0.363*** (0.0280)	0.052*** (0.0142)	0.167*** (0.0156)	0.165*** (0.0175)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	425	425	408	408	425	425

(b) Inequality

	(1) M = $1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.221*** (0.0448)	0.059 (0.0475)	-0.458*** (0.0721)	-0.048 (0.0423)	-0.258*** (0.0527)	-0.197*** (0.0508)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285	285	277	277	285	285

(c) Poverty

	(1) M = $1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.213*** (0.0423)	0.044 (0.0430)	-0.507*** (0.0649)	-0.025 (0.0360)	-0.283*** (0.0475)	-0.253*** (0.0515)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285	285	277	277	285	285

(d) Public expenditures in education

	(1) M = $1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	0.735** (0.3155)	0.124 (0.2713)	1.355** (0.6035)	0.085 (0.2805)	0.710** (0.3572)	0.542 (0.3671)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	137	137	132	132	137	137

(e) Share of public expenditures in education devoted to tertiary education

	(1) M = $1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.199** (0.0966)	0.037 (0.0805)	-0.357** (0.1381)	0.080 (0.0820)	-0.248* (0.1258)	-0.163 (0.1221)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105	105	102	102	105	105

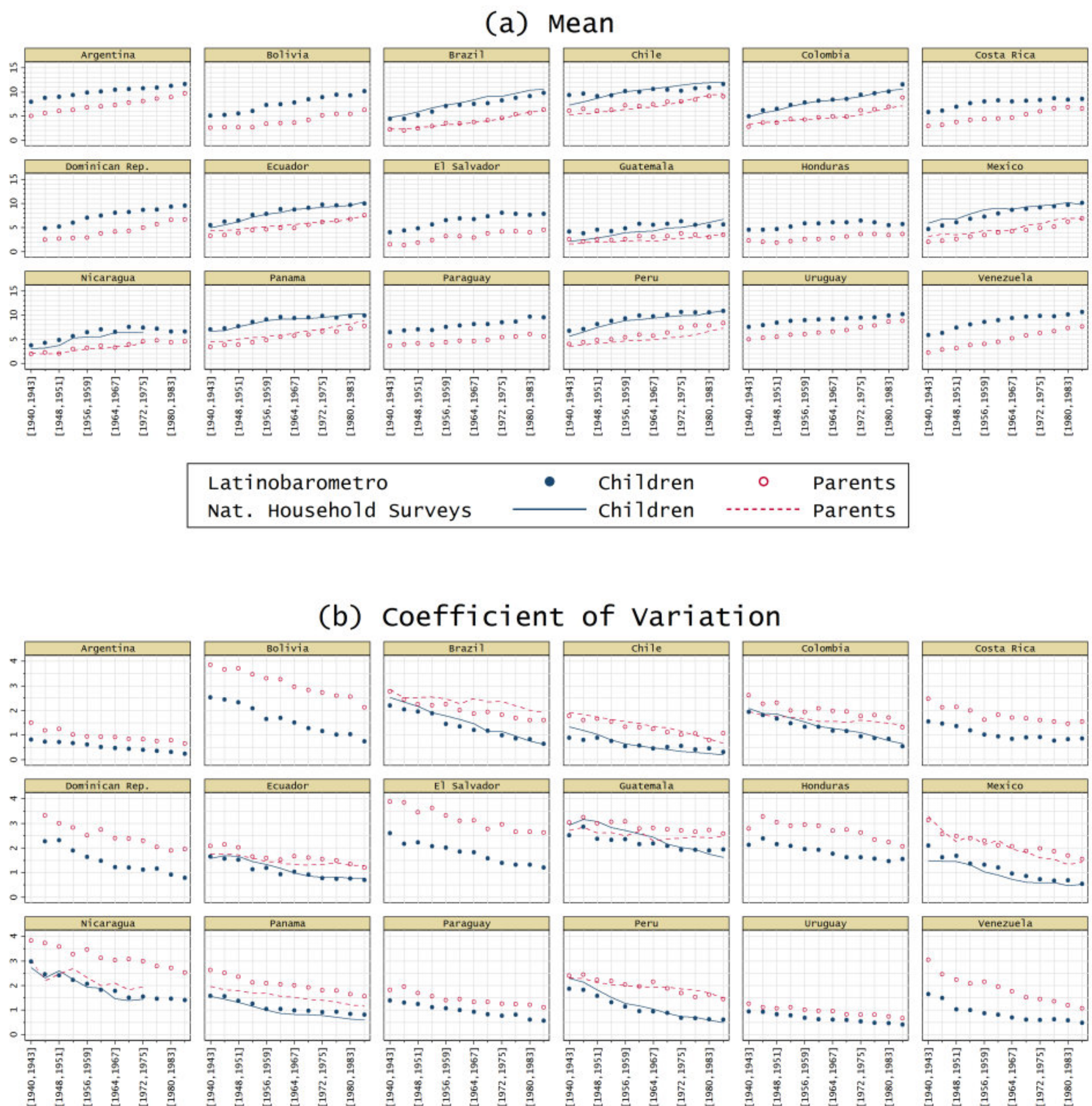
(f) Returns to education

	(1) M = $1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.101** (0.0433)	-0.005 (0.0406)	-0.303*** (0.0752)	-0.035 (0.0434)	-0.179*** (0.0460)	-0.159*** (0.0427)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285	285	277	277	285	285

Notes: The tables show regression estimates for θ in equation (8). The respective dependent variables are: (a) GDP per capita, (b) Gini coefficient of disposable household per capita income, (c) Poverty headcount ratio - 2USD/day, (d) Public expenditures in education per pupil as % of GDP per capita, (e) Ratio of public expenditures in tertiary education and public expenditures in primary and secondary education, and (f) Ratio of hourly wages of people with high and low education. The intergenerational mobility index M is the main independent variable included in the regressions: (1) $M = 1-\beta$, (2) $M = 1-\rho$, (3) $M = BUM$, (4) $M = UCP$, (5) $M = M1$, (6) $M = M2$; see Section 3. Dependent and independent variables are standardized to have mean zero and standard deviation of one. All regressions include country dummies. Dependent variable in t associated to independent variable of cohort $t-50$. Robust standard errors in parentheses. Statistical significance level * 0.1 ** 0.05 *** 0.01. *Sources*: Latinobarometro 1998-2015, own estimates of intergenerational mobility; SEDLAC; World Bank Data.

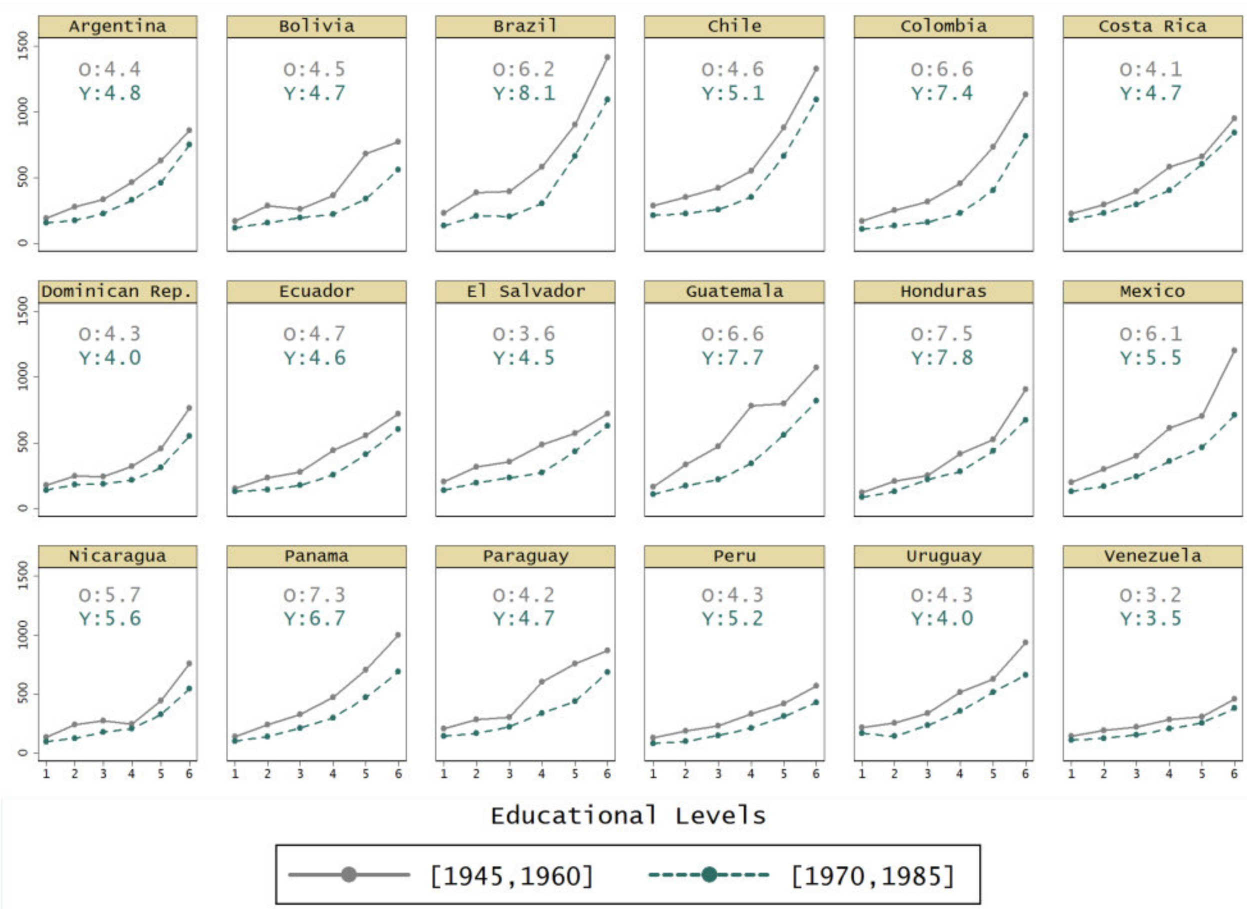
10 Figures

Figure 1: Completed years of education. Sample means and coefficients of variation by cohorts.



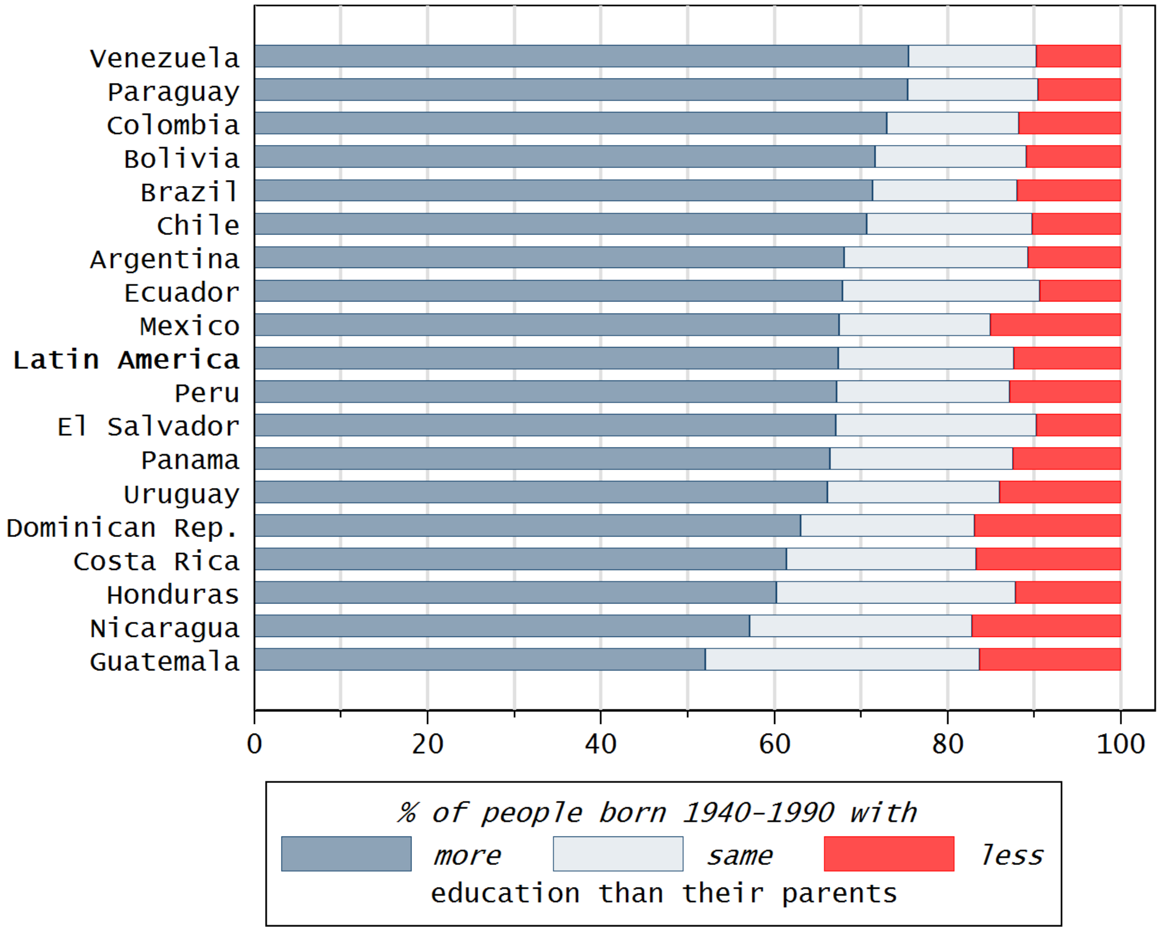
Notes: Cohorts refer to the year of birth of the children. *Source*: Latinobarometro 1998-2015, National Household Surveys 1994-2015.

Figure 2: Education as indicator for well-being: average income by educational level.



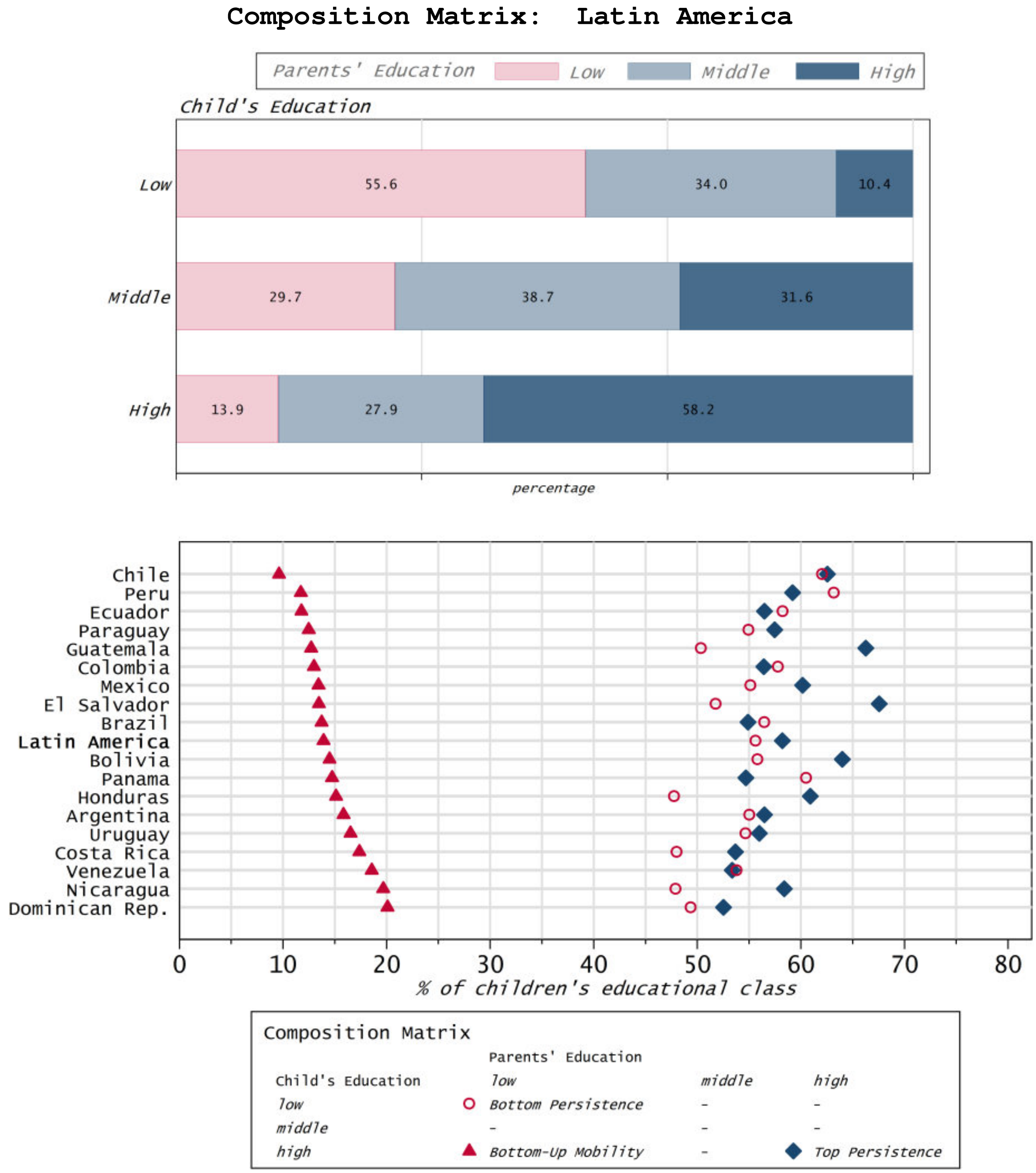
Notes: The dots show average household per capita income (constant 2005 PPP international USD) for each educational level. Educational levels: 1 without education or primary incomplete; 2 primary complete; 3 secondary incomplete; 4 secondary complete; 5 tertiary incomplete; 6 tertiary complete. Numbers show the ratio of the monetary returns to education for people with a completed tertiary degree (category 6) and without education or with incomplete primary education (category 1). O: Older Cohort. Y: Younger Cohort. Example on how to read this numbers: In Argentina, individuals with completed tertiary degree born between 1945 and 1960 have a 4.4 times higher average household per capita income than their peers without education or with incomplete primary education. *Source*: SEDLAC circa 2005, own estimates.

Figure 3: Absolute educational mobility in Latin America.



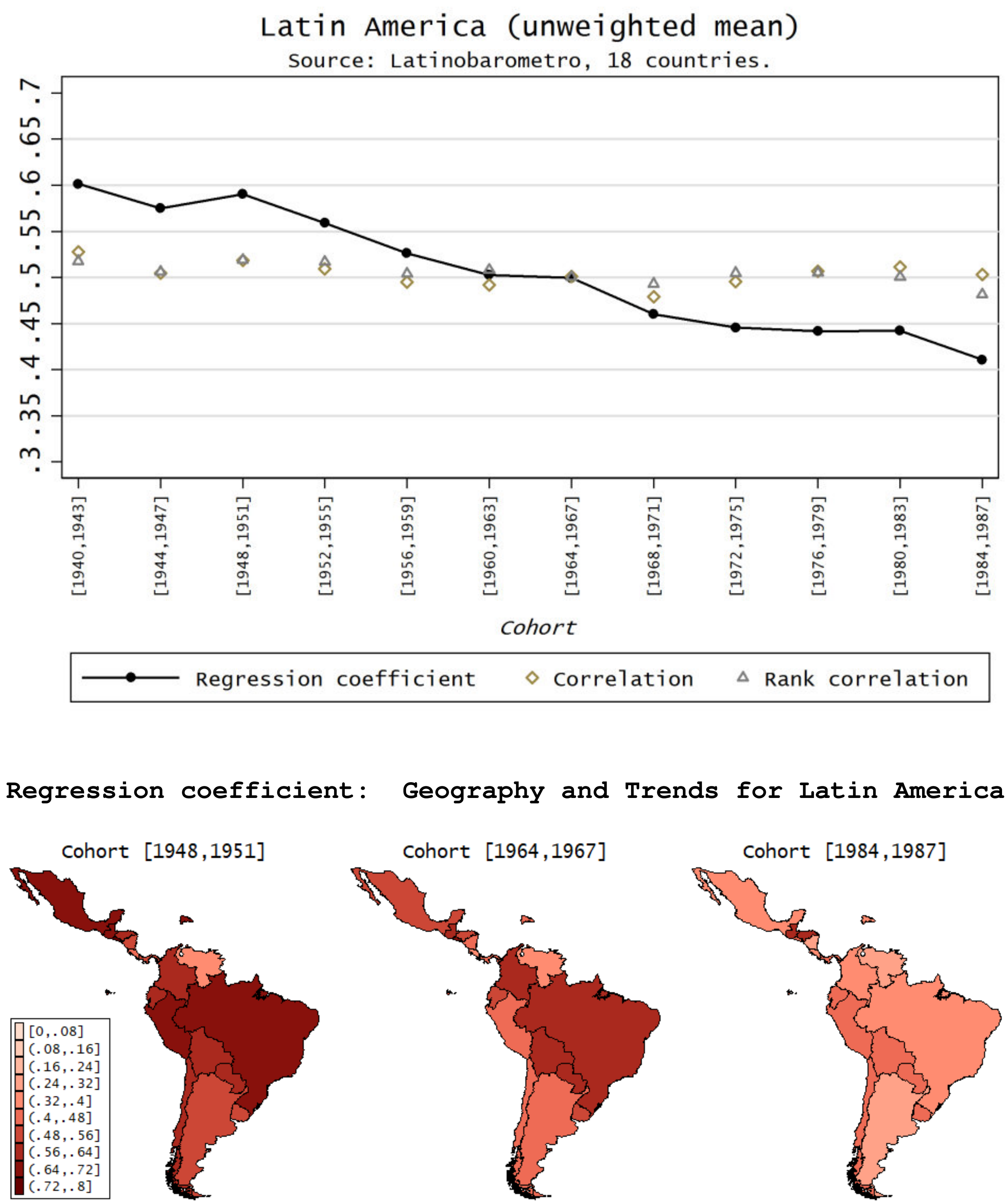
Notes: Education measured in completed years of education. *Source*: Latinobarometro 1998-2015, own estimates.

