Intergenerational Mobility in Developed and Developing Countries

Inaugural-Dissertation zur Erlangung
des akademischen Grades eines Doktors der Wirtschaftswissenschaft
des Fachbereichs Wirtschaftswissenschaft der Freien Universität Berlin

vorgelegt von Guido Neidhöfer, M.Sc.
aus Rom

Berlin, 2017

Erstgutachter:
Prof. Dr. Dr. Giacomo Corneo, Freie Universität Berlin

Zweitgutachter:
Prof. Dr. Viktor Steiner, Freie Universität Berlin

Tag der Disputation:
12. Dezember 2017

Zusammenarbeit mit Koautoren und Veröffentlichungen

Kapitel 2

- Koautor: Timm Bönke; Eigenleistung: 50 %
- Veröffentlichungen:
  - Bönke, T., & Neidhöfer, G. (2014). Parental Background Matters: Intergenerational Mobility and Assimilation of Italian Immigrants in Germany. Free University of Berlin School of Business and Economics Discussion Paper 2014/21.
  - Bönke, T., & Neidhöfer, G. (2016). Parental Background Matters: Intergenerational Mobility and Assimilation of Italian Immigrants in Germany. German Economic Review. https://doi.org/10.1111/geer.12114

Kapitel 3

- Koautor: Maximilian Stockhausen; Eigenleistung: 50 %
- Veröffentlichungen:
  - Neidhöfer, G., & Stockhausen, M. (2016). Dynastic Inequality Compared Multigenerational Mobility in the US , the UK , and Germany. Free University of Berlin School of Business and Economics Discussion Paper 2016/22.

Kapitel 3

- Keine Koautoren; Eigenleistung: 100 %
- Veröffentlichungen:
  - Neidhöfer, G. (2016). Intergenerational Mobility and the Rise and Fall of Inequality: Lessons from Latin America. Free University of Berlin School of Business and Economics Discussion Paper 2016/3.

Kapitel 4

- Koautoren: Joaquin Serrano und Leonardo Gasparini; Eigenleistung: 33,33 %
- Veröffentlichungen:
  - Neidhöfer, G., Serrano, J., & Gasparini, L. (2017). Educational Inequality and Intergenerational Mobility in Latin America: A New Database. Free University of Berlin School of Business and Economics Discussion Paper 2017/20.

Intergenerational Mobility in Developed and Developing Countries

Guido Neidhöfer

Contents

Part I.

Introduction

Motivation & Contribution

Ever since humans organize within societies anecdotal evidence suggests that the power of affluent families over certain resources may persist over the course of time. Recent research finds, however, that substantial differences exist in the degree of intergenerational persistence of wealth and social status between societies, economic systems, and even groups of people. For instance, in modern egalitarian societies social mobility is generally higher than in industrial economies with high income inequality (Björklund and Jäntti, 1997); among small-scale human populations, pastoral and agricultural societies show higher levels of wealth transmission within families than foraging bands (Borgerhoff Mulder et al., 2009); and the children of migrants are generally more upwardly mobile than the average of the native population in their host country (Borjas, 1993). The evaluation of these differences, which may ground in institutional characteristics, production technologies or cultural factors, is crucial to deepen our understanding of the existence of economic inequality, its persistence, and the factors associated with it.

The analysis of intergenerational persistence – or its antonym, *intergenerational mobility* – allows furthermore to address important issues concerning social justice and equality of opportunity. For instance, if a substantial economic gap between families exists in one generation, how likely is it that the magnitude of this gap persists in the following generations? How likely is it that families change their ranks on the social ladder? And, does the degree of association between parents' and children's outcomes change over time, possibly as consequence of a policy reform such as in the field of education? The answers to these questions help us to understand the degree to which social policies and structural changes may persistently affect the roots of social stratification.

This dissertation deals with four different topics where intergenerational mobility takes an important part in the analysis: i) the economic assimilation of immigrants in the host country, ii) the long-run (or dynastic) persistence of socio-economic status, iii) the detrimental effect of high levels of income inequality on equality of opportunity, and iv) economic performance and human development. The overall contribution of this work is to give a multifaceted analysis of the intergenerational persistence of economic inequality, as well as the causes and consequences associated with this phenomenon.