Figure 4: Composition of the educational classes by parental education (People born 1940-1990).



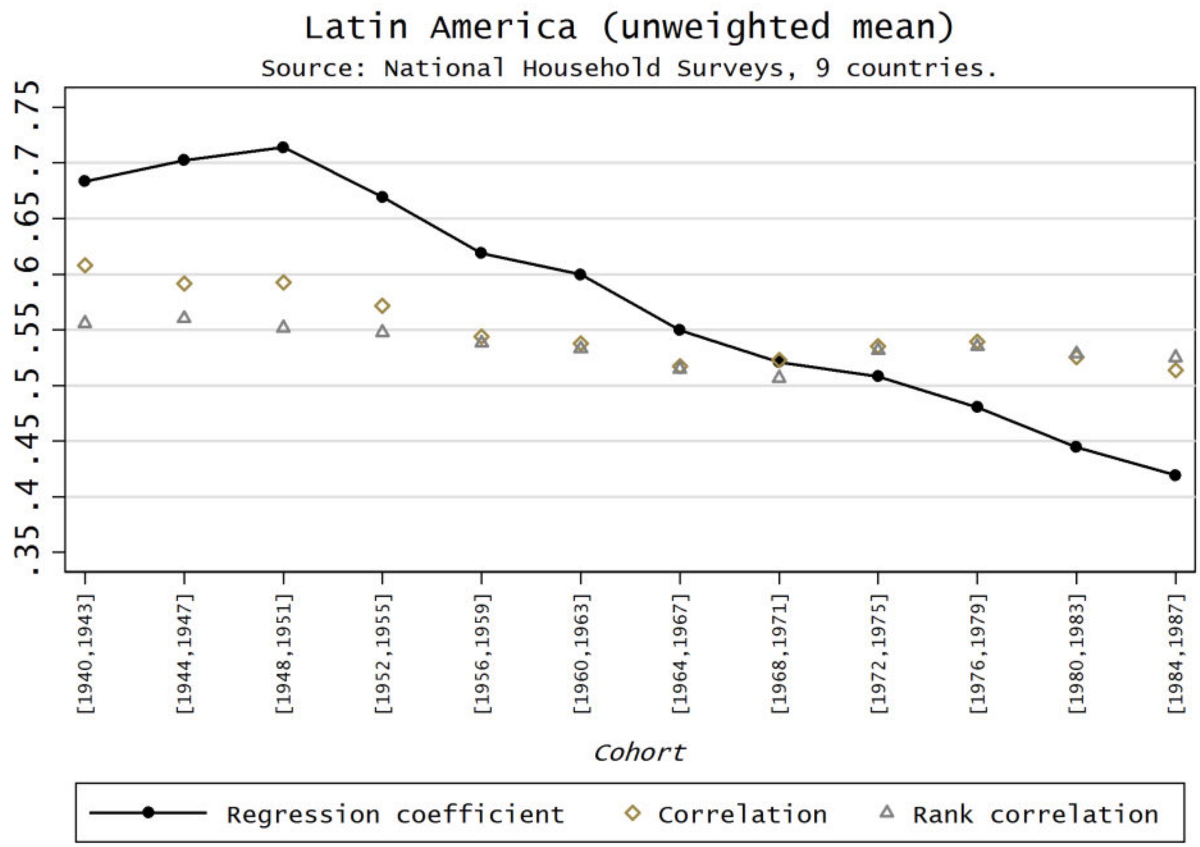
Notes: Educational transitions within families from the point of view of the children's generation. The points show the percentage of individuals in three different cells of the matrix. *Bottom persistence*: Individuals with low education and low parental education. *Bottom-Up Mobility*: Individuals with high education and low parental education. *Top persistence*: Individuals with high education and high parental education. Educational classes (low, middle, high) refer to three quantiles of the within-country and within-cohort distributions. Benchmarks USA (PSID, own estimates) / Germany (SOEP, own esimates): *Bottom persistence* 61.5 % / 56.5 %, *Top persistence* 51.2 % / 55.8 %, *Bottom-up mobility* 21.5 % / 17.8 %. *Source*: Latinobarometro 1998-2015, own estimates.

Figure 5: Educational persistence in Latin America: Regression and correlation coefficients.



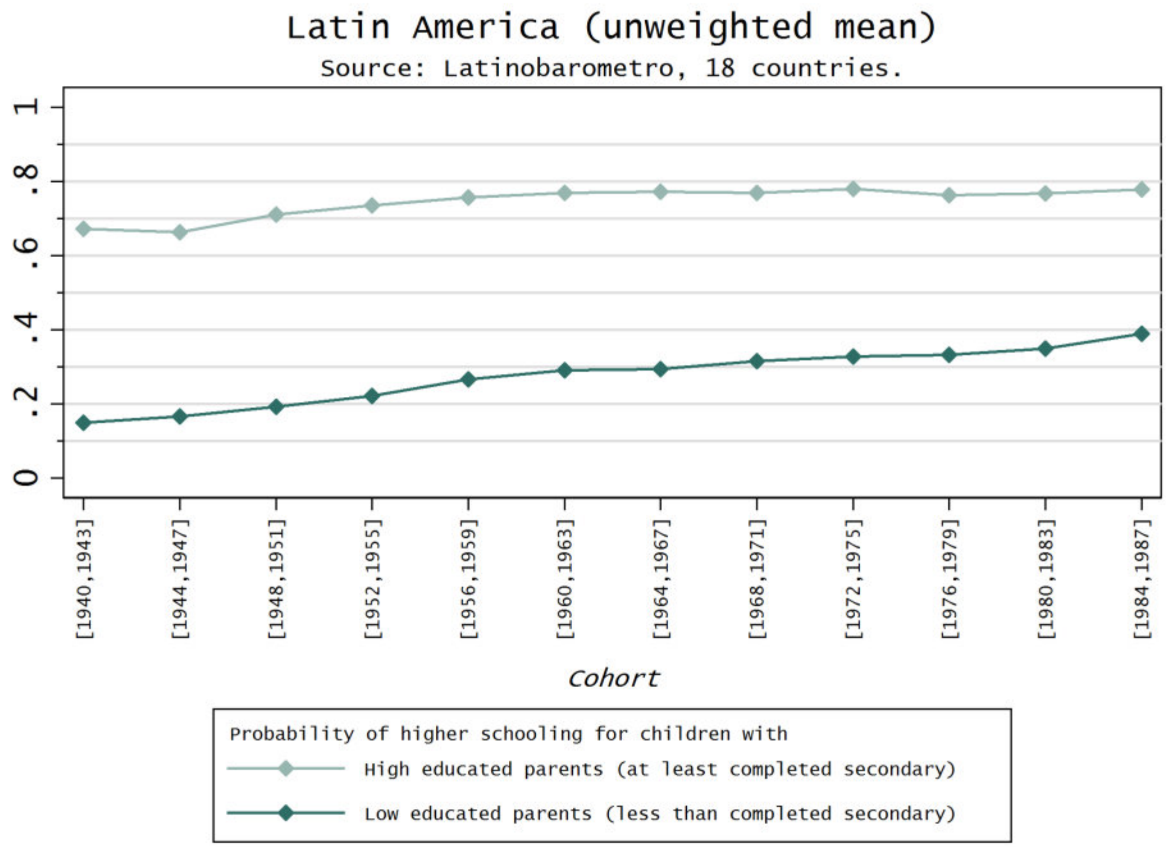
Notes: Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. Bootstrapped confidence interval. *Source*: Latinobarometro 1998-2015, own estimates.

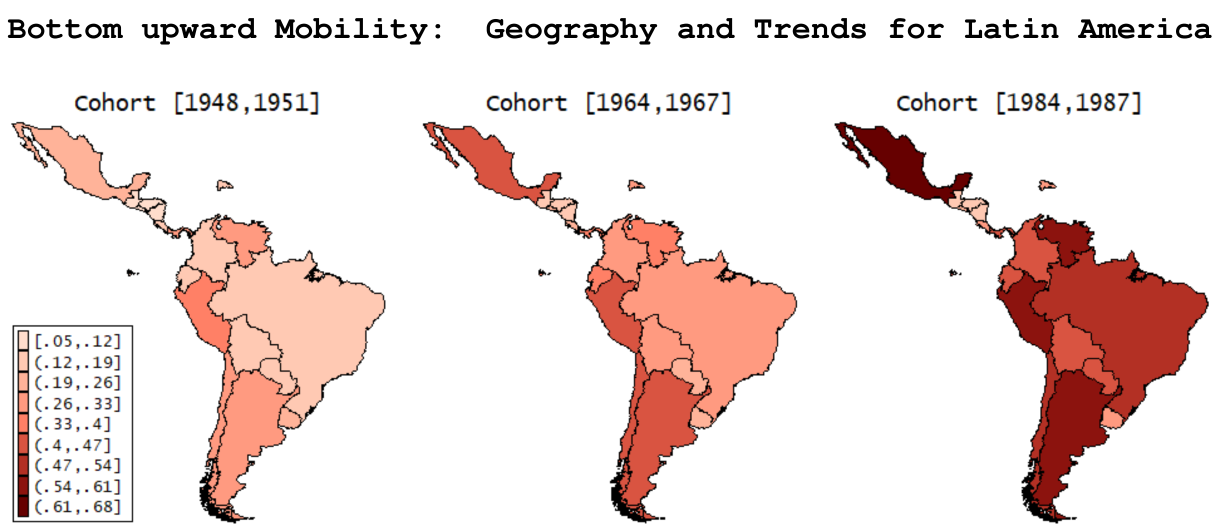
Figure 6: Educational persistence in Latin America: Regression and correlation coefficients.



Notes: Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. Bootstrapped confidence interval. *Source*: National Household Surveys 1994-2015, own estimates.

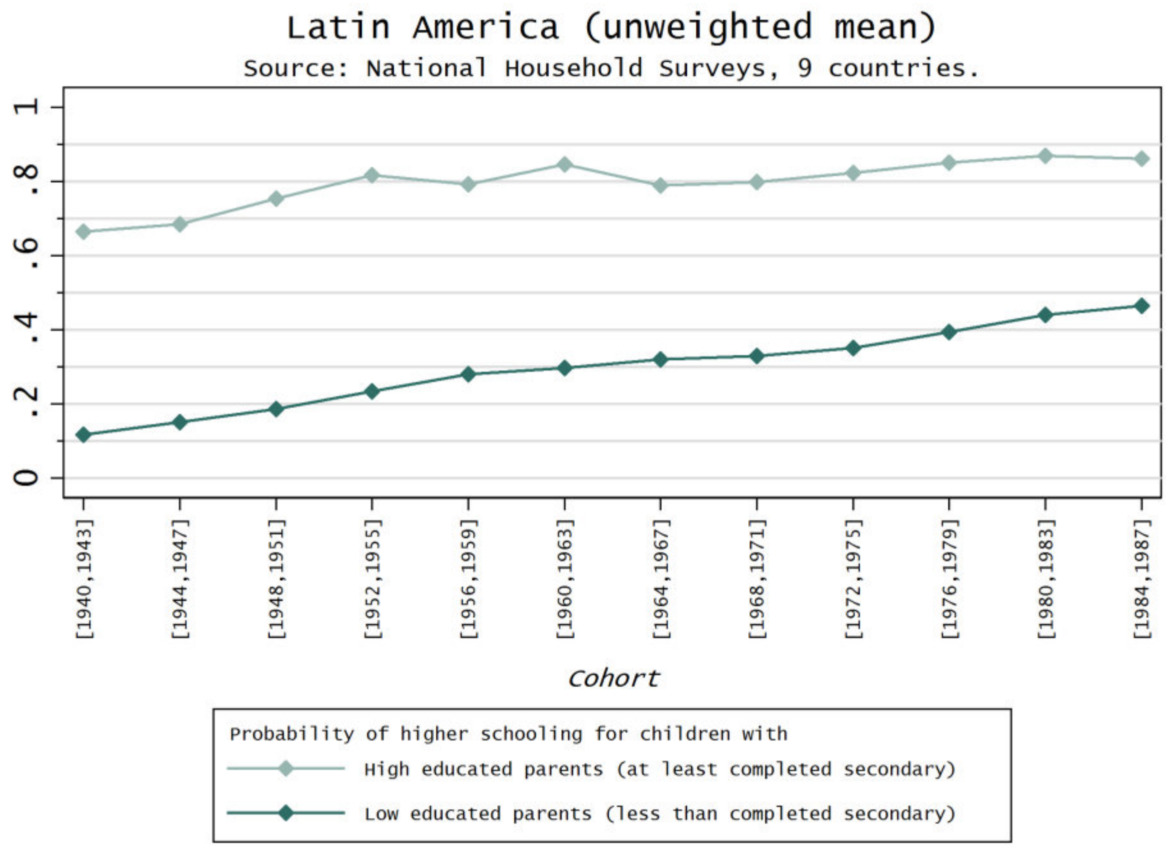
Figure 7: Educational inequality in Latin America: Bottom-Upward Mobility (*BUM*) and Upper Class Persistence (*UCP*).





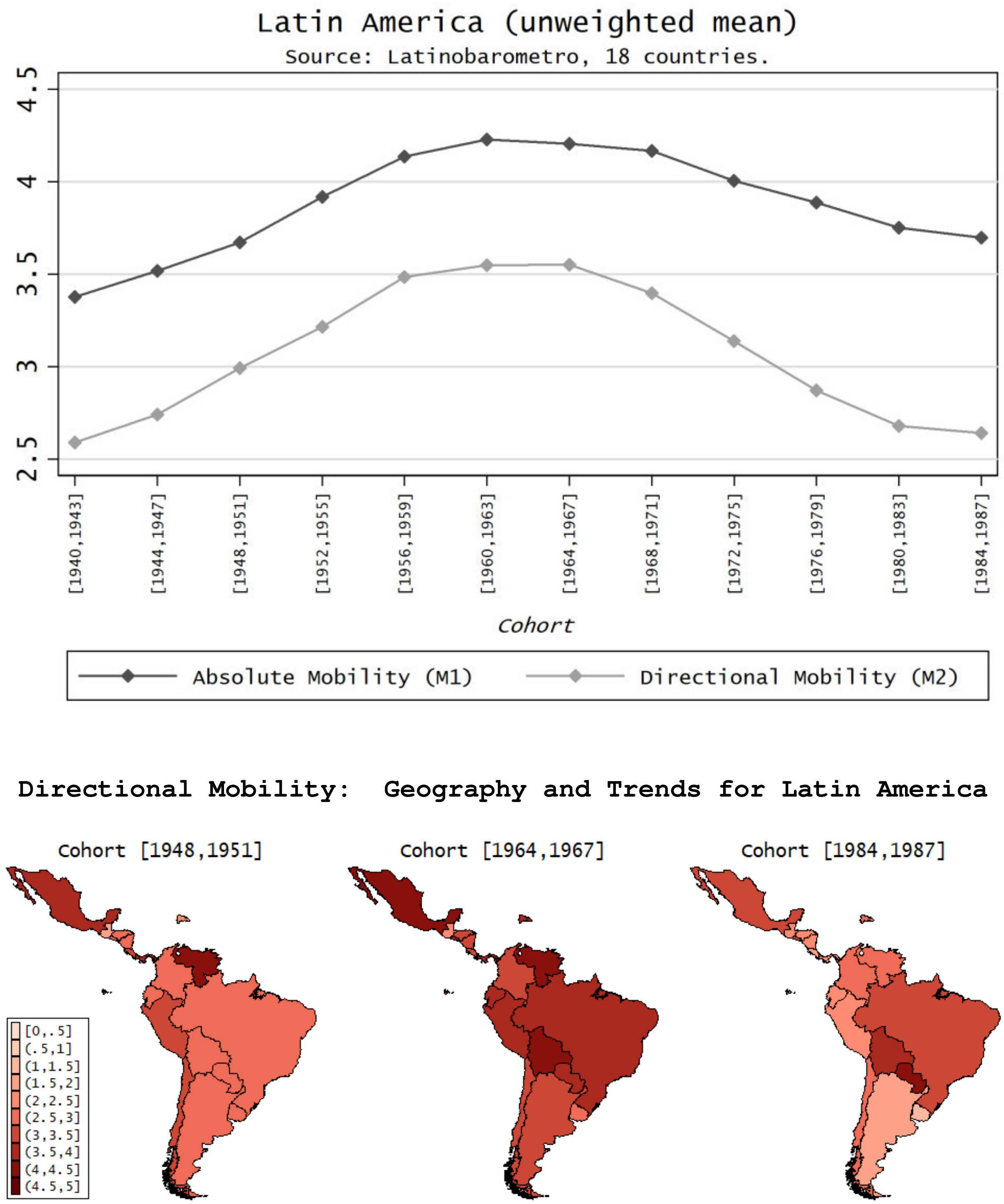
Notes: Estimated probability of higher education (at least completed secondary) of children with different parental educational background. Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. Bootstrapped confidence interval. *Source*: Latinobarometro 1998-2015, own estimates.

Figure 8: Educational inequality in Latin America: Bottom-Upward Mobility (*BUM*) and Upper Class Persistence (*UCP*).



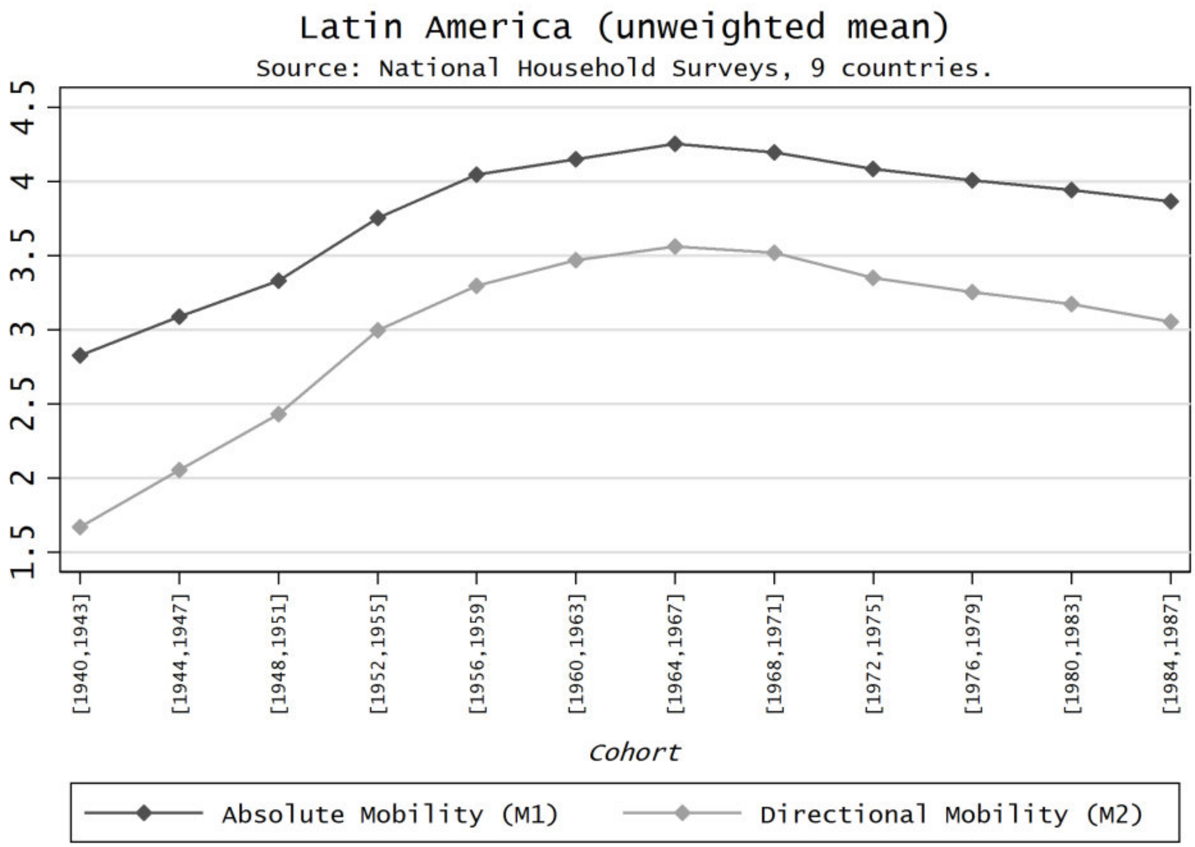
Notes: Estimated probability of higher education (at least completed secondary) of children with different parental educational background. Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. Bootstrapped confidence interval. *Source*: National Household Surveys 1994-2015, own estimates.

Figure 9: Educational mobility in Latin America: absolute ($M1$) and directional ($M2$) mobility in years of education.



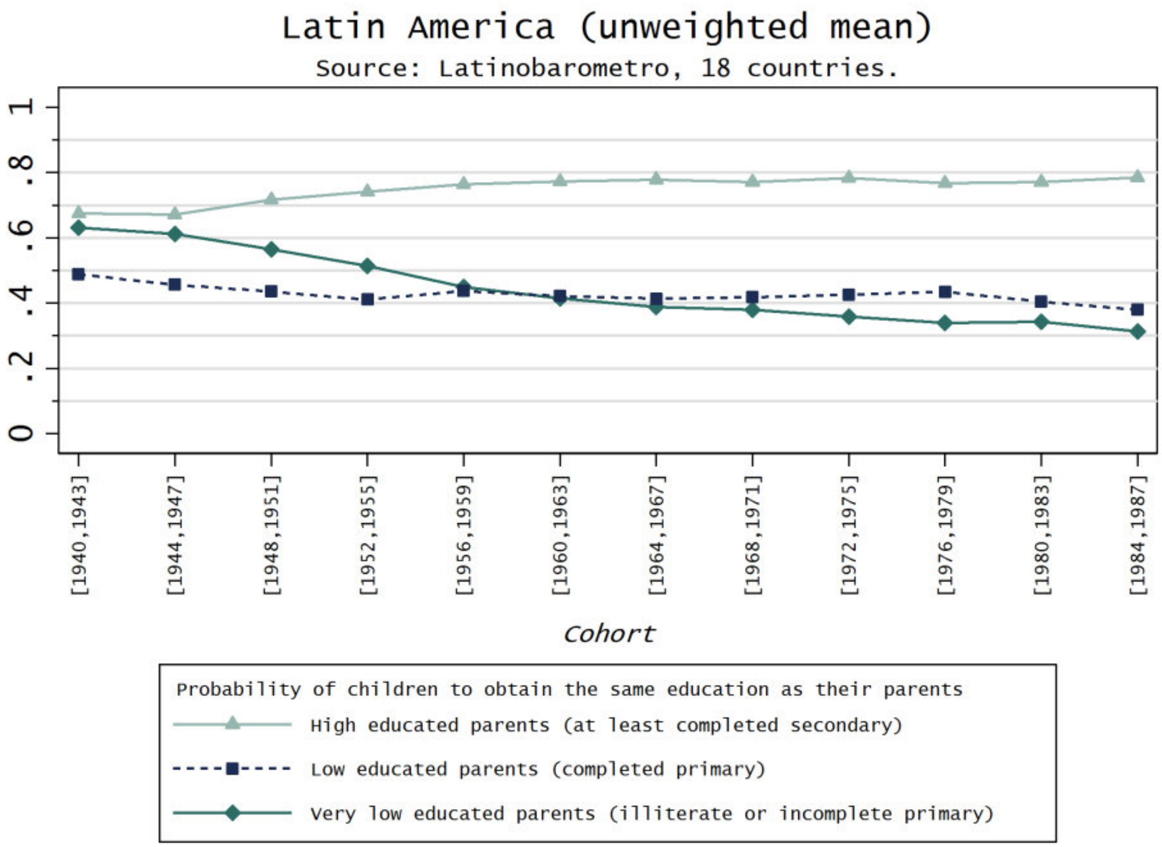
Notes: Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. *Source*: Latinobarometro 1998-2015, own estimates.

Figure 10: Educational mobility in Latin America: absolute ($M1$) and directional ($M2$) mobility in years of education.



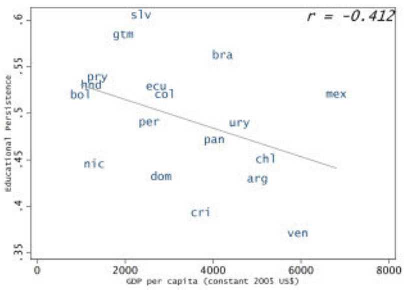
Notes: Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. *Source*: National Household Surveys 1994-2015, own estimates.

Figure 11: Educational persistence at the tails of the distribution.

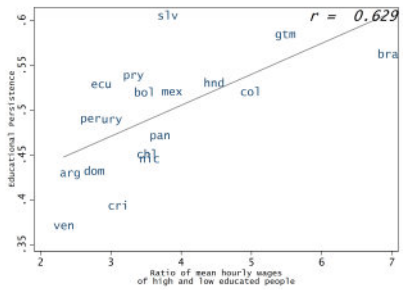


Notes: Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. *Source*: Latinobarometro 1998-2015, own estimates.

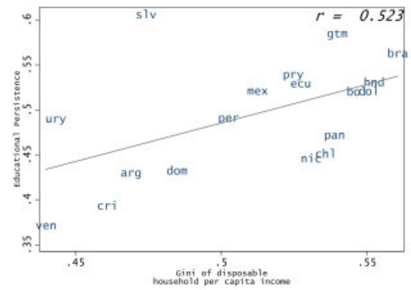
Figure 12: Intergenerational mobility, economic performance, and institutional characteristics.



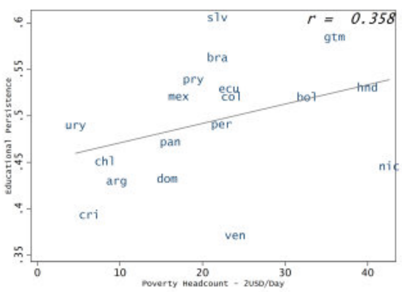
(a) GDP per capita
(Source: World Bank)



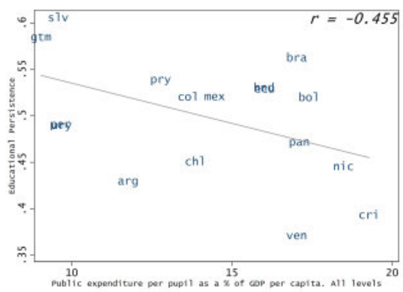
(b) Returns to Education
(Source: SEDLAC)



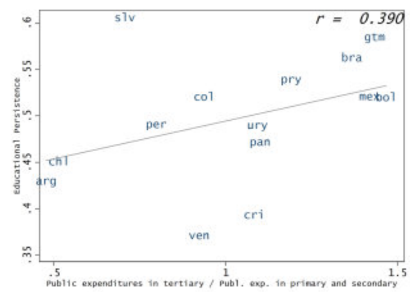
(c) Inequality
(Source: SEDLAC)



(d) Poverty
(Source: SEDLAC)



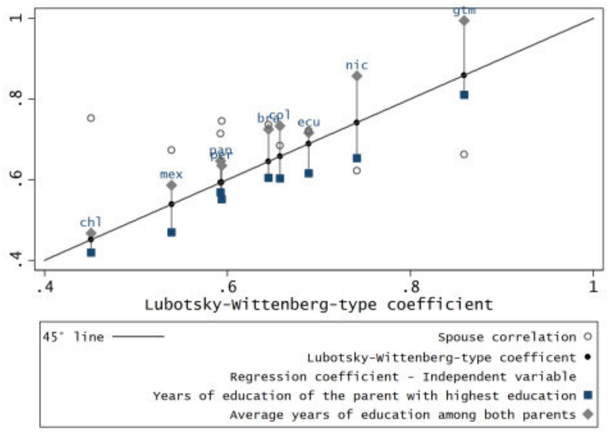
(e) Public expenditure per pupil
as % of GDP per capita.
(Source: World Bank)

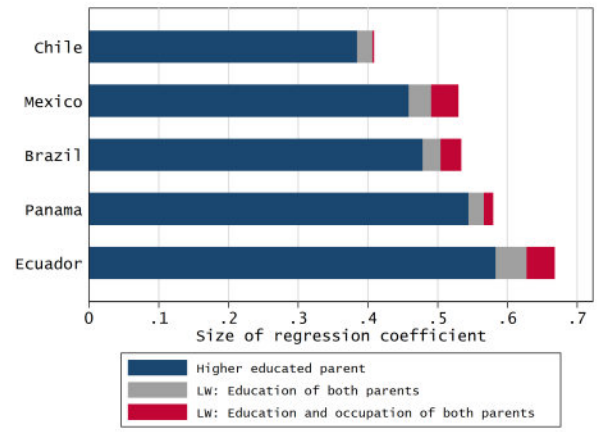


(d) Type of public expenditure
in education
(Source: World Bank)

Notes: Average degree of educational persistence β (regression coefficient) of the cohorts 1940-1990 is associated with the corresponding macroeconomic or institutional characteristic measured as average over the years 1990-2014. *Sources*: Latinobarometro 1998-2015, own estimates of educational persistence; SEDLAC; World Bank Data.

Figure 13: Multiple approximations of parental educational background and social status – Lubotsky-Wittenberg type estimates.





Notes: Left figure shows the average regression coefficients over all cohorts for different specifications of parental educational background: the baseline estimate, using the years of education of the parent with higher education among the two as proxy for parental educational background; the estimate using the average years of education among both parents as independent variable; the weighted sum of the coefficients of the parent with the higher and lower education, included in the same regression, where the weights are obtained applying the method proposed by Lubotsky and Wittenberg (2006). Right figure shows the regression coefficients of the surveys with available information on parental occupation. Here the Lubotsky-Wittenberg type coefficient includes the education and occupation of both parents in the regression. Full estimates and standard errors are included in the Supplemental Material. *Source*: National Household Surveys 1994-2015, own estimates.

SUPPLEMENTAL MATERIAL

For Online Publication

A Summary of Data Sources

A.1 Household Surveys

Our main source of information for all 18 Latin American countries in our analysis is the Latinobarómetro survey. Since 1995, Latinobarómetro records individual and household characteristics of a nationally representative sample of adult respondents in 18 Latin American countries, including questions about own and parental education since 1998. The Dominican Republic was first included in 2004. The annual survey uses a sample of 1000 to 1200 individuals per country, representing more than 600 million inhabitants. The representativeness of the survey has varied over time, reaching 100% of the total population in all countries around the year 2000.[19] It is carried out by local firms under technical supervision of the Latinobarómetro Corporation, a private non-profit organization based in Santiago, Chile. The study is financed by Latin American and non-Latin American governments, the private sector, and international organizations.[20] For the present study, we use the survey waves that include retrospective questions on parental education (1998 to 2015). We complement this with National Household Surveys that include information on parental educational achievements collected through retrospective questions.

Data from Brazil comes from the *Pesquisa Nacional por Amostra de Domicilios* (PNAD), which is carried out annually by the *Instituto Brasilero de Geografía y Estadísticas* (IBGE). This survey included mobility modules in 1982, 1988, 1996, and 2014. Since the coding of the educational variable is not comparable between 2014 and the other three survey waves, we opt to use only 2014 in our analysis. The survey is nationally and regionally representative, rural and urban, except for the rural areas of the Northern Region, which roughly corresponds to the Amazon rainforest and accounts for 2.3% of Brazil's population in the 2000 Census.

[19] The exact degree of representativeness for each country and survey wave can be consulted at http://www.latinobarometro.org/ > Documents > Technical Records.

[20] Including, among others: IADB (Inter-American Development Bank), UNDP (United Nations Development Program), AECI (Agencia Española de Cooperación Internacional), SIDA (Swedish International Development Cooperation Agency), CIDA (Canadian International Development Agency), CAF (Corporación Andina de Fomento), OAS (Organization of American States), United States Office of Research, IDEA International, UK Data Archive.

For Chile, we use the *Encuesta de Caracterización Socioeconómica Nacional* (CASEN), which is a nationally and regionally representative household survey carried out by the Ministry of Social Development (in collaboration with the National Institute of Statistics, INE) through the Department of Economics at the *Universidad de Chile*, which is responsible for the data collection, digitalization, and consistency checking of the database.[21] The survey is regularly implemented every two years since 1985 during November through, in some cases, mid-December. We use surveys from 2006 to 2015, since previous surveys do not capture information about parents.

In Peru, the *Encuesta Nacional de Hogares* (ENAHO) has gathered data across four waves since 1997, with further waves planned for the future. The fourth wave of the survey is nationally representative and is officially used to estimate poverty rates. Since 2001, the survey was enlarged and a new sample frame was used, including questions about parents. We use surveys from 2001 through 2015. However, from 2002 forward, the survey only asked the household head about parental education. Since most household heads are male, the sex composition of our sample is therefore unbalanced.

For the other countries, we use different versions of Living Standards Measurement Surveys, originally developed and promoted by the World Bank, which are all nationally representative. Data from Ecuador comes from the *Encuesta de Condiciones de Vida* (ECV) for years 1994, 1995, 1998 and 2006. In the case of Colombia, we use the *Encuesta Nacional de Condiciones de Vida* (ECV), which was carried out by the *Departamento Administrativo Nacional de Estadística* (DANE). We use surveys for six years between 2003 and 2013. Although Guatemala is a country with relatively few household surveys, the *Encuesta Nacional sobre Condiciones de Vida* (ENCOVI) includes information about individuals' parents (2000, 2006 and 2011). Panama carried out Living Standards Measurement Surveys in 1997, 2003 and 2008, which are called *Encuesta Nacional sobre Condiciones de Vida* (ENV).

The source of information for our estimations of Mexico's statistics is the Mexican Family Life Survey (MxFLS), which is a longitudinal and multi-thematic survey, representative of the Mexican

[21] Before 2011 the survey was carried out by the Ministry of Planning (MIDEPLAN).

population at the national, urban, rural, and regional levels. The MxFLS is developed and managed by researchers from the Iberoamerican University (UIA, per its name in Spanish) and the Center for Economic Research and Teaching (CIDE, per its name in Spanish) in collaboration with researchers from Duke University. Currently, the MxFLS contains information for a 10-year period, collected in three waves: 2002, 2005-2006 and 2009-2012.

Finally, for Nicaragua the only useful resource for our analysis we could find besides Latinobarometro is the 1998 wave of the *Encuesta Nacional de Hogares sobre Medición de Nivel de Vida* (EMNV).

Table A1: *Household surveys used to construct the intergenerational mobility estimates*

Country	**Name of survey**	**Acronym**	**Coverage**	**Survey waves**
Argentina	*Latinobarometro*		National	1998, 2000-2011, 2013, 2015
Bolivia	*Latinobarometro*		National	1998, 2000-2011, 2013, 2015
Brazil	*Pesquisa Nacional por Amostra de Domicilios*	PNAD	National	2014
	Latinobarometro		National	1998, 2000-2011, 2013, 2015
Chile	*Encuesta de Caracterización Socioeconómica Nacional*	CASEN	National	2006, 2009, 2011, 2013, 2015
	Latinobarometro		National	1998, 2000-2011, 2013, 2015
Colombia	*Encuesta Nacional de Condiciones de Vida*	ECV	National	2003, 2008, 2010, 2011, 2012, 2013
	Latinobarometro		National	1998, 2000-2011, 2013, 2015
Costa Rica	*Latinobarometro*		National	1998, 2000-2011, 2013, 2015
Dominican Rep.	*Latinobarometro*		National	2004-2011, 2013, 2015

Table A1: *Household surveys used to construct the intergenerational mobility estimates*

Country	**Name of survey**	**Acronym**	**Coverage**	**Survey waves**
Ecuador	*Encuesta de Condiciones de Vida*	ECV	National	1994, 1995, 1998, 2006
	Latinobarometro		National	1998, 2000-2011, 2013, 2015
El Salvador	*Latinobarometro*		National	1998, 2000-2011, 2013, 2015
Guatemala	*Encuesta Nacional sobre Condiciones de Vida*	ENCOVI	National	2000, 2006, 2011
	Latinobarometro		National	1998, 2000-2005, 2007-2011, 2013, 2015
Honduras	*Latinobarometro*		National	1998, 2000-2011, 2013, 2015
Mexico	*Encuesta Nacional sobre Niveles de Vida de los Hogares*	MXFLS	National	2002, 2005-2006, 2009-2012
	Latinobarometro		National	1998, 2000, 2006-2011, 2013, 2015
Nicaragua	*Encuesta Nacional de Hogares sobre Medición de Nivel de Vida*	EMNV	National	1998
	Latinobarometro		National	1998, 2000-2011, 2013, 2015
Panama	*Encuesta de Niveles de Vida*	ENV	National	1997, 2003, 2008

Table A1: *Household surveys used to construct the intergenerational mobility estimates*

Country	**Name of survey**	**Acronym**	**Coverage**	**Survey waves**
	Latinobarometro		National	1998, 2000-2011, 2013, 2015
Paraguay	*Latinobarometro*		National	1998, 2000-2011, 2013, 2015
Peru	*Encuesta Nacional de Hogares*	ENAHO	National	2001-2015
	Latinobarometro		National	1998, 2000-2011, 2013, 2015
Uruguay	*Latinobarometro*		National	1998, 2000-2011, 2013, 2015
Venezuela	*Latinobarometro*		National	1998, 2000-2011, 2013, 2015

A.2 Codification of Educational Attainment

Completed Years of Education	Modal Educational Level
0	Illiterate
1	Incomplete primary
2	’
3	’
4	’
5	’
6	Complete primary
7	’
8	Incomplete secondary
9	’
10	’
11	Complete secondary
12	’
13	Incomplete university or technical training
14	Complete technical training
15	Complete university

A.3 Selection

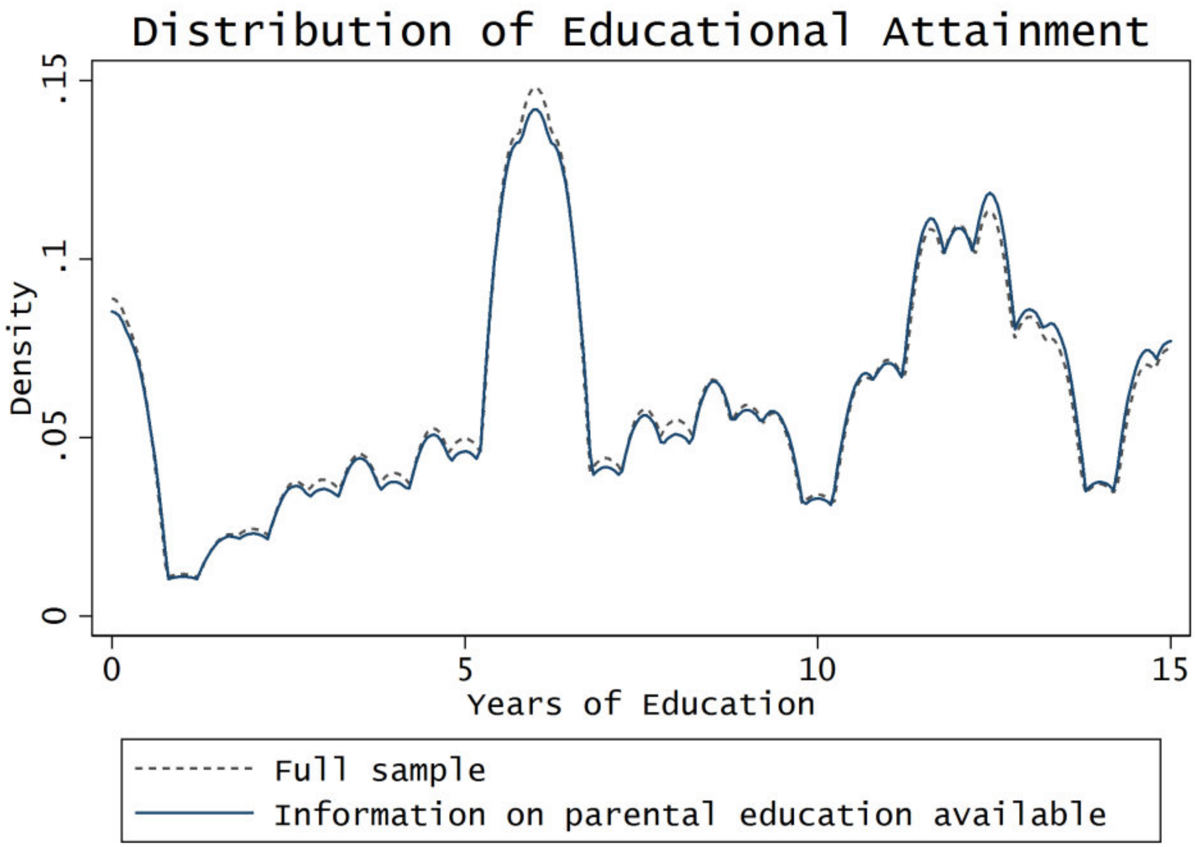
The amount of information about parental educational background that is missing is relatively small for Latinobarómetro – on average about 12% of all individuals in the survey with available information on own education. For some of the National Household Surveys, the number is much higher, ranging from 2 % in Guatemala to 61 % in Peru and 83 % in Brazil. These differences depend on the fact that in some household surveys not all individuals are asked about their parents’ education: among respondents - only household heads in some waves of the Peruvian survey and one randomly chosen individual per household in Brazil - the share of missing information is sensibly lower (e.g. 12 % in Peru and 22 % in Brazil).