Henceforth, the focus of the analysis will be on intergenerational mobility measured as the association of parental background with the educational achievements of their children. To explain the existence of this association, theoretical and empirical studies across many disciplines have identified several interrelated channels of intergenerational transmission:

among others, parental investments in the human capital of their children, bequests, the genetic transmission of earning abilities, and the heritage of certain values and cultural identities (see e.g. Sacerdote, 2010). Most economic models of intergenerational transmission are built on the main assumption that parents derive utility, apart from their own present consumption level, also from the future consumption level of their children. Furthermore, parents may have direct "warm-glow" benefits from bequests and investments in their children's human capital. Hence, following the seminal model developed by Becker and Tomes (1979) and the adaptations performed by Solon (1999), one of the established ways to conceptualize the *rise and fall* of families within the distribution resulting from parent-child transmissions is through the following autoregressive process of the first order:

$$Y_i^t = \alpha + \beta Y_i^{t-1} + \varepsilon_i,$$

where Y is a measure of socio-economic status, permanent income or lifetime earnings for two subsequent generations $(t-1, t)$ within family i. For simplicity, the model so far assumes perfect assortative mating and only one child per family. In this equation, α is the average level of Y common to all individuals in generation t, and ε an idiosyncratic shock. The coefficient β measures the degree of transmission from parents $(t-1)$ to children (t). Higher values of β display a higher association between parents' and children's well-being, and therefore a lower intergenerational mobility, and vice versa.

Based on this conceptual framework, in the following chapters parental background and the socio-economic status of children are measured by educational attainment. Additionally, measures are computed that indicate the relative educational position of an individual and his or her parents with respect to their reference groups, defined as the group of people competing for positions on the labour market (e.g. people born in the same year, living in the same country etc.). Hence, besides measuring educational mobility in absolute terms, the intergenerational association of social status is approximated adopting an outcome measure that is closer to the concept of human capital and accounts for the relative value of educational attainments on labour market outcomes. The latter constitutes a methodological contribution of this work to the literature on intergenerational mobility.

Contribution This thesis comprises four self-contained empirical analyses that build on the economic model of intergenerational transmission briefly summarized above. The studies follow similar empirical strategies, appositely extended to be suitable to answer the respective research questions.

The first Chapter entitled "Intergenerational Mobility and the Assimilation of Immigrants" is based on Bönke and Neidhöfer (2016). In this study, we analyse the intergenerational assimilation of a large and homogeneous group of low skilled immigrants that have been argued in the past to integrate rather unsuccessful into native society. An intergenerational assimilation model by Dustmann and Glitz (2011) is tested empirically on German household survey data and validated against registry data uniquely provided for this study by the Italian Embassy in Germany. Our results highlight that Italian second generation immigrants show high rates of intergenerational mobility. Furthermore, after controlling for parental educational background, Italian second generation immigrants are not less likely than natives to achieve a high schooling degree. Hence, these findings suggest that the overall lower educational outcomes of children born to Italian immigrants do not reflect a failed integration of Italians into the German society. Rather, when taking account of the lower educational achievements of their parents in comparison to the native population, they reflect the process of an ongoing assimilation, which is driven by high intergenerational mobility. We argue that these findings are not specific to the group of Italian immigrants in Germany but are rather generally applicable to the intergenerational assimilation of large and homogeneous groups of migrants in a setting where ethnic background and peer behaviour inside the immigrant group could hypothetically undermine successful integration into native society.

The second Chapter is entitled "Intergenerational Mobility and the Long-Run Persistence of Human Capital" and based on Neidhöfer and Stockhausen (2016). This study extends the common two-generational framework usually applied in the literature on intergenerational mobility and evaluates the association between the socio-economic status of grandparents and grandchildren. The main contribution of this work is to analyse long run social mobility patterns in a cross-country setting using harmonized survey data sets. On the grounds of highly comparable estimates across countries we are able to test recent theories of multigenerational persistence of socio-economic status postulated by scholars. For instance, we apply an estimation procedure proposed by Braun and Stuhler (2016a) to estimate a so called *heritability parameter* that enables to verify the existence of a "universal law of social mobility" (see Clark, 2014). Furthermore, we test whether the process of intergenerational transmission of human capital follows an autoregressive process of order one – i.e. whether the economic outcomes of offspring are exclusively influenced by the outcomes of their parents – also known as a first order Markov chain and usually assumed in the baseline conceptual framework shown above. Our findings show some clear patterns: First, the validity of a first-order Markov chain in the intergenerational transmission of human capital do not find general support but is rather country-specific. Second, our finding of different heritability parameters across countries and time does not support the existence of a universal law. Third, the direct and independent effect of grandparents' social status on grandchildren's educational outcomes tends to vary by gender and institutional context.

The third Chapter entitled "Intergenerational Mobility and the Rise and Fall of Income Inequality" analyses the relationship between income inequality and intergenerational mobility, based on Neidhöfer (2016). This study is motivated by the fact that countries with high income inequality also show a strong association between parents' and children's economic well-being – i.e. low intergenerational mobility – and is the first to test this relationship in a between *and* within country setup, thus controlling for cross-country heterogeneity. I use two sets of harmonized micro data including different household surveys from 18 Latin

American countries and combine these with panel data at the country level. The results show that experiencing higher income inequality in childhood is associated with lower intergenerational mobility measured in adulthood. Furthermore, the influence of economic growth and public education expenditures is evaluated: both have a positive, significant, and substantial association with intergenerational mobility. Hence, the findings of this study point altogether to the importance of investments in the human capital of disadvantaged children to *level the playing field*, supporting social mobility and equality of opportunity.

The last Chapter is entitled "Educational Inequality, Intergenerational Mobility and Economic Development" and based on Neidhöfer et al. (2017). The main motivation of this analysis is that although the causes and consequences of the intergenerational persistence of inequality are a topic of great interest among different fields in economics, issues of data availability have restricted a broader and cross-national perspective on the topic so far. Based on rich sets of harmonized household survey data, we contribute to filling this gap by computing time series for several indices of relative and absolute intergenerational educational mobility for 18 Latin American countries over 50 years. This chapter introduces the resulting panel data base and describes the observed patterns of intergenerational mobility trends in Latin America. We find that, on average, intergenerational mobility has been rising in Latin America. This pattern seems to be driven by high upward mobility of children from low-educated families, while there is substantial immobility at the top of the distribution. However, significant cross-country differences can be observed which are associated with the degree of assortative mating, income inequality, poverty, economic growth and public educational expenditures, confirming the findings of the previous chapter.

Note: For a better readability of this thesis, the content of the chapters has been slightly changed in comparison to the published versions of the single studies.

Part II.

Essays on Intergenerational Mobility in Developed and Developing Countries

1. Intergenerational Mobility and the Assimilation of Immigrants

Bönke, T., & Neidhöfer, G. (2016). Parental Background Matters: Intergenerational Mobility and Assimilation of Italian Immigrants in Germany. *German Economic Review*.

https://doi.org/10.1111/geer.12114

2. Intergenerational Mobility and the Long-Run Persistence of Human Capital

2.1. Introduction

In many developed countries, the levels of income concentration experienced by current generations are as high as those experienced by their ancestors at the beginning of the 20th century (Piketty, 2014). Although trends of cross sectional inequality are informative in themselves, they neglect the movement of families within the income distribution - as well as their opportunities to improve their socio-economic status - over the course of time. Indeed, theories of justice suggest to focus on both dimensions of inequality: the static dimension, i.e. the income distribution at a given point in time, and the dynamic dimension (Rawls, 1971). The latter can be evaluated analysing the persistence of inequality between generations, or rather its antonym: social intergenerational mobility.

Recently, the relevance of the intergenerational dimension for distributional analyses has gained increasing attention by researchers and policy makers. A growing number of studies evaluates social intergenerational mobility measuring the degree of association between parents' and children's outcomes (e.g. income, earnings, occupation, or educational attainment). However, while this procedure seems to be suitable as a broad measure for equality of opportunity in a society (Chetty et al., 2014c; Corak, 2013a), it is still not clear whether it leads to erroneous conclusions about the persistence of inequality in the long run. For instance, empirical studies show that long run mobility tends to be overestimated if it is extrapolated from the canonical two-generational mobility framework (e.g. Lindahl et al., 2015). Generally, the existing evidence is still mixed and refers to single countries. Researchers drew contrasting conclusions about, first, the long run persistence of socio-economic status, and, second, the existence of a direct effect that grandparents exert on the economic outcomes of their grandchildren. Therefore, it is of scientific importance and political relevance to add further evidence and to empirically verify different facets of intergenerational mobility over multiple generations. One of the main contributions of this study is to provide a comprehensive analysis on the subject in a common framework using harmonized data for three countries with different welfare regimes, the US, the UK, and Germany.