In order to determine if selectivity issues bias our estimates, we compare the unrestricted sample of all individuals in the household survey with the sample of individuals for whom we have information regarding parental education. As shown in Table A2, differences in averages and variances of years of education are negligible in both data sets and mostly not statistically significant. However, a comparison of the distribution of years of education in both samples shows a slight overrepresentation of individuals with higher education and underrepresentation of individuals with lower education in the restricted sample, i.e. individuals with available information on parental education (see Figure A1). Hence, under the assumption that individuals are less likely to report or remember the education of their parents if their parents have low levels of education, intergenerational mobility estimates using household surveys might be upwardly biased. Since this pattern is observed in all surveys, the cross-country comparisons, as well as the interpretation of cross-country differences in estimates, are still valid.

Table A2: Selection bias by the availability of information on parental education

Household Survey	Parental education	Average years of education		Variance of years of education	
	Share of individuals with no information	Unrestricted sample	Restricted sample	Unrestricted sample	Restricted sample
Latinobarometro	0.12	8.17	8.29	20.09	20.24
PNAD	0.22	8.39	8.78	23.54	23.49
CASEN	0.26	9.27	9.53	15.38	15.49
ECV	0.11	7.42	7.67	22.75	22.99
ECV	0.04	7.75	7.84	19.30	19.29
ENCOVI	0.02	4.25	4.24	18.14	18.15
MXFLS	0.18	7.83	8.00	15.11	15.34
EMNV	0.16	4.61	4.70	18.78	19.32
ENV	0.04	8.00	8.01	17.85	18.01
ENAHO	0.12	8.30	8.35	22.70	22.63

Figure A1: Selection bias by the availability of information on parental education



Source: Latinobarometro, own estimates.

B Description of the Database

We provide databases containing all mobility indicators described in this project. The variables contained in each database are described in Table B1. The data is divided in four different sets of different periodization of the birth cohorts, separated at intervals of one to four years, respectively. In addition to the main statistics and the identification variables of each country, survey and cohort, we also include complementary variables that may be useful, such as mean and variance of the years of education of individuals and their parents, the average age of individuals and the share of males in the sample for each cohort. Finally, we add a variable that contains the number of observations used for the estimation of mobility statistics to make it possible to evaluate the quality of the estimates. Tables B2, B3 and B4 show descriptive statistics of the summary measures described in Section 3 for each country and the Latin American average using both data sources.

Table B1: Summary table of the database.

Variable	Label	Definition	Mean	Std. Dev.	Min	Max
country	Country name	Name of country				
idenpa	Country code	World Bank country code				
cohort	Cohort	Cohort indicator				
survey	Survey name	Name of the survey				
N	Number of observations	Number of observations used to estimate indicators	3768.30	7881.32	19	45679
b	Intergenerational persistence parameter	Conditional correlation between years of education of children and parents (beta)	0.50	0.14	0.02	0.92
bstd	Intergenerational correlation (b standarized)	Parameter b weighted by the ratio of standard deviations of years of schooling of childen and parents	0.51	0.09	0.06	0.79
corr_spearman	Spearman's correlation	Spearman's rank correlation coefficient (rho)	0.50	0.08	-0.05	0.67
blog	Intergenerational elasticity	Parameter b estimated using the logarithm of the outcome of interest (years of schooling)	0.35	0.12	0.00	0.69
prob_high	Prob(high education) | High parental education	Predicted probability of upper class persistence (UCP)	0.76	0.13	0.11	0.97
prob_low	Prob(high education) | Low parental education	Predicted probability of bottom upward mobility (BUM)	0.30	0.15	0.04	0.81
M1	Absolute mobility	Absolute mobility (M1)	3.81	0.69	1.62	5.64
M2	Directional mobility	Directional mobility (M2)	2.95	0.86	0.59	5.06
educ	Years of schooling	Average of own years of schooling	8.14	2.18	2.22	14.26
educ_parents	Parental Years of schooling	Average of parents' years of schooling (the highest level of educational attainment among the two)	5.19	2.11	1.39	12.58
var	Variance of years of schooling	Variance of own years of schooling	17.08	5.42	0.84	33.08
var_parents	Variance of parental years of schooling	Variance of parents' years of schooling	17.71	4.31	6.79	32.96
age	Age	Average age of individuals in sample	40.93	13.57	23.00	72.54
male	Share of males	Share of males in sample	0.49	0.06	0.34	0.81

Table B2: Descriptive Statistics: Regression and Correlation Coefficients.

Panel A – *Source*: Latinobarometro, own estimates.

	Regression coeff.				Correlation coeff.			
	Mean	C.V.	Min.	Max.	Mean	C.V.	Min.	Max.
Argentina	0.44	0.17	0.32	0.54	0.51	0.06	0.46	0.56
Bolivia	0.54	0.14	0.40	0.64	0.55	0.04	0.51	0.60
Brazil	0.56	0.21	0.38	0.74	0.50	0.08	0.44	0.59
Chile	0.49	0.11	0.42	0.56	0.62	0.10	0.54	0.79
Colombia	0.54	0.16	0.38	0.72	0.54	0.07	0.50	0.63
Costa Rica	0.41	0.12	0.34	0.49	0.42	0.07	0.36	0.47
Dominican Rep.	0.44	0.27	0.33	0.65	0.42	0.17	0.34	0.57
Ecuador	0.54	0.10	0.47	0.63	0.53	0.06	0.48	0.58
El Salvador	0.62	0.19	0.43	0.81	0.56	0.09	0.48	0.63
Guatemala	0.59	0.08	0.50	0.67	0.51	0.07	0.46	0.57
Honduras	0.54	0.09	0.44	0.63	0.47	0.10	0.40	0.54
Mexico	0.52	0.22	0.34	0.72	0.51	0.06	0.46	0.59
Nicaragua	0.43	0.14	0.32	0.56	0.42	0.11	0.36	0.50
Panama	0.49	0.12	0.42	0.59	0.51	0.06	0.43	0.56
Paraguay	0.55	0.14	0.40	0.70	0.52	0.08	0.43	0.60
Peru	0.51	0.20	0.39	0.70	0.56	0.05	0.51	0.64
Uruguay	0.48	0.12	0.41	0.58	0.49	0.06	0.42	0.53
Venezuela	0.39	0.21	0.31	0.60	0.42	0.11	0.36	0.52
Latin America	0.50	0.16	0.39	0.64	0.50	0.08	0.44	0.58

Panel B – *Source*: National Household Surveys, own estimates.

	Regression coeff.				Correlation coeff.			
	Mean	C.V.	Min.	Max.	Mean	C.V.	Min.	Max.
Brazil	0.59	0.27	0.37	0.84	0.51	0.08	0.44	0.58
Chile	0.40	0.26	0.26	0.57	0.51	0.09	0.43	0.59
Colombia	0.60	0.18	0.42	0.76	0.52	0.07	0.49	0.62
Ecuador	0.61	0.13	0.51	0.73	0.59	0.05	0.55	0.64
Guatemala	0.80	0.10	0.66	0.92	0.63	0.04	0.60	0.67
Mexico	0.47	0.21	0.36	0.65	0.53	0.11	0.49	0.70
Nicaragua	0.65	0.18	0.50	0.80	0.53	0.11	0.44	0.59
Panama	0.56	0.16	0.45	0.73	0.59	0.06	0.54	0.67
Peru	0.55	0.30	0.32	0.80	0.54	0.11	0.45	0.64
Latin America	0.58	0.20	0.43	0.76	0.55	0.08	0.49	0.63

Notes: Mean, coefficient of variation (C.V.), minimum and maximum values of the complete time series for the respective country.

Table B3: Descriptive Statistics: Upper Class Persistence and Bottom Upward Mobility.

Panel A – *Source*: Latinobarometro, own estimates.

	Upper class persistence				Bottom-Up Mobility			
	Mean	C.V.	Min.	Max.	Mean	C.V.	Min.	Max.
Argentina	0.84	0.06	0.71	0.91	0.38	0.26	0.21	0.58
Bolivia	0.81	0.09	0.69	0.90	0.26	0.43	0.12	0.46
Brazil	0.76	0.11	0.55	0.84	0.27	0.44	0.11	0.48
Chile	0.85	0.05	0.79	0.94	0.37	0.17	0.28	0.49
Colombia	0.78	0.09	0.65	0.88	0.28	0.36	0.11	0.42
Costa Rica	0.65	0.12	0.50	0.74	0.22	0.23	0.13	0.30
Dominican Rep.	0.52	0.24	0.32	0.71	0.25	0.34	0.10	0.37
Ecuador	0.78	0.15	0.54	0.88	0.31	0.36	0.12	0.43
El Salvador	0.81	0.11	0.61	0.90	0.19	0.35	0.08	0.28
Guatemala	0.70	0.10	0.59	0.81	0.14	0.26	0.09	0.20
Honduras	0.71	0.12	0.58	0.86	0.14	0.18	0.11	0.18
Mexico	0.83	0.07	0.71	0.91	0.37	0.45	0.13	0.66
Nicaragua	0.62	0.16	0.45	0.79	0.16	0.29	0.06	0.21
Panama	0.78	0.06	0.70	0.89	0.36	0.20	0.23	0.42
Paraguay	0.80	0.07	0.69	0.91	0.25	0.32	0.16	0.40
Peru	0.86	0.07	0.73	0.93	0.42	0.24	0.24	0.56
Uruguay	0.70	0.07	0.62	0.79	0.23	0.12	0.17	0.28
Venezuela	0.61	0.34	0.25	0.84	0.35	0.34	0.15	0.54
Latin America	0.74	0.12	0.59	0.86	0.27	0.30	0.14	0.40

Panel B – *Source*: National Household Surveys, own estimates.

	Upper class persistence				Bottom-Up Mobility			
	Mean	C.V.	Min.	Max.	Mean	C.V.	Min.	Max.
Brazil	0.85	0.07	0.71	0.92	0.36	0.39	0.15	0.55
Chile	0.82	0.10	0.66	0.92	0.45	0.40	0.17	0.71
Colombia	0.83	0.08	0.71	0.91	0.34	0.43	0.12	0.56
Ecuador	0.77	0.12	0.53	0.86	0.25	0.43	0.06	0.41
Guatemala	0.79	0.11	0.61	0.87	0.12	0.44	0.04	0.21
Mexico	0.79	0.11	0.58	0.94	0.24	0.29	0.08	0.32
Nicaragua	0.58	0.27	0.31	0.80	0.13	0.39	0.05	0.19
Panama	0.79	0.05	0.71	0.83	0.30	0.27	0.16	0.40
Peru	0.88	0.03	0.82	0.92	0.41	0.27	0.19	0.57
Latin America	0.79	0.10	0.63	0.89	0.29	0.37	0.11	0.44

Notes: Mean, coefficient of variation (C.V.), minimum and maximum values of the complete time series for the respective country.

Table B4: Descriptive Statistics: Absolute and Directional Mobility.

Panel A – *Source*: Latinobarometro, own estimates.

	Absolute mobility (M1)				Directional mobility (M2)			
	Mean	C.V.	Min.	Max.	Mean	C.V.	Min.	Max.
Argentina	3.4	0.08	2.7	3.6	2.8	0.15	1.9	3.2
Bolivia	4.3	0.12	3.3	4.8	3.6	0.17	2.5	4.3
Brazil	4.0	0.14	2.9	4.5	3.3	0.17	2.2	3.9
Chile	3.4	0.12	2.7	3.9	2.8	0.16	1.8	3.2
Colombia	4.0	0.11	2.9	4.5	3.1	0.15	2.2	3.7
Costa Rica	3.9	0.09	3.5	4.5	2.8	0.25	1.6	3.8
Dominican Rep.	4.4	0.14	3.3	5.0	3.3	0.19	2.4	4.1
Ecuador	3.8	0.11	3.2	4.4	3.1	0.17	2.2	3.9
El Salvador	4.0	0.14	3.0	4.6	3.4	0.12	2.5	3.9
Guatemala	3.2	0.11	2.7	3.6	2.2	0.15	1.7	2.6
Honduras	3.5	0.09	3.2	3.9	2.7	0.17	2.0	3.3
Mexico	4.3	0.12	3.2	5.0	3.7	0.15	2.6	4.4
Nicaragua	3.9	0.15	2.8	4.7	2.7	0.23	1.7	3.6
Panama	4.2	0.09	3.4	4.8	3.5	0.19	2.1	4.3
Paraguay	3.8	0.06	3.4	4.3	3.2	0.11	2.8	4.0
Peru	4.1	0.10	3.5	4.6	3.3	0.18	2.5	4.0
Uruguay	3.2	0.11	2.6	3.6	2.3	0.26	1.3	2.9
Venezuela	4.4	0.11	3.7	5.2	3.8	0.16	2.7	4.5
Latin America	3.9	0.11	3.1	4.4	3.1	0.17	2.1	3.7

Panel B – *Source*: National Household Surveys, own estimates.

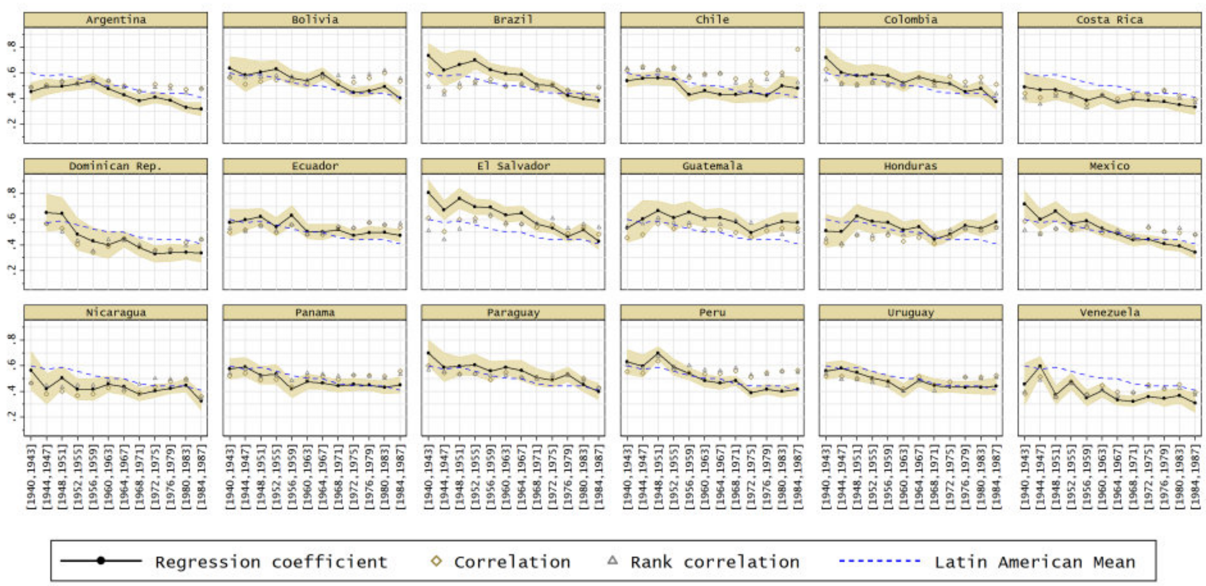
	Absolute mobility (M1)				Directional mobility (M2)			
	Mean	C.V.	Min.	Max.	Mean	C.V.	Min.	Max.
Brazil	4.6	0.17	3.2	5.6	4.1	0.20	2.4	5.1
Chile	3.9	0.13	3.0	4.4	3.1	0.20	1.9	3.7
Colombia	4.0	0.15	2.7	4.5	3.1	0.25	1.5	3.8
Ecuador	3.4	0.14	2.5	3.8	2.4	0.35	0.6	3.1
Guatemala	2.7	0.26	1.6	3.7	1.9	0.45	0.6	3.1
Mexico	4.3	0.11	3.3	5.0	3.6	0.16	2.8	4.6
Nicaragua	3.2	0.21	2.1	4.0	2.2	0.34	0.9	2.9
Panama	3.4	0.11	3.0	4.1	2.5	0.23	1.5	3.4
Peru	4.5	0.13	3.1	5.0	3.8	0.20	2.0	4.5
Latin America	3.8	0.16	2.7	4.5	3.0	0.26	1.6	3.8

Notes: Mean, coefficient of variation (C.V.), minimum and maximum values of the complete time series for the respective country.

C Additional Material

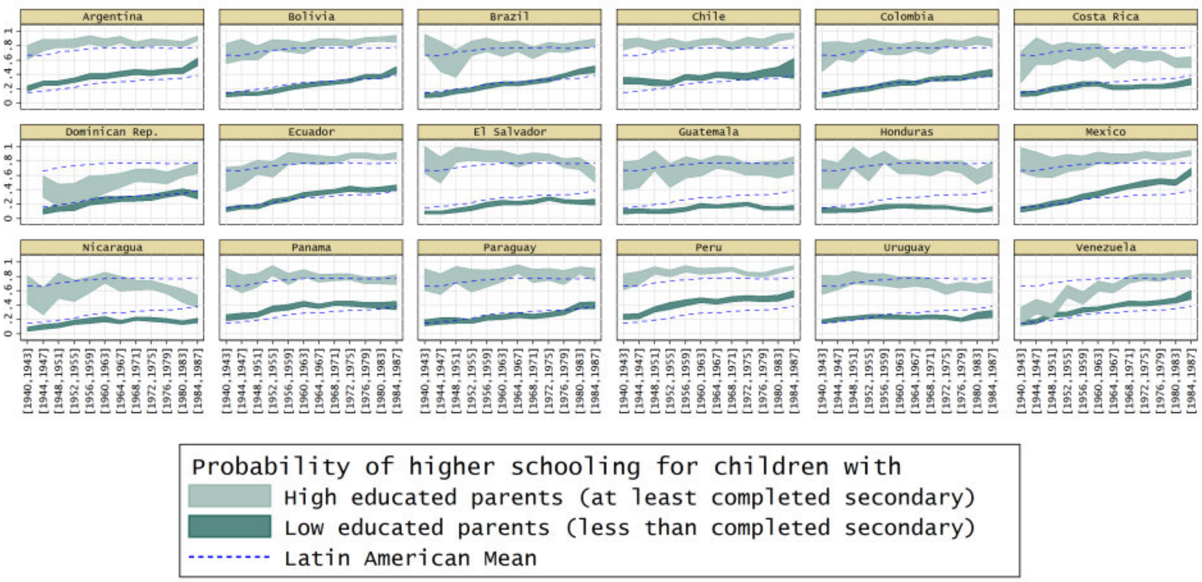
C.1 Country-Wise Estimates

Figure C1: Educational persistence in Latin America: Regression and correlation coefficients by country. *Source*: Latinobarometro 1998-2015, own estimates.



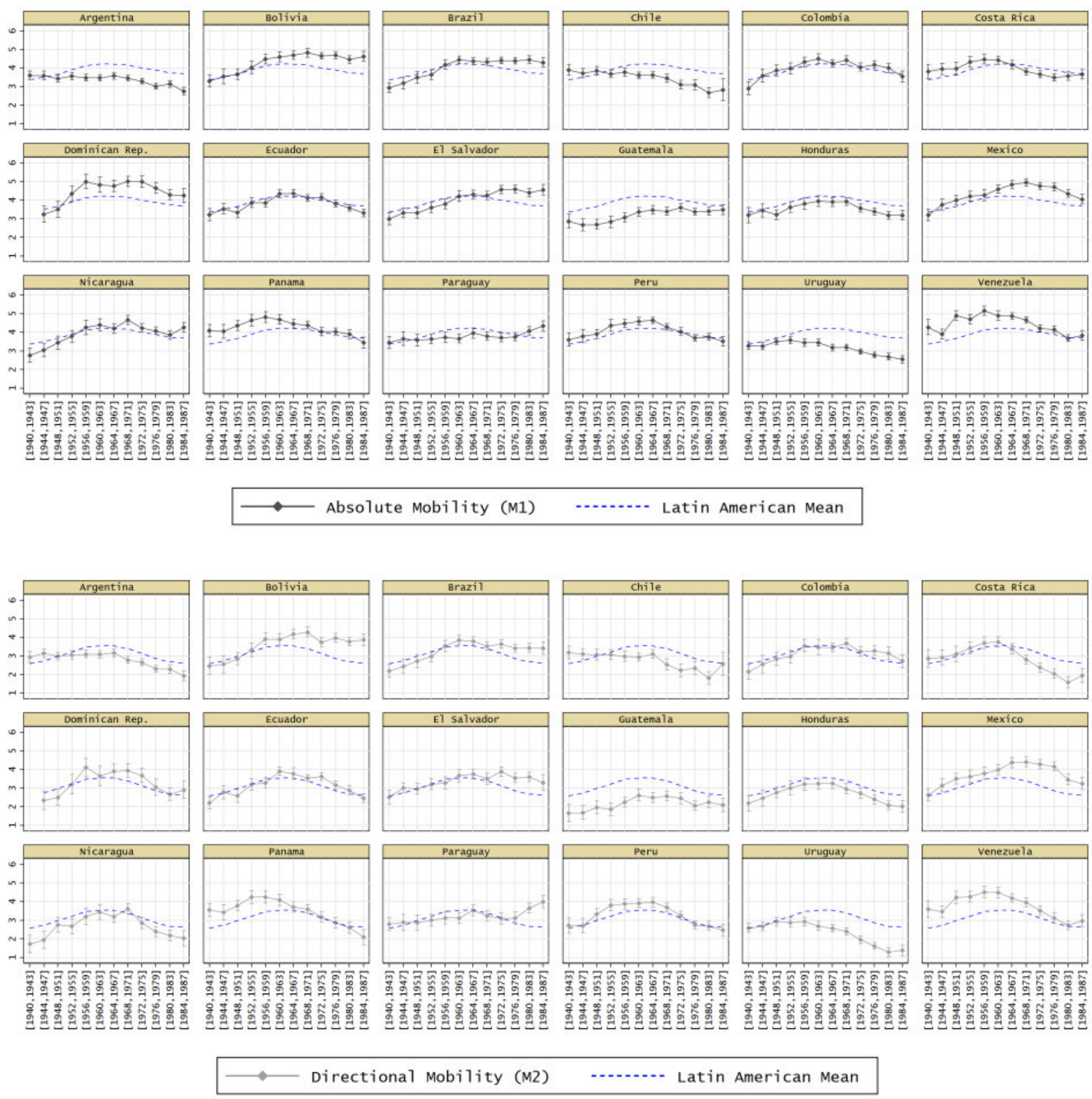
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure C2: Educational inequality in Latin America: Bottom-Upward Mobility (*BUM*) and Upper Class Persistence (*UCP*). *Source*: Latinobarometro 1998-2015, own estimates.



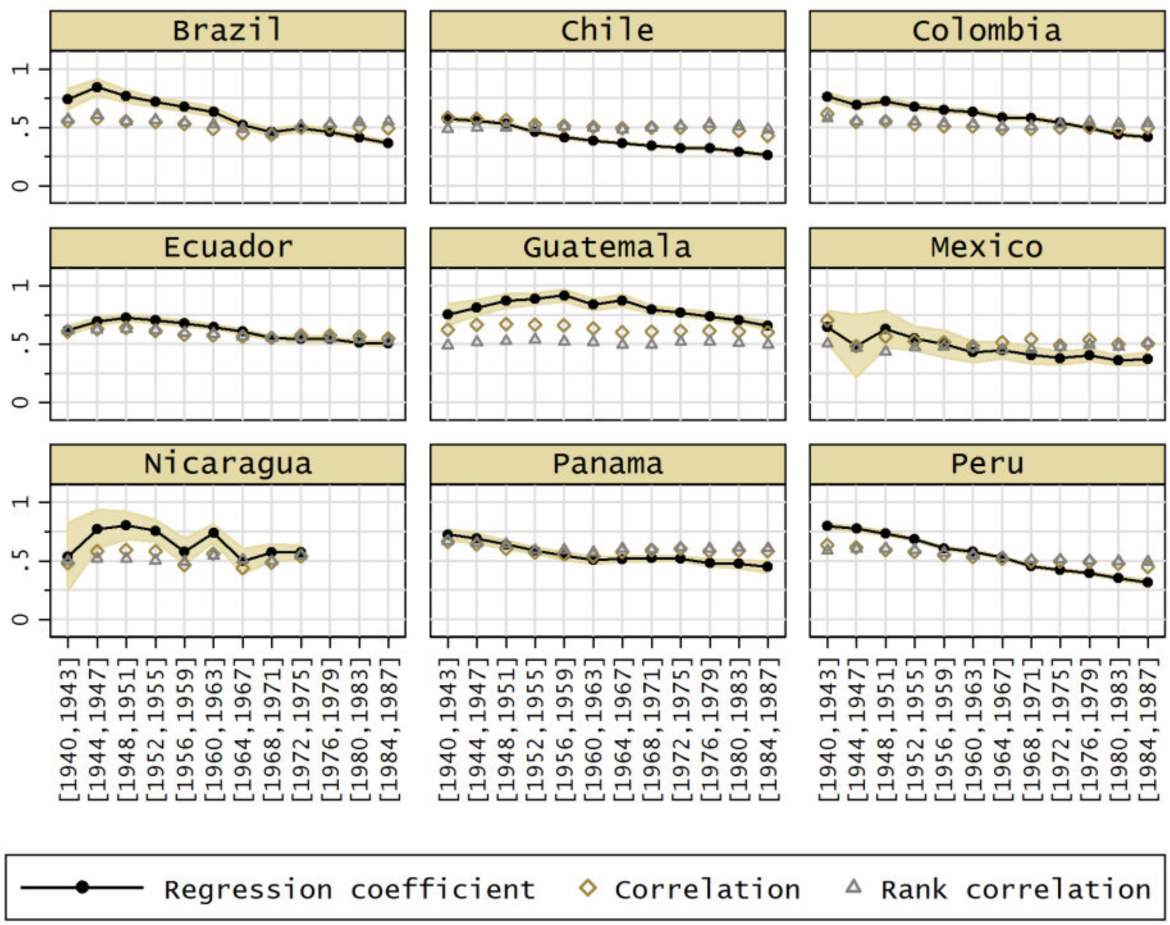
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure C3: Educational mobility in Latin America: absolute ($M1$) and directional ($M2$) mobility in years of education. *Source*: Latinobarometro 1998-2015, own estimates.



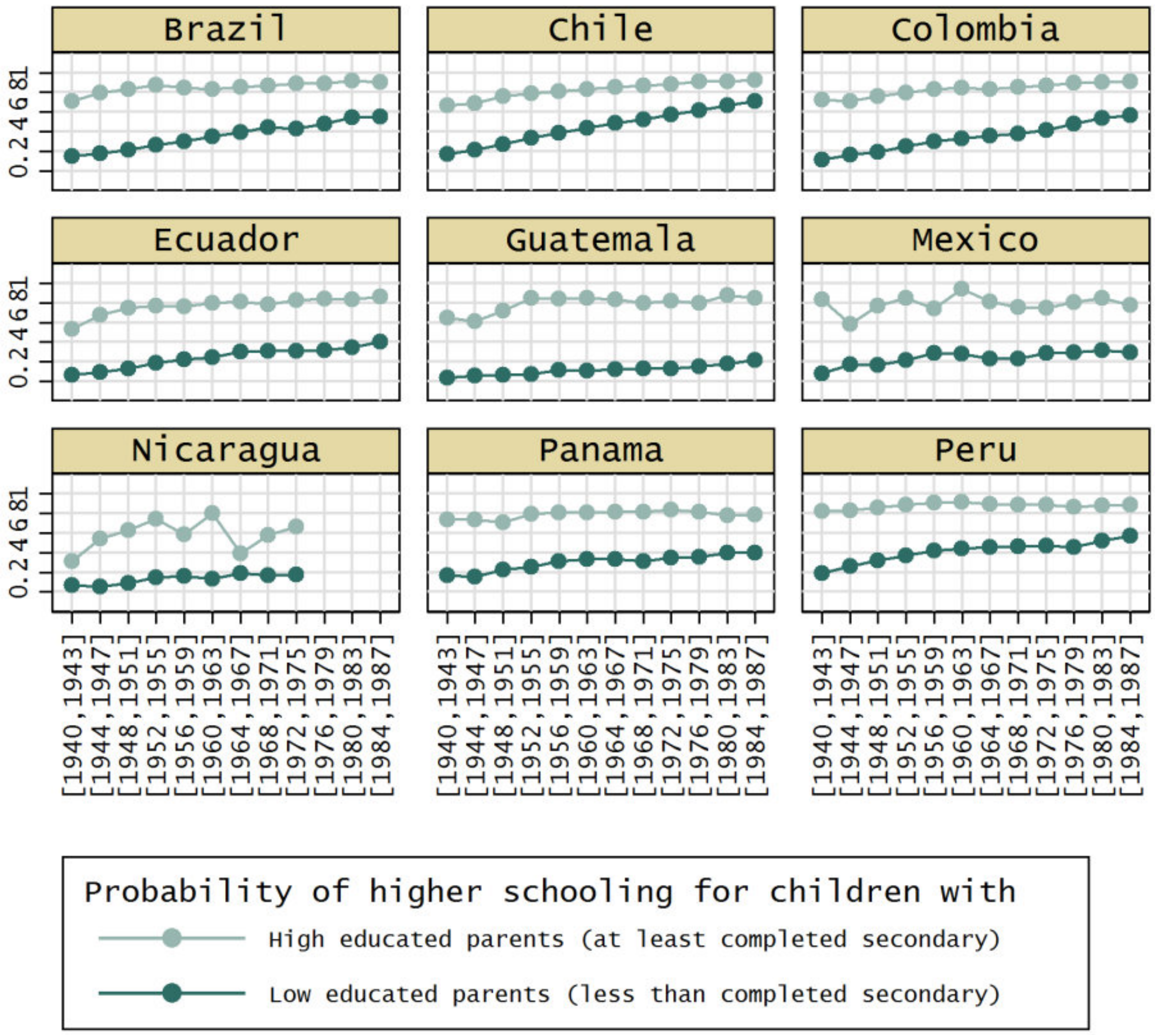
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure C4: Educational persistence in Latin America: Regression and correlation coefficients by country. *Source*: National Household Surveys 1994-2015, own estimates.



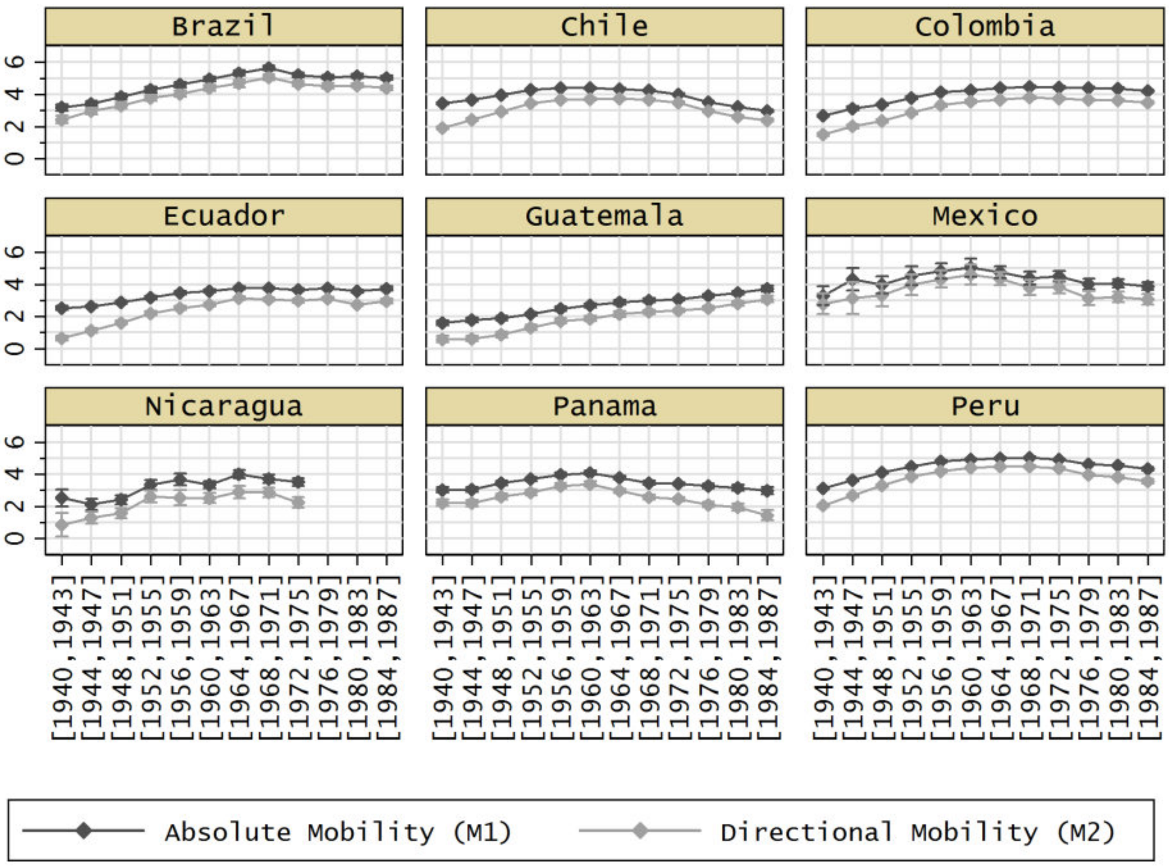
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure C5: Educational inequality in Latin America: Bottom-Upward Mobility (*BUM*) and Upper Class Persistence (*UCP*). *Source*: National Household Surveys 1994-2015, own estimates.



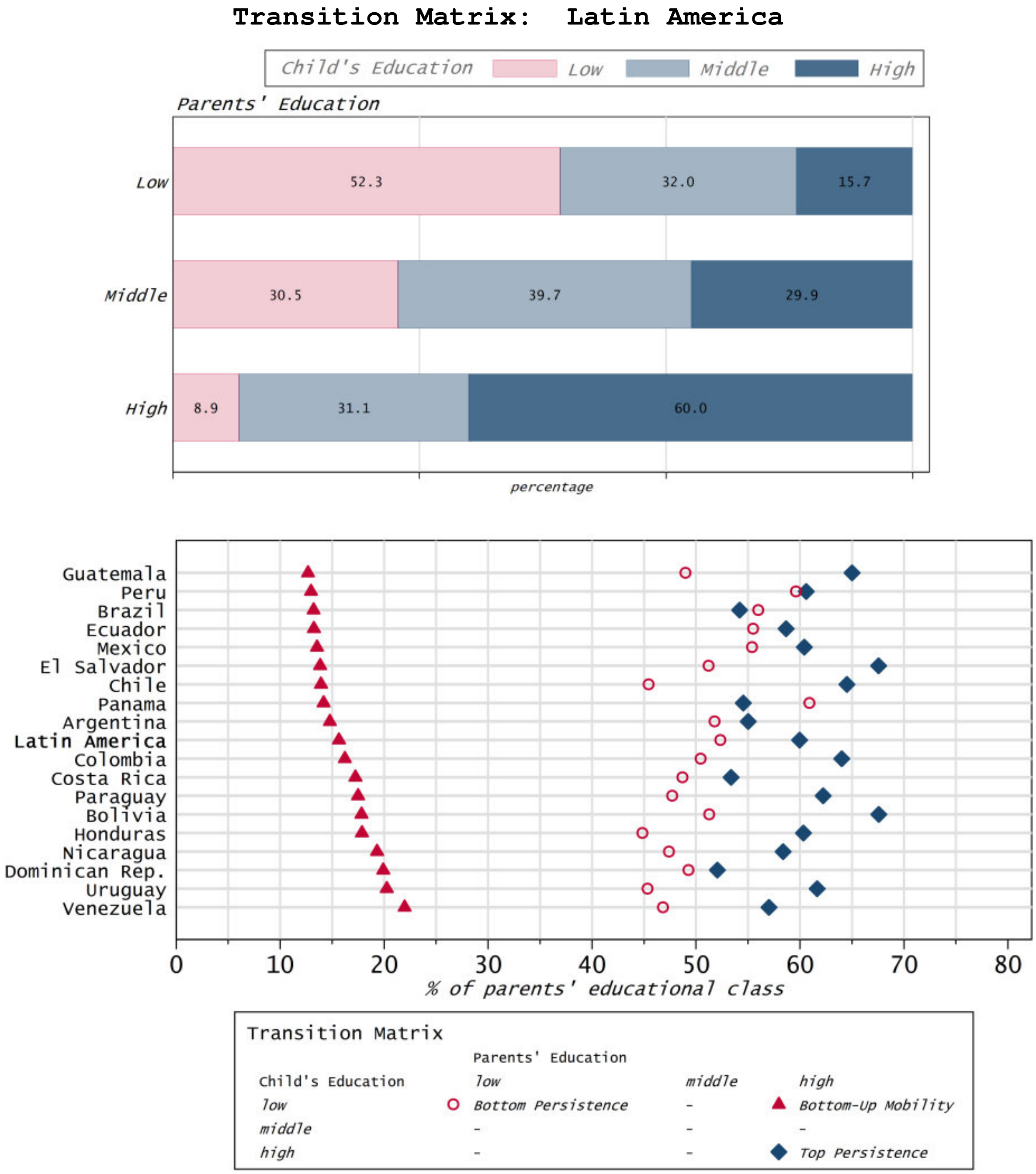
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure C6: Educational mobility in Latin America: absolute ($M1$) and directional ($M2$) mobility in years of education. *Source*: National Household Surveys 1994-2015, own estimates.