From a normative perspective, the analysis of long run intergenerational persistence of social status is crucial for a social planner who strives to *level the playing field*. Inasmuch, as the degree of intergenerational mobility of today's adults reflects the distribution of opportunities of yesterday's children, the analysis of mobility over three consecutive generations mirrors the circumstances faced by parents investing in their children's human capital. Hereby, since the vast recent literature on multigenerational persistence mainly focuses on single countries, it is valuable to evaluate the role played by the historical and institutional context. In this work, we therefore analyse the long run transmission of social status in three countries with very different institutional characteristics and historical backgrounds, providing comparable and consistent estimates of intergenerational mobility over three generations.

We perform the analysis with data from nationally representative household surveys that allow us to link individuals to their parents' and grandparents', and to reconstruct the educational history of families over three consecutive generations. The surveys are highly comparable and enable us to perform a harmonized cross-country analysis, testing recent theories of multigenerational persistence like Gregory Clark's controversial hypothesis of a "universal law of social mobility" (Clark, 2014). Furthermore, we test for the existence of a direct and independent effect that grandparents exert on their grandchildren, i.e. the part of the association between outcomes which is not mediated by parents. Additionally, to the best of our knowledge, we are the first to empirically account for ethnic capital – i.e the quality of the ethnic environment in which parents make their investments (Borjas, 1992) – within a multigenerational set-up.

Our main findings are the following: We find the strongest association between grandparents' and grandchildren's educational attainment in Germany and substantially lower associations in the UK. The US lies in between. Furthermore, we provide evidence that questions Clark's hypothesis of a fairly low and constant rate of social mobility over time and space. Although we cannot reject all implications of Clark's hypothetical construct, his strongest conclusion that the long run persistence of social status is independent of the specific historical and institutional context finds no support in our data. In particular, we even find cross-country differences in the effect of direct interaction between grandparents and grandchildren.

In Section 2.2 we review the literature on multigenerational mobility and introduce some of the most influential theories of long run persistence. Section 2.3 describes the data. Section 2.4 presents descriptive evidence on intergenerational mobility over two and three generations in the US, the UK, and Germany: First, assessing multigenerational mobility as equalizer of dynastic inequality in 2.4.1; Then, accounting for short-run and long-run mobility trends in 2.4.2; Last, applying non-parametric approaches in 2.4.3. Our test results on the theories of multigenerational persistence are presented and discussed in Section 2.5. Section 2.6 concludes.

2.2. Conceptual Framework and Literature Review

A widely accepted approach to measure multigenerational relationships is through a generalization of the conceptual framework explained in the introduction to this thesis. In particular, multigenerational persistence of socio-economic status is measured estimating the following linear regression model:

$$y_{it} = \alpha + \beta_{-m} \cdot y_{it-m} + \varepsilon_{it}, \tag{2.2.1}$$

where y_{it} is an outcome indicator of the socio-economic status of individual i belonging to generation t, and y_{it-m} of her ancestors' outcomes that date back m generations. The slope coefficient β_{-m} describes how much of the outcome advantage or disadvantage is transmitted within families over m generations on average. Thus, it can be interpreted as the persistence of inequality between families over the course of time.

As explained above, such analysis is usually performed on two subsequent generations, i.e. on parents and children. Since parents are arguably the most influential source for the formation of human capital, the association between parents' and children's outcomes is certainly of primary interest. Furthermore, although the channels of transmission are still not fully investigated, it generally seems plausible to assume a direct effect of parents on their children. Indeed, seminal theoretical contributions in economics on the intergenerational transmission of inequality build on a mainly two generational set up (Becker and Tomes, 1979, 1986; Loury, 1981; Solon, 1992a). In addition, in many available data sets it is possible and less complicated to link parents and children, in contrast to higher ordered ancestors.

If the aim is to predict or extrapolate long run mobility patterns, the straightforward method that follows from the regression based procedure presented in equation (2.2.1) relies on a restrictive assumption, namely that the process is autoregressive of order one, and implies that

$$\beta_{-m} \approx \left(\beta_{-1}\right)^m \quad \forall m \epsilon \mathbb{N}^+.$$

The finding of a directly estimated coefficient which is higher than the extrapolation would suggest ($\beta_{-m} > \left(\beta_{-1}\right)^m$) was defined as "iterated regression fallacy". Stuhler (2014), who introduced the term, proves and extensively discusses the drawbacks of the iteration based extrapolation procedure for the analysis of multigenerational mobility (see also Braun and Stuhler, 2016b).