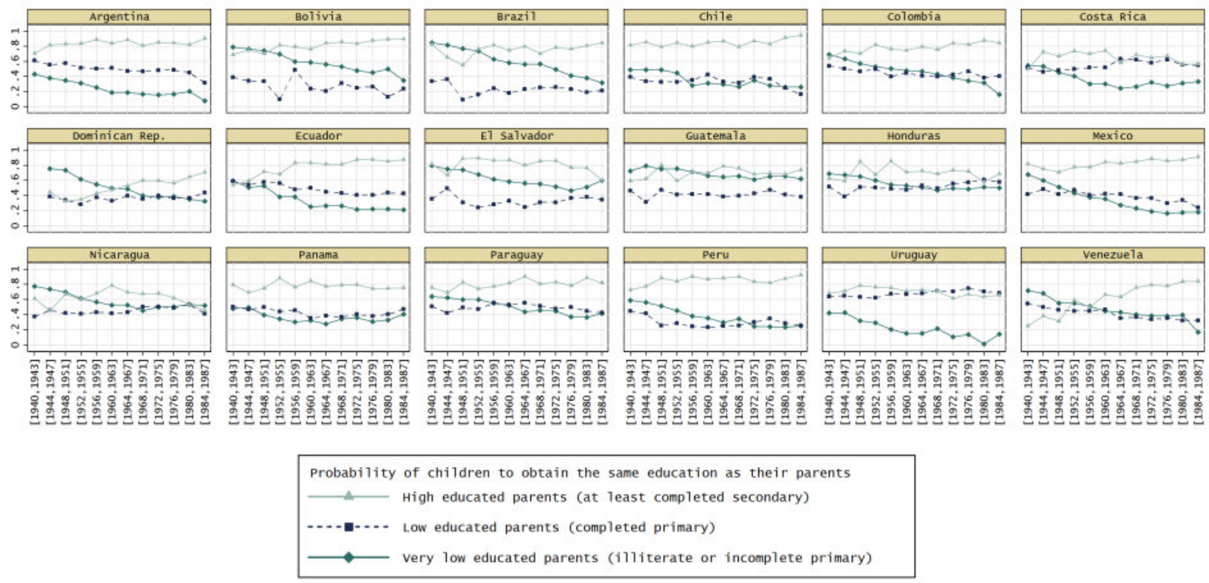
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure C7: Educational persistence in Latin America: Insights from transition matrices (People born 1940-1990).



Notes: Educational transitions within families from the point of view of the parents' generation. The points show the percentage of individuals in three different cells of the matrix. *Bottom persistence*: Individuals with low education and low parental education. *Bottom-Up Mobility*: Individuals with high education and low parental education. *Top persistence*: Individuals with high education and high parental education. Educational classes (low, middle, high) refer to three quantiles of the within-country and within-cohort distributions. Benchmarks USA (PSID, own estimates) / Germany (SOEP, own esimates): *Bottom persistence* 56.8 % / 53.2 %, T*op persistence* 54.0 % / 56.4 %, B*ottom-up mobility* 12.6 % / 15.2 %. *Source*: Latinobarometro 1998-2015, own estimates.

Figure C8: Educational inequality in Latin America: Persistence at the tails of the distribution. *Source*: Latinobarometro 1998-2015, own estimates.



Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations.

Table C1: Different approximations of parental background – Lubotsky-Wittenberg type estimates

Panel A

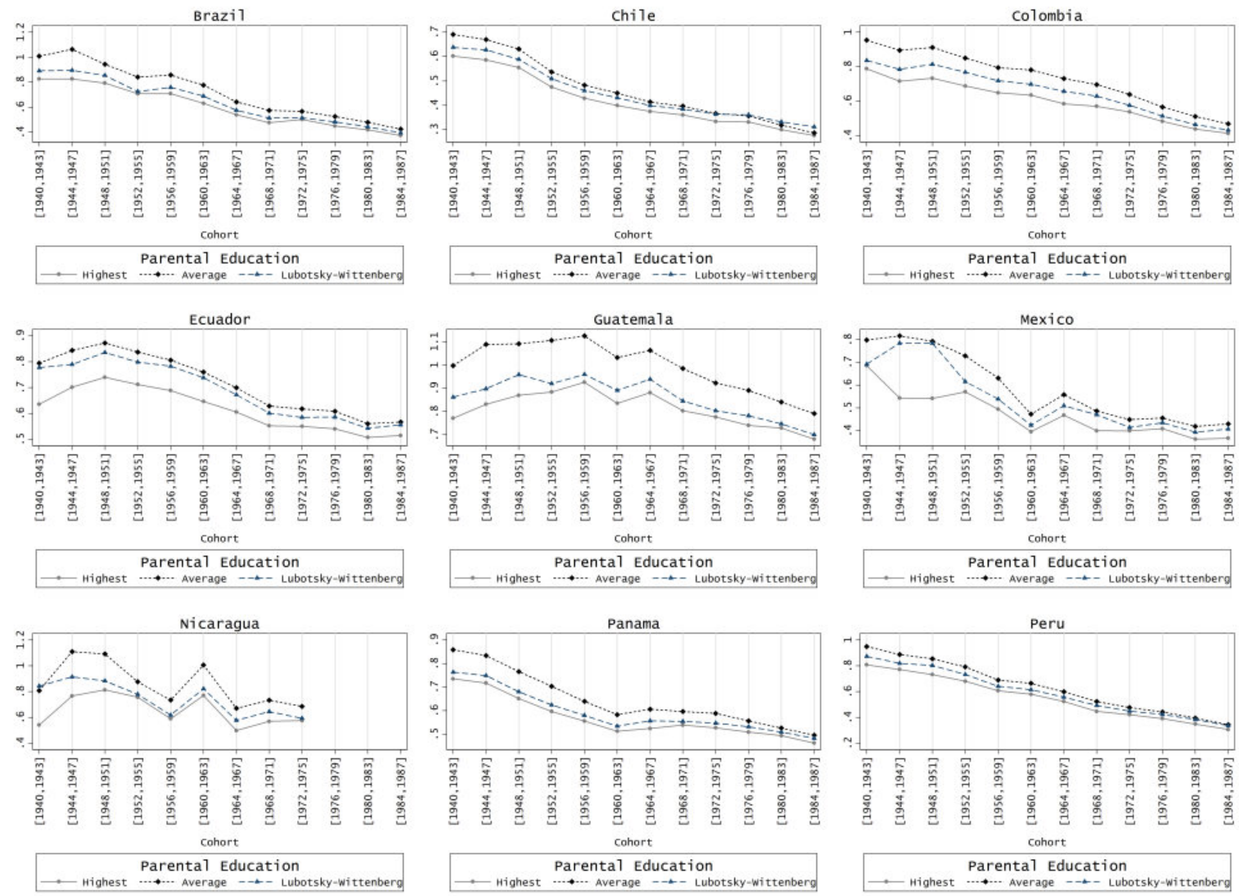
Independent variable(s) | Country	Brazil		Chile		Colombia		Ecuador		Guatemala		Mexico		Nicaragua		Panama		Peru	
(1) Highest Education	0.604	*0.165*	0.419	*0.112*	0.603	*0.120*	0.616	*0.083*	0.811	*0.074*	0.469	*0.100*	0.653	*0.121*	0.568	*0.088*	0.551	*0.171*
(2) Average Education	0.725	*0.218*	0.467	*0.137*	0.733	*0.161*	0.716	*0.116*	0.995	*0.111*	0.586	*0.158*	0.857	*0.173*	0.646	*0.119*	0.634	*0.204*
(3) LW: Education of Both Parents	0.645	*0.180*	0.451	*0.115*	0.657	*0.137*	0.689	*0.109*	0.859	*0.085*	0.539	*0.146*	0.741	*0.133*	0.592	*0.092*	0.594	*0.183*
N (full sample)	23,041		341,264		194,810		86,909		55,043		12,039		5,346		29,115		234,694	

Panel B

Independent variable(s) | Country	Brazil		Chile		Ecuador		Mexico		Panama	
(4) Highest Education	0.479	*0.005*	0.384	*0.004*	0.583	*0.0065*	0.459	*0.015*	0.544	*0.008*
(5) LW: Education of Both Parents	0.504	*0.005*	0.406	*0.004*	0.628	*0.006*	0.491	*0.016*	0.566	*0.008*
(6) LW: Education of Both Parents and Highest Occupation	0.534	*0.006*	0.409	*0.004*	0.668	*0.006*	0.530	*0.017*	0.580	*0.008*
N	20,058		57,144		34,267		4,815		8,901	

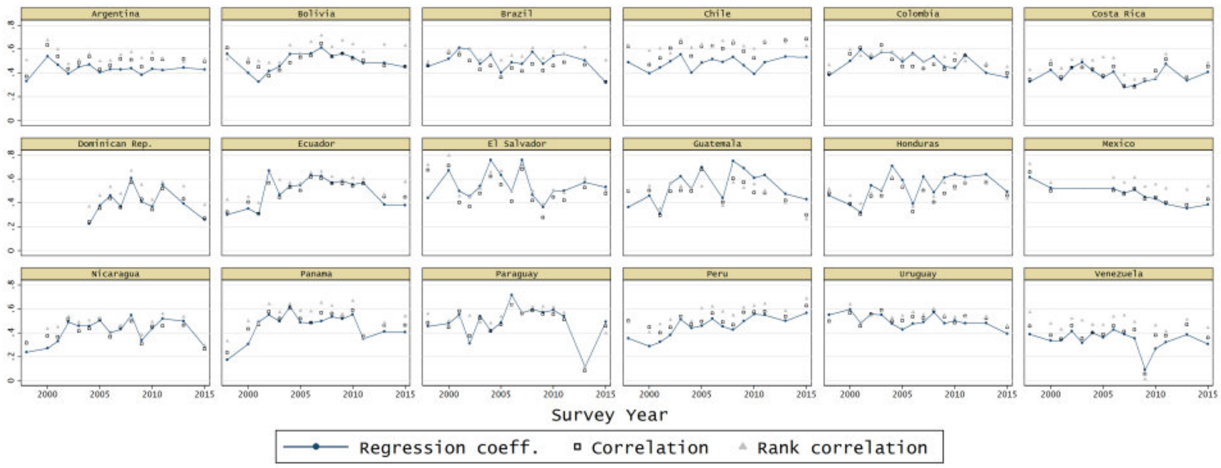
Notes: Panel A shows the average regression coefficients over all cohorts and their respective standard deviations (in italics). (1) is the baseline estimate, using the years of education of the parent with higher education among the two as proxy for parental educational background. (2) is the estimate using the average years of education among both parents as independent variable. (3) is the weighted sum of the coefficients of the parent with the higher and lower education, included in the same regression, where the weights are obtained applying the method proposed by Lubotsky and Wittenberg (2006). Panel B shows the regression coefficients of the surveys with available information on parental occupation and their respective bootstrapped standard error in italics (100 replications). (4) is the baseline estimate, using the years of education of the parent with higher education among the two as proxy for parental background; these estimates differ from (1) because they were estimated on different samples (only one survey wave with sample restricted to individuals with available information on parental occupation). (5) is the Lubotsky-Wittenberg type coefficient including the education of both parents in the regression. (6) is the Lubotsky-Wittenberg type coefficient including the education and occupation of both parents in the regression. *Source*: National Household Surveys, own estimates.

Figure C9: Trends for different approximations of parental background – Lubotsky-Wittenberg type estimates. *Source*: National Household Surveys 1994-2015, own estimates.



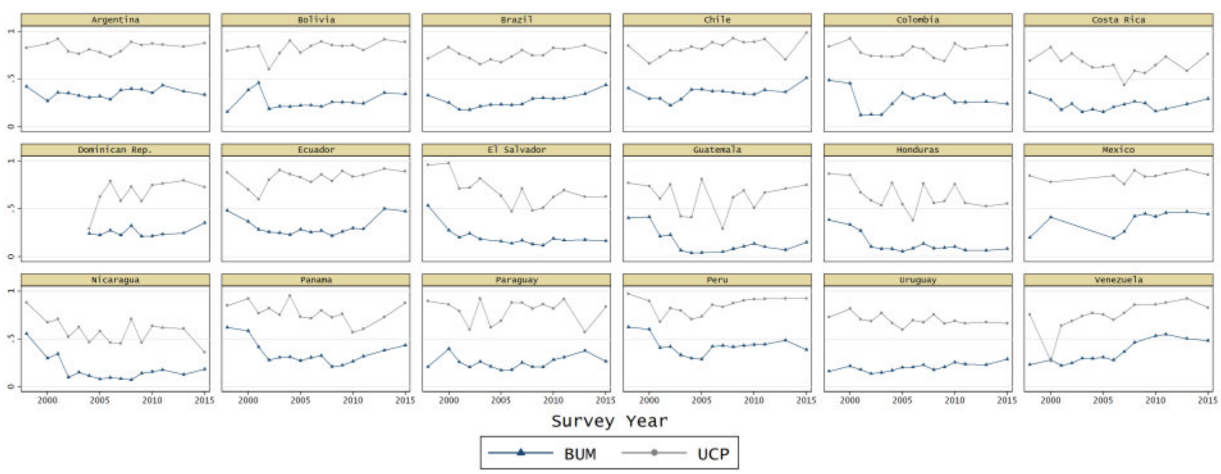
C.2 Estimates by Survey Year

Figure C10: Educational persistence in Latin America: Regression and correlation coefficients by country. *Source*: Latinobarometro 1998-2015, own estimates.



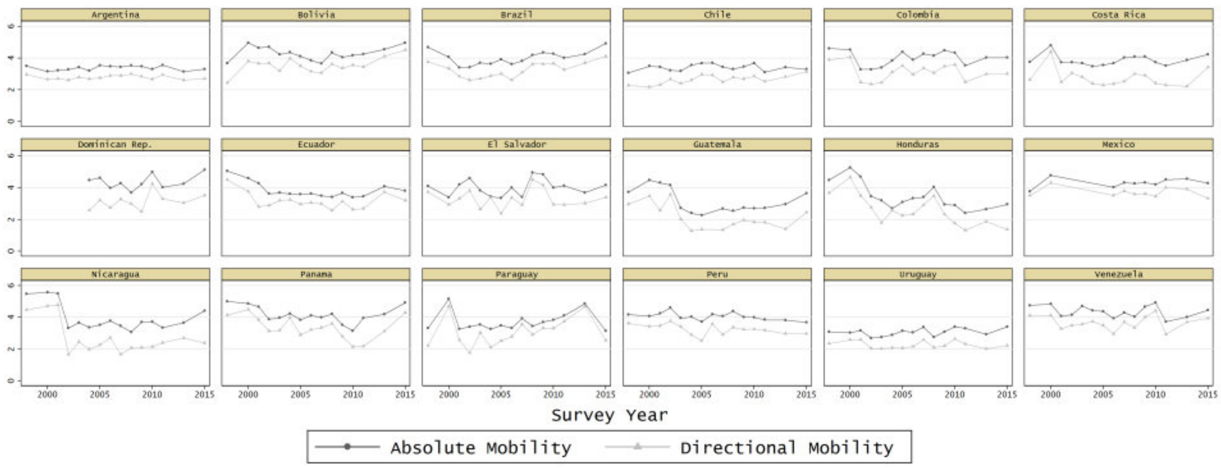
Notes: Samples restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations.

Figure C11: Educational inequality in Latin America: Bottom-Upward Mobility (BUM) and Upper Class Persistence (UCP). *Source*: Latinobarometro 1998-2015, own estimates.



Notes: Samples restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations.

Figure C12: Educational mobility in Latin America: absolute ($M1$) and directional ($M2$) mobility in years of education. *Source*: Latinobarometro 1998-2015, own estimates.



Notes: Samples restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations.

C.3 Heterogeneity by Gender and Assortative Mating

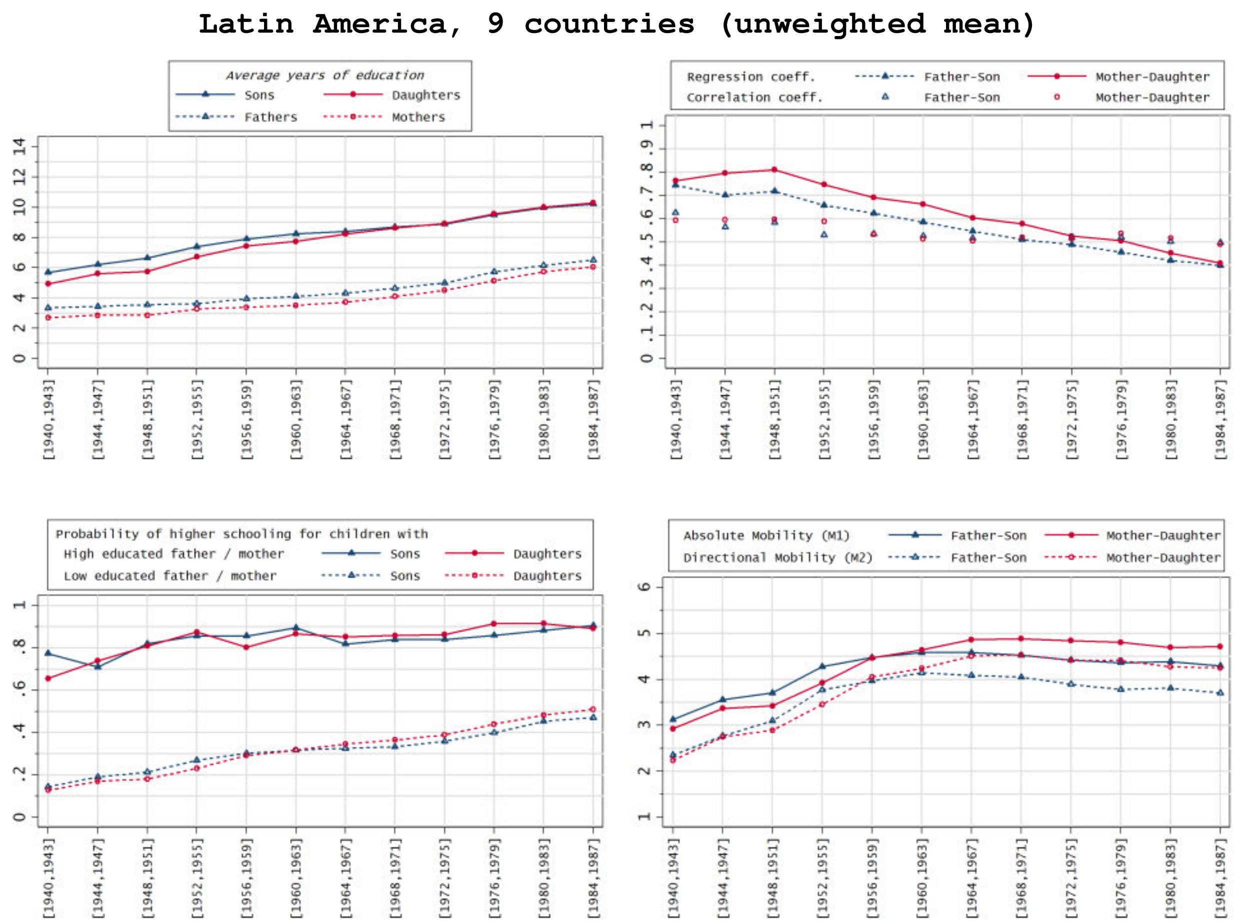
We disentangle our estimates by father-son and mother-daughter lineages. These estimates provide an overview of how social, cultural, or institutional factors may influence the educational mobility of men and women differently. For instance, families might dedicate more resources to the education of male offspring, either because the returns on sons' education are expected to be higher or because of traditional gender roles. For this last reason, imitation might cause the educational attainments of children to be related more strongly to the education of the parent with the same sex Schneebaum et al. (2015). Then, we relate our intergenerational mobility estimates to the degree of assortative mating, i.e. the likelihood of people with similar socioeconomic status to marry each another. This analysis is particularly interesting since there seems to be a fundamental interrelation between the two concepts; e.g. because higher spouse correlations are argued to cause a stronger heritability of unobserved and observable endowments. However, few studies are able to empirically prove this relationship Chadwick and Solon (2002); Ermisch et al. (2006); Guell et al. (2015). We can perform this evaluation for the nine countries where we have information on both paternal and maternal educational attainment.