The topic came up recently because of an increasing interest in the long run persistence of economic inequality. A new wave of studies by economists and sociologists emerged that analyses intergenerational mobility over three or more generations with different methodologies. While older studies mostly did not reject the hypothesis that the underlying process of intergenerational transmission of socio-economic status is of Markovian nature – i.e. that the socio-economic status of grandparents and older ancestors is totally mediated by the status of parents – recent studies basically reject this hypothesis and agree that the iterated extrapolation underestimates the long run persistence of economic inequality. For instance, earlier empirical works on multigenerational mobility did not find any significant association between grandparents' and grandchildren's outcomes, when controlling for parental outcomes (Behrman and Taubman, 1985; Peters, 1992; Ridge, 1974; Warren and Hauser, 1997).[1] This first line of research was, however, more focused on testing the implication of a negative grandparental coefficient as theorized by Becker and Tomes (1979) or finding a direct causal effect of grandparents.

In contrast, recent studies test the iteration procedure against direct or grouped observational data over three or more generations. One of the first empirical studies to show that an extrapolation by iteration might not fully capture the actual degree of intergenerational persistence is Lindahl et al. (2015) using longitudinal data from the Swedish Malmö study. Other recent studies mainly support these findings measuring intergenerational associations over three, four, or even more generations.[2] Two prominent approaches try to explain this divergence between the predicted and the actual degree of intergenerational persistence. The first argues in favour of a so-called *latent factor* that determines the transmission of socio-economic status (Clark, 2014; Clark and Cummins, 2015). The second states that there is a direct and causal effect that grandparents exert on their grandchildren (Mare, 2011, among others).

A commonly adopted way to evaluate the statistical association between grandparents and grandchildren, abstracting from the mediating role of parents, is to estimate a regression which includes both the socio-economic status of parents and grandparents:

$$y_{it} = a + b_{-1} \cdot y_{it-1} + b_{-2} \cdot y_{it-2} + \vartheta_{it}. \tag{2.2.2}$$

Hereby, a positive significant coefficient of grandparents is often interpreted in the sense that an independent effect of grandparents persists over and above the effect of parents. However, as Braun and Stuhler (2016b), Solon (2014a), and Stuhler (2014) point out, the observation of a significant coefficient for grandparental outcomes does not automatically signalize a causal relationship. A direct causal effect of grandparents is a possible explanation, but omitted variable bias could explain a positive grandparental coefficient as well. Omitted

[1] One exemption is Hodge (1966) who rejects the hypothesis of a first-order Markov chain in the transmission of occupations. For a review of earlier literature on multigenerational mobility, see also Warren and Hauser (1997).

[2] Recent studies evaluate the intergenerational persistence of distinct outcomes over three or more generations, such as earnings (Lindahl et al., 2015; Lucas and Kerr, 2013), wealth (Adermon et al., 2015), occupation (Chan and Boliver, 2013; Hertel and Groh-Samberg, 2014; Knigge, 2016), education (Braun and Stuhler, 2016b; Celhay and Gallegos, 2015; Kroeger and Thompson, 2016), cognitive abilities (Hällsten, 2014), longevity (Piraino et al., 2014), and mental health (Johnston et al., 2013). Studies that measure the transmission over more than four generations mostly do not rely on direct family linkages, but instead use the informative content of surnames (Barone and Mocetti, 2015; Clark and Cummins, 2015; Collado et al., 2013). Olivetti et al. (2016) estimate intergenerational mobility over three generations using first names. The only studies, apart from the present work, to analyse multigenerational mobility in a framework including more than one country are Clark (2014) and Hertel and Groh-Samberg (2014). For recent exhaustive overviews, see Pfeffer (2014); Solon (2014a).

variables could be, for instance, the education or occupational status of the other parent. *Ethnic capital*, understood as the quality of the ethnic environment in which parents make their investments, might be another factor of interest, which has been found to play an important role for the intergenerational transmission of human capital (Borjas, 1992). Indeed, the *latent factor model* argues that b_{-2} is positive and significantly larger than zero when estimating equation (2.2.2), because the variable included to measure the socio-economic status of grandparents captures an unobserved part of parents' socio-economic status which is fundamental for the intergenerational transmission mechanism; i.e. any kind of endowment, like abilities, preferences, or cultural heritage (see Clark and Cummins, 2015).