As shown in Figure C13, the estimates for father-son and mother-daughter pairs show the same trend and are rather similar for younger cohorts. Coinciding with the expansion of educational attainment among women, the mobility of daughters also rises considerably and approaches the mobility levels experienced by sons, on average. Generally, the patterns confirm the picture of rising intergenerational mobility in Latin America driven by high upward mobility from the bottom and with substantial immobility at the top of the distribution.

Taking into account the high degree of assortative mating in Latin American countries, these findings are not particularly surprising: when the education of both parents is similar, the education of only one of the two is a valid proxy for the education of the other. Our findings show that assortative mating in Latin America, measured by the correlation of father's and mother's educational attainment, is constantly high over time (around 0.7, with countries ranging between 0.6 and 0.8; see Figure C14). Interestingly, most countries show a slight but decreasing trend. Indeed, existing research finds an inverse relationship between assortative mating and intergenerational mobility Guell et al. (2015).

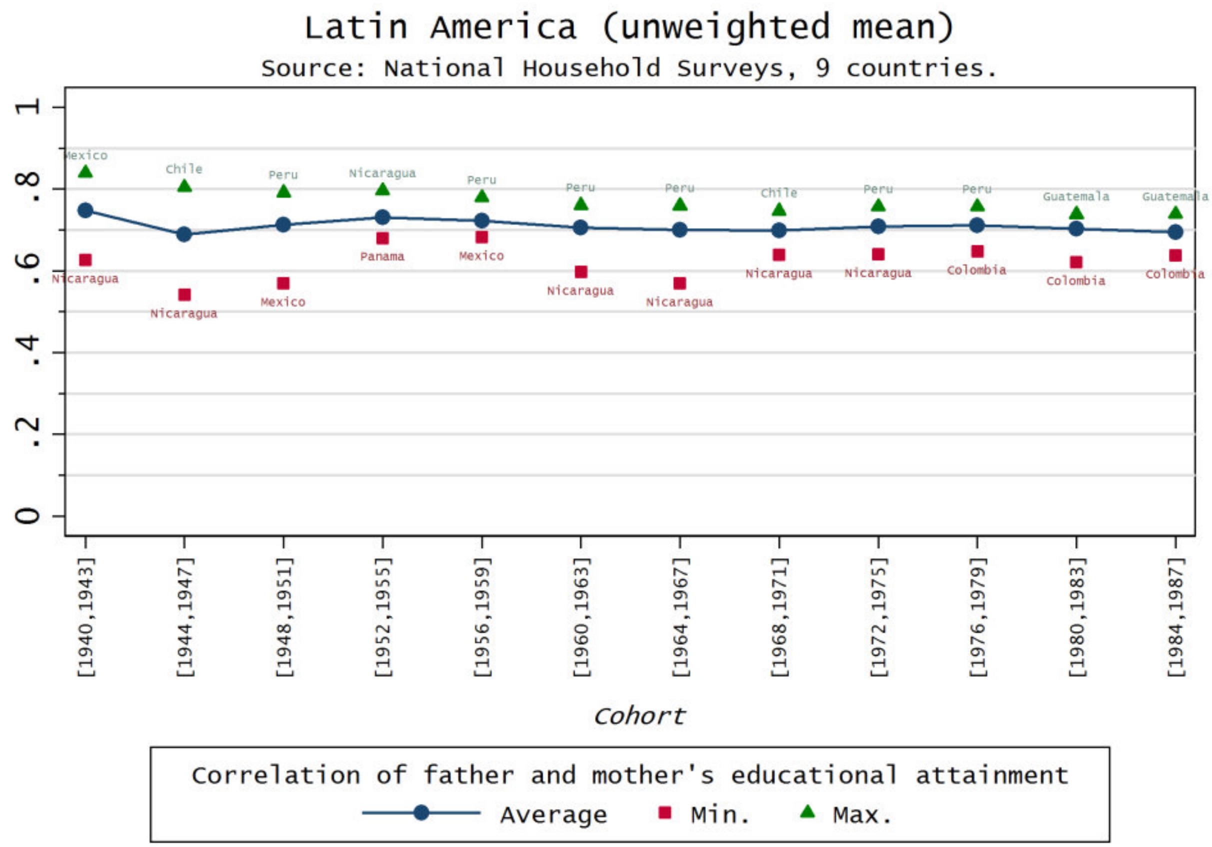
We test the relationship between assortative mating and intergenerational mobility using our database, regressing the seven estimated mobility indexes on the estimated degree of spouse correlation in the parent's generation controlling for cross country heterogeneity by fixed effects. As shown in Table C2, the degree of spouse correlation is positively and significantly associated with educational persistence (measured by the regression coefficient, the correlation coefficient and the rank correlation) and negatively associated with the index of bottom upward mobility. The relationship with the index for upper class persistence and the measures of directional and absolute mobility point at the same picture – higher spouse correlation associated with lower intergenerational mobility – but are not statistically significant. Hence, our findings confirm the expected association between assortative mating and intergenerational mobility.

Figure C13: Average educational attainment by gender and intergenerational mobility for father-son and mother-daughter pairs.



Source: National Household Surveys 1994-2015, own estimates.

Figure C14: Assortative mating – spouse correlation in educational attainments (parental generation).



Notes: Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. *Source*: National Household Surveys 1994-2015, own estimates.

Figure C15: Educational persistence in Latin America for father-son and mother-daughter pairs. *Source*: National Household Surveys 1994-2015, own estimates.

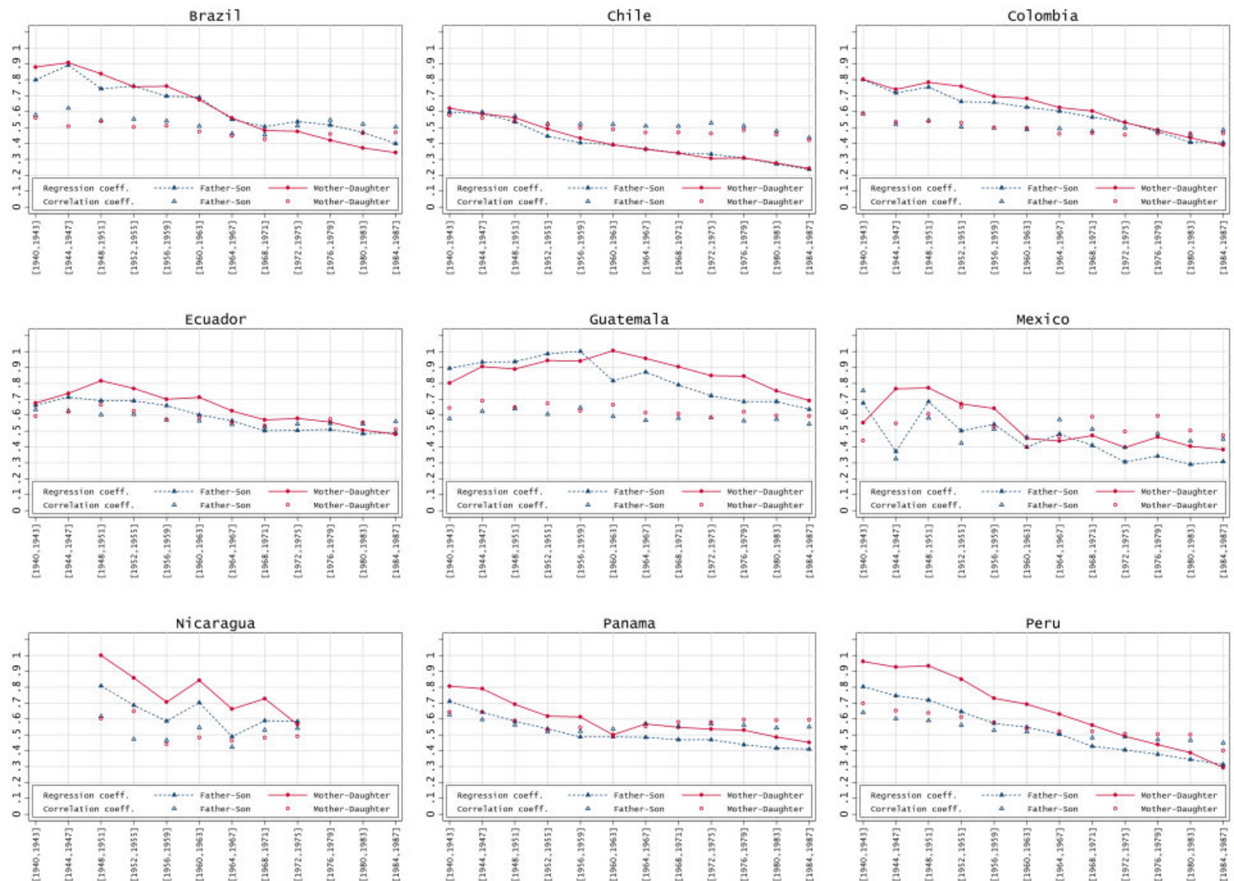


Figure C16: Average educational attainment, intergenerational mobility for father-son and mother-daughter pairs, and assortative mating. *Source*: National Household Surveys 1994-2015, own estimates.

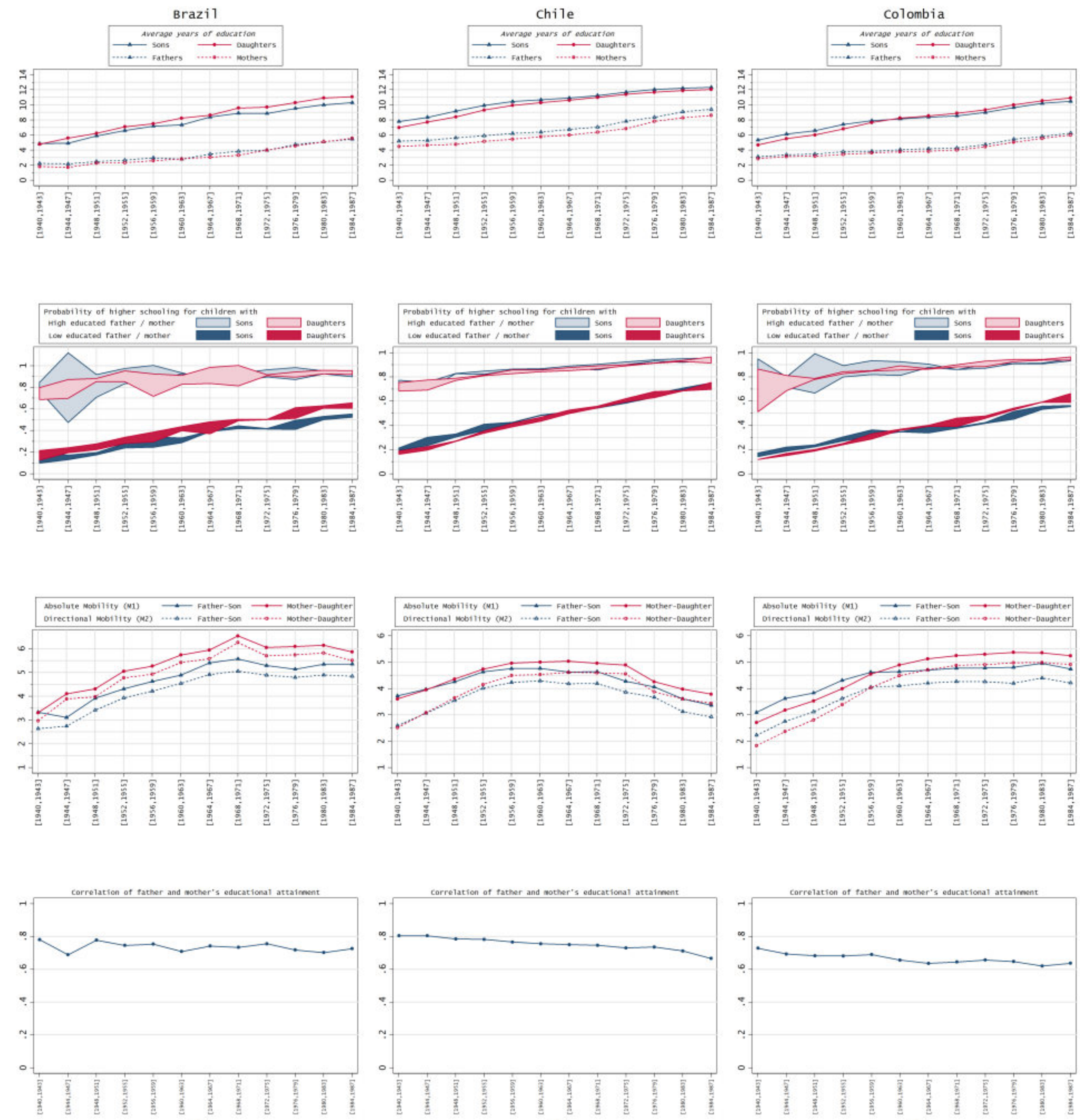


Figure C17: Average educational attainment, intergenerational mobility for father-son and mother-daughter pairs, and assortative mating. *Source*: National Household Surveys 1994-2015, own estimates.

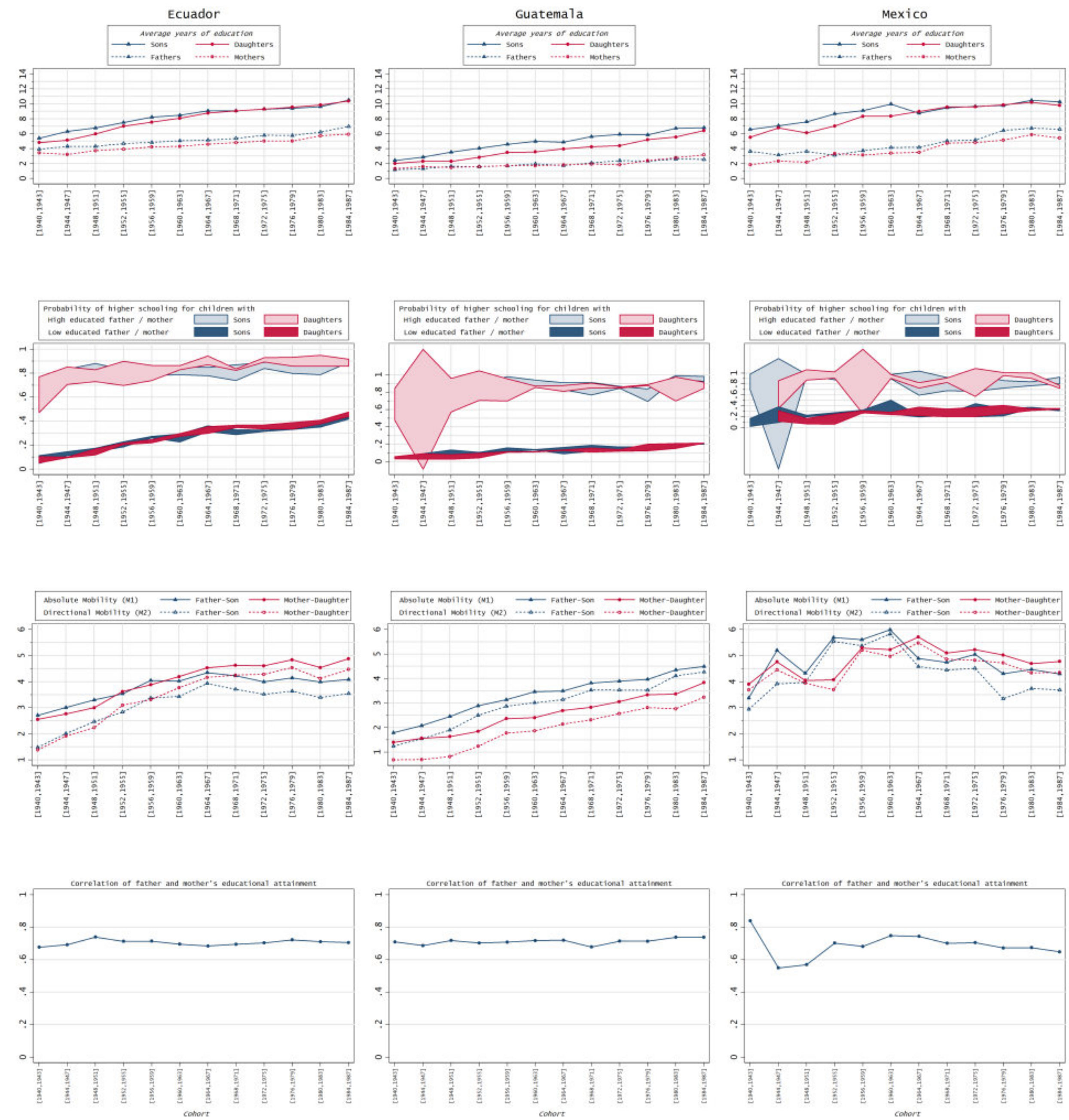


Figure C18: Average educational attainment, intergenerational mobility for father-son and mother-daughter pairs, and assortative mating. *Source*: National Household Surveys 1994-2015, own estimates.

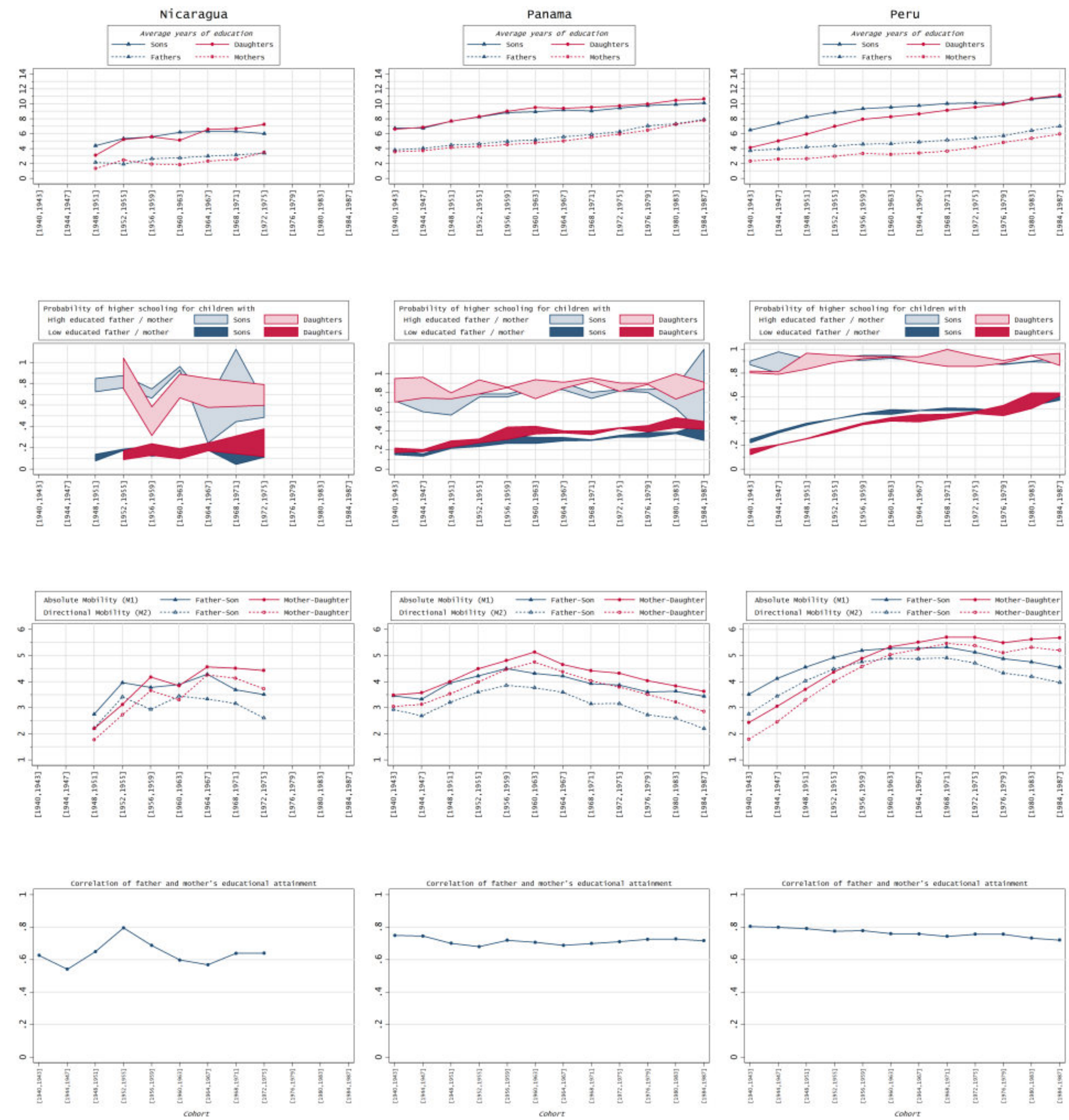


Table C2: Assortative mating and intergenerational mobility – linear regressions.

	(1) β	(2) ρ	(3) r	(4) BUM	(5) UCP	(6) $M1$	(7) $M2$
Spouse correlation (parents)	0.948***	0.513***	0.133**	-0.996***	0.204	-0.992	-1.027
	(0.3443)	(0.1588)	(0.0647)	(0.3782)	(0.2750)	(1.7515)	(1.9566)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105	105	105	105	105	105	105

Notes: Table shows the coefficients of the computed spouse correlation index in linear regressions using the single mobility indexes as dependent variables. All regressions include country dummies. Robust standard errors in parentheses. Statistical significance level * 0.1 ** 0.05 *** 0.01. *Source*: National Household Surveys 1994-2015, own estimates.

D Robustness

D.1 Other specifications of one generation for macro analysis

Table D1: Intergenerational mobility and economic performance. Lag of 40 years.

(a) Economic growth

	(1) $M = 1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	0.129***	-0.048**	0.332***	0.053***	0.081***	0.056***
	(0.0181)	(0.0197)	(0.0262)	(0.0150)	(0.0167)	(0.0203)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	605	605	587	587	605	605

(b) Inequality

	(1) $M = 1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.272***	0.025	-0.653***	-0.092	-0.062	0.032
	(0.0628)	(0.0582)	(0.0861)	(0.0633)	(0.0693)	(0.0672)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285	285	283	283	285	285

(c) Poverty

	(1) $M = 1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.255***	-0.024	-0.669***	-0.015	-0.051	0.057
	(0.0639)	(0.0625)	(0.0817)	(0.0472)	(0.0724)	(0.0626)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285	285	283	283	285	285

(d) Public expenditures in education

	(1) $M = 1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	0.585	0.077	2.024***	0.436	-0.210	-0.368
	(0.4376)	(0.4033)	(0.5542)	(0.4544)	(0.5015)	(0.5586)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	181	181	178	178	181	181

(e) Share of public expenditures in education devoted to tertiary education

	(1) $M = 1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.012	-0.097	-0.095	-0.228*	0.116	0.038
	(0.1174)	(0.1080)	(0.1489)	(0.1349)	(0.1475)	(0.1202)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105	105	104	104	105	105

(f) Returns to education

	(1) $M = 1-\beta$	(2) $1-\rho$	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.192***	0.007	-0.356***	-0.011	-0.028	0.079
	(0.0549)	(0.0457)	(0.1020)	(0.0593)	(0.0721)	(0.0748)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285	285	283	283	285	285

Notes: The tables show regression estimates for θ in equation (8). The respective dependent variables are: (a) GDP per capita, (b) Gini coefficient of disposable household per capita income, (c) Poverty headcount ratio - 2USD/day, (d) Public expenditures in education per pupil as % of GDP per capita, (e) Ratio of public expenditures in tertiary education and public expenditures in primary and secondary education and (f) Ratio of hourly wages of people with high and low education. The intergenerational mobility index M is the main independent variable included in the regressions: (1) $M = 1-\beta$, (2) $M = 1-\rho$, (3) $M = BUM$, (4) $M = UCP$, (5) $M = M1$, (6) $M = M2$; see Section **??**. Dependent and independent variables are standardized to have mean zero and standard deviation of one. All regressions include country dummies. Dependent variable in t associated to independent variable of cohort $t-40$. Robust standard errors in parentheses. Statistical significance level * 0.1 ** 0.05 *** 0.01. *Sources*: Latinobarometro 1998-2015, own estimates of intergenerational mobility; SEDLAC; World Bank Data.

Table D2: Intergenerational mobility and economic performance. Lag of 30 years.

(a) Economic growth

	(1) M = 1 − β	(2) 1 − ρ	(3) BUM	(4) UCP	(5) M1	(6) M2
M	0.160***	-0.048**	0.294***	0.033*	-0.034	-0.121***
	(0.0205)	(0.0215)	(0.0261)	(0.0169)	(0.0240)	(0.0268)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	785	785	767	767	785	785

(b) Inequality

	(1) M = 1 − β	(2) 1 − ρ	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.306***	0.073	-0.500***	-0.005	0.249***	0.244***
	(0.0758)	(0.0594)	(0.0854)	(0.0749)	(0.0819)	(0.0625)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285	285	284	284	285	285

(c) Poverty

	(1) M = 1 − β	(2) 1 − ρ	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.294***	-0.006	-0.467***	0.010	0.284***	0.285***
	(0.0674)	(0.0799)	(0.0827)	(0.0719)	(0.0740)	(0.0474)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285	285	284	284	285	285

(d) Public expenditures in education

	(1) M = 1 − β	(2) 1 − ρ	(3) BUM	(4) UCP	(5) M1	(6) M2
M	0.243	0.898***	1.380***	0.738*	-1.089**	-1.069***
	(0.4043)	(0.3253)	(0.4984)	(0.4387)	(0.4295)	(0.3645)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214	214	211	211	214	214

(e) Share of public expenditures in education devoted to tertiary education

	(1) M = 1 − β	(2) 1 − ρ	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.315***	0.061	-0.222	-0.114	0.385***	0.375***
	(0.1120)	(0.0813)	(0.1358)	(0.2003)	(0.1105)	(0.0866)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105	105	105	105	105	105

(f) Returns to education

	(1) M = 1 − β	(2) 1 − ρ	(3) BUM	(4) UCP	(5) M1	(6) M2
M	-0.120*	0.039	-0.156*	0.094*	0.227***	0.176***
	(0.0648)	(0.0518)	(0.0901)	(0.0553)	(0.0659)	(0.0467)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	285	285	284	284	285	285

Notes: The tables show regression estimates for θ in equation (8). The respective dependent variables are: (a) GDP per capita, (b) Gini coefficient of disposable household per capita income, (c) Poverty headcount ratio - 2USD/day, (d) Public expenditures in education per pupil as % of GDP per capita, (e) Ratio of public expenditures in tertiary education and public expenditures in primary and secondary education, and (f) Ratio of hourly wages of people with high and low education. The intergenerational mobility index M is the main independent variable included in the regressions: (1) $M = 1-\beta$, (2) $M = 1-\rho$, (3) $M = BUM$, (4) $M = UCP$, (5) $M = M1$, (6) $M = M2$. Dependent and independent variables ar standardized to have mean zero and standard deviation of one. All regressions include country dummies. Dependent variable in t associated to independent variable of cohort $t-30$. Robust standard errors in parentheses. Statistical significance level * 0.1 ** 0.05 *** 0.01. *Sources*: Latinobarometro 1998-2015, own estimates of intergenerational mobility; SEDLAC; World Bank Data.

D.2 Non-linear correlation of educational levels

Some of the measures that are usually applied to study intergenerational mobility assume that the relationship between the outcomes of parents and children is linear. However, this assumption is questioned by analyses showing that the slope coefficients might vary for families in different parts of the distribution (Bratberg et al., 2017). In particular, when measuring educational attainment, the assumption of years of education as a cardinal measure and of an underlying monotonic and linear relationship between parents' and children's schooling is questioned. However, cross country studies show a high correlation between linear and non-linear measures of relative intergenerational mobility (see Blanden, 2013). Figure D1 shows an evaluation of non-linear patterns in the correlation of parents' and children's years of education. Generally, the issue certainly requires specific attention that goes beyond the scope of this work. For the sake of completeness, we here show the robustness of our cross-country estimates applying a measure that takes into account that the correlation of educational levels might be of non-linear nature.

The applied measure is the correlation of error terms in a bivariate ordered probit model. The model estimates the joint probability distribution of two ordered categorical variables, in our case parents' and children's education in levels. This method is used by Magee et al. (2000), among others, to estimate assortative mating patterns in educational levels.[22] The outcome variables in our application both have seven categories: (1) illiterate, (2) incomplete primary, (3) complete primary, (4) incomplete secondary, (5) complete secondary, (6) incomplete higher education, and (7) complete higher education.

Assume that the two latent variables defining the educational level y of parents (p) and children (c) are determined by:

$$y^*_{pi} = X'_{pi}\delta_p + \varepsilon_{pi} \tag{14}$$

$$y^*_{ci} = X'_{ci}\delta_c + \varepsilon_{ci} \tag{15}$$

where i denotes the family. δ_p and δ_c are vectors of parameters for X_p and X_c that include age and sex and satisfy the exogeneity conditions $E[X_{pi}\varepsilon_{pi}] = E[X_{ci}\varepsilon_{ci}] = 0$. ε_p and ε_c are the error terms, distributed as a bivariate standard normal. Denote the cutoffs of the observed categorical variables indicating parents' educational level $j\varepsilon(1,2,3,4,5,6,7)$ as c_{pj}, where $c_{pj-1} < c_{pj}$, and let $c_{pj} = -\infty$ for $j = 0$ and $c_{pj} = \infty$ for $j = 7$. The indicator for the child is determined in the same way. Then the probability that the parent and the child have the same educational level m is

$$Pr(y_{pi} = m\,, y_{ci} = m) = Pr(c_{pm-1} < y^*_{pi} \leq c_{pm}, c_{cm-1} < y^*_{ci} \leq c_{cm}).$$

[22] For further examples, see Sajaia (2008).

The parameter of interest here is the association measure ρ^{ε} that is the correlation between the two error terms ε_p and ε_c. Figures D2 and D3 show ρ^{ε} estimated separately for each cohort and compare it with the Pearson correlation coefficient ρ measured on the same ordered variables. As is evident, ρ^{ε} is always higher than ρ in all countries and surveys, but the trends are almost constantly parallel.

References of Section D

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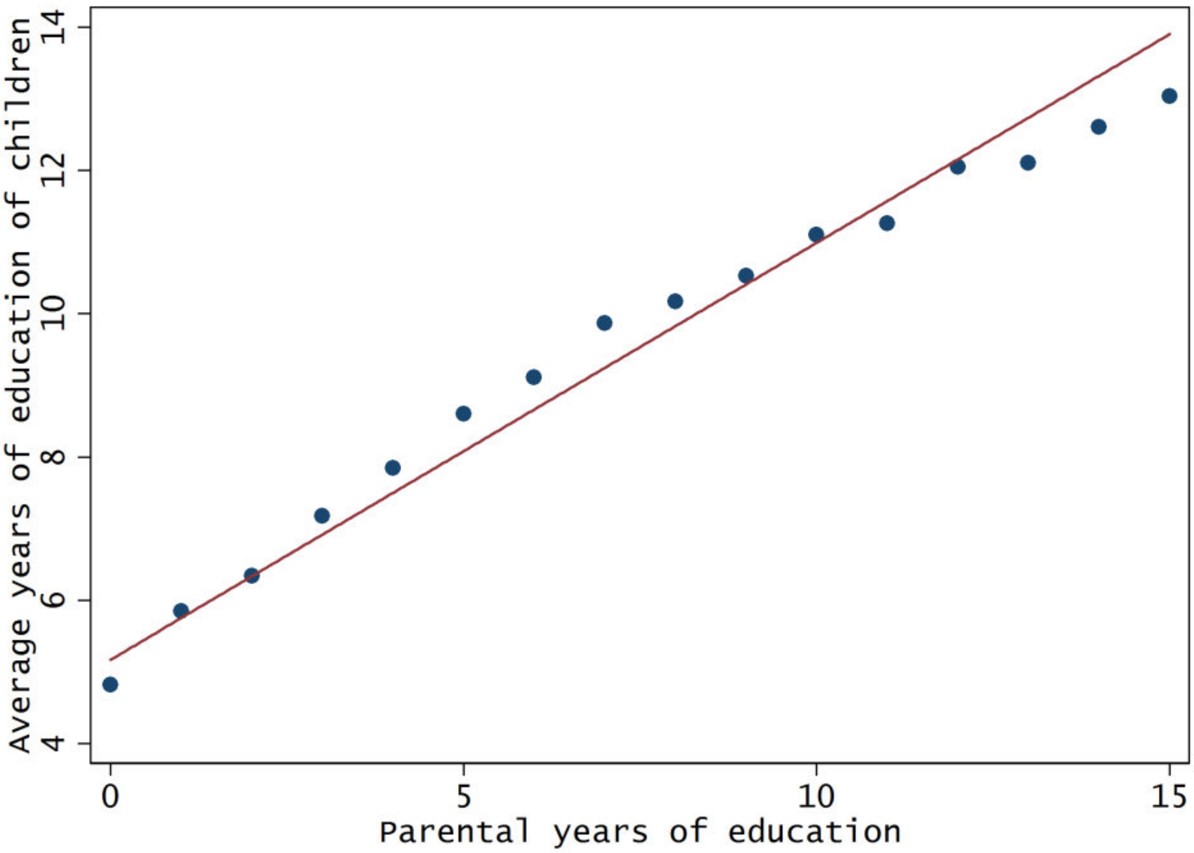
Magee, L., Burbidge, J., Robb, L. (2000), The Correlation Between Husband's and Wife's Education: Canada, 1971-1996. SEDAP Research Paper No. 24

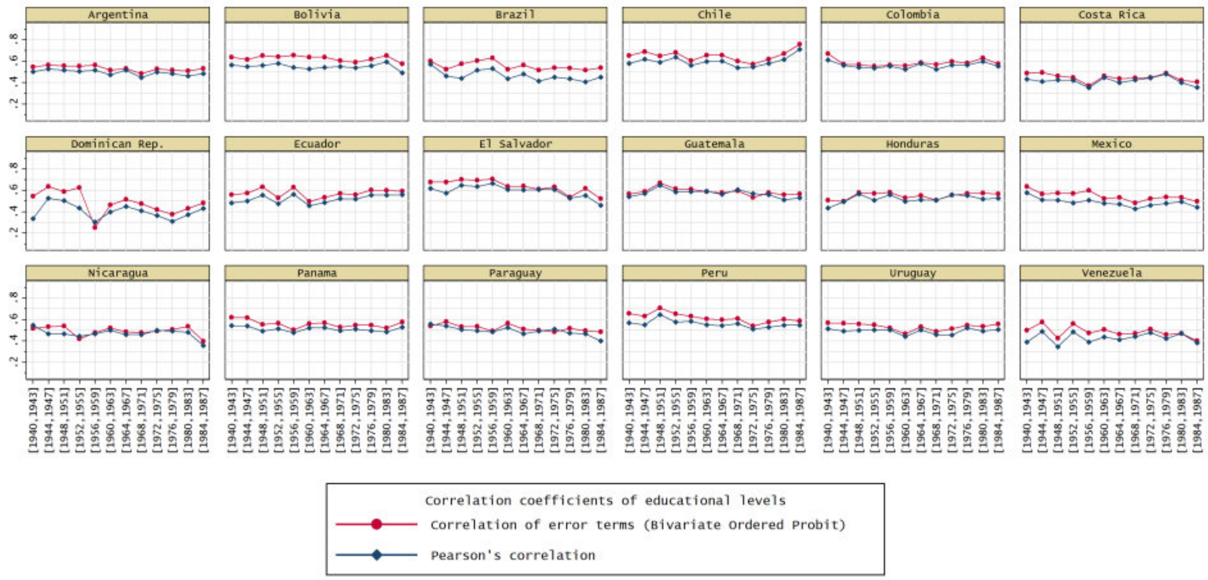
Sajaia, Z. (2008), Maximum likelihood estimation of a bivariate ordered probit model: implementation and Monte Carlo simulations. The Stata Journal, 4(2): 1-8.

Figure D1: Children's average years of education for each level of parental education.



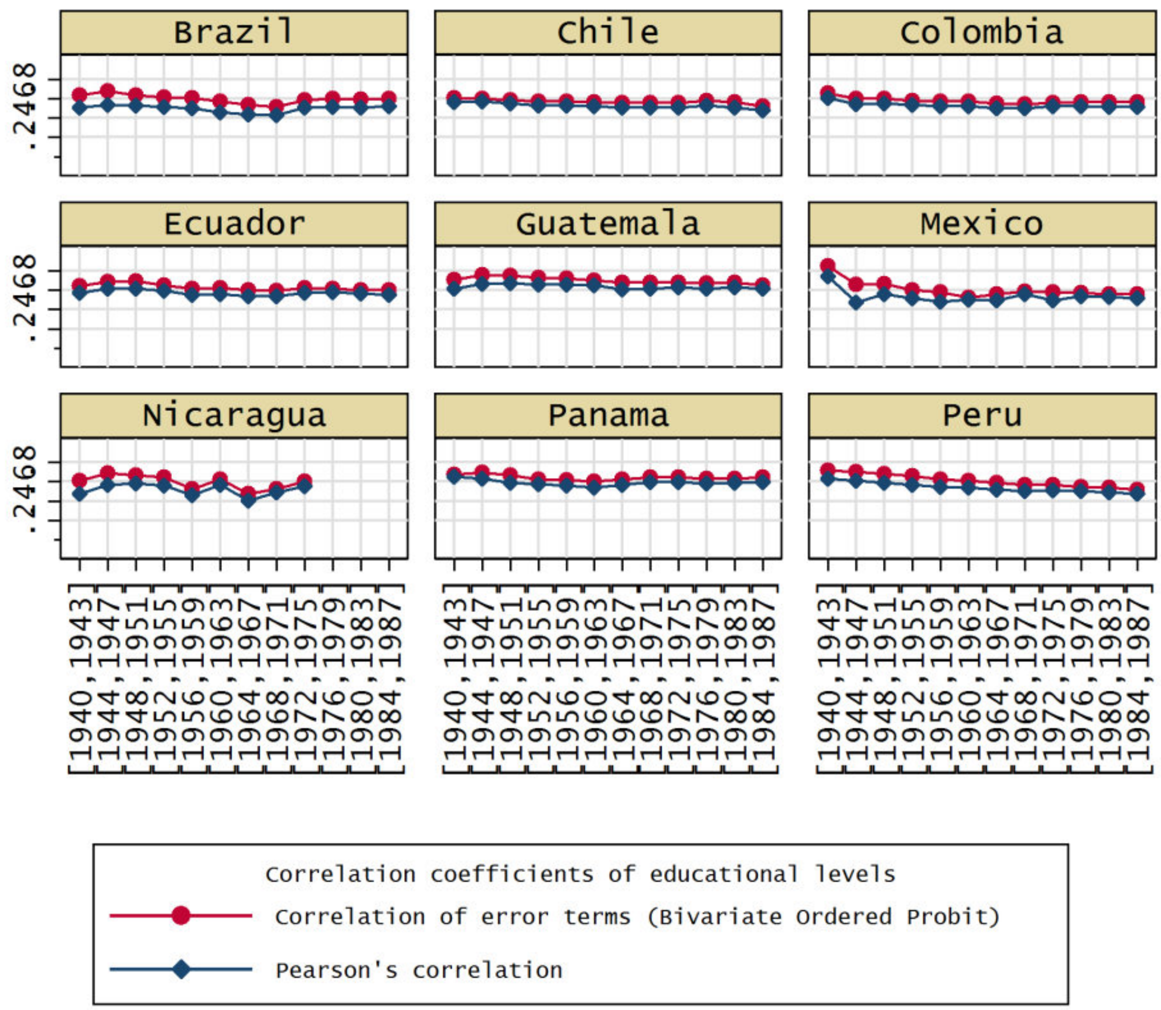
Notes: Samples for each cohort and country restricted to individuals older than 22. *Source*: Latinobarometro 1998-2015, own estimates.

Figure D2: Educational persistence in Latin America: Correlation coefficients by country. Latinobarometro.



Notes: Samples for each cohort and country restricted to individuals older than 22. *Source*: Latinobarometro 1998-2015, own estimates.

Figure D3: Educational persistence in Latin America: Correlation coefficients by country. National Household Surveys.



Notes: Samples for each cohort and country restricted to individuals older than 22. *Source*: National Household Surveys 1994-2015, own estimates.