2.2.1. *The latent factor model*

Braun and Stuhler (2016b) formalize the association between the observable outcome y_{it} and the unobservable endowment e_{it} following the *latent factor model* as

$$y_{it} = \rho e_{it} + u_{it} \tag{2.2.3}$$

$$e_{it} = \lambda e_{it-1} + v_{it} \tag{2.2.4}$$

in a one-parent one-offspring family setting, assuming that both error terms u_{it} and v_{it} are uncorrelated with other variables and past values. The parameter λ can be interpreted as a "heritability" coefficient and captures the degree of unobservable endowments passed on from generation $t-1$ to generation t. The parameter ρ is called "transferability" coefficient and measures the scope of inherited endowments that can be converted into the observed outcome. If the variances of y_{it} and e_{it} are normalized to one, the observed correlation in outcome y between generation t and generation $t-m$ comes up to

$$\beta_{-m} = \rho^2 \lambda^m. \tag{2.2.5}$$

Therefore, multigenerational persistence is higher if both the degree of inheritability λ and transferability ρ is higher. As Braun and Stuhler (2016b) show, estimating equation (2.2.1) for children's on parents' status and grandparents' status separately, using direct individual observations which can be linked over three generations (instead of grouped observations over surname groups as in Clark and Cummins, 2015), λ and ρ can be identified as

$$\frac{\beta_{-2}}{\beta_{-1}} = \frac{\rho^2\lambda^2}{\rho^2\lambda} = \lambda, \tag{2.2.6}$$

$$\sqrt{\frac{(\beta_{-1})^2}{\beta_{-2}}} = \rho. \tag{2.2.7}$$

Since constant variances are assumed, the regression coefficients equal the correlation coefficients. Adopting this specification, Braun and Stuhler (2016b) test the hypothesis made by Clark (2014) on the heritability coefficient λ, and on the existence of a "universal law" of multigenerational persistence, i.e. the true rate of intergenerational persistence is almost the same in every country and time period. Using their own estimated correlations for Germany and the estimates in Lindahl et al. (2015) for Sweden, they find evidence against a constant heritability coefficient. Besides, their estimates for λ are significantly lower than the value suggested by Clark (0.75).[3]

2.2.2. *The grandparental effect model*

Another branch of research tries to explain the excess persistence arguing that differences in status inequality across generations are not exclusively transmitted from parents to children. Grandparents might exert a direct and independent effect on their grandchildren, too, for example by investing in their grandchildren's human capital and by shaping their preferences while living in the same multigenerational household (e.g. Mare, 2011; Pfeffer, 2014). Other sorts of direct effects of grandparents could lie in the genetic transmission of certain traits that "jump" a generation, the strength of family networks or reputation, and the role of inheritances. A discussion of the ways in which grandparents can affect their grandchildren can be found e.g. in Kroeger and Thompson (2016) and Solon (2014a). All these are possible explanations of a positive significant grandparental coefficient in equation (2.2.2) which go beyond technical issues like measurement error and omitted variable bias as discussed above.[4] So, to test for a direct effect of grandparents, abstracting from merely technical reasons driving the statistical relationship, requires an extension of the baseline model displayed in equation (2.2.2).

A common approach is to include additional variables to control for other socio-economic characteristics of the parents. For instance, information on the outcomes of both fathers and mothers are included in the regression instead of taking only the highest or the mean of the two. This way, unobserved characteristics that might explain the underlying transmission of status are covered more properly and a positive significant grandparental coefficient is a closer indicator of a direct relationship. However, the grandparental coefficient could still be biased upward due to the omission of other characteristics. *Ethnic capital* is an important feature that has been found to largely explain the different patterns of intergenerational transmission from parents to children between blacks and whites or natives and immigrants (e.g. Borjas, 1992). A similar relationship might also exist in a three-generational framework and is, thus, of particular importance. Our data allows to analyse this aspect controlling for

[3]Further evidence against such a high heritability coefficient is provided in a recent study by Nybom and Vosters (2016) within a two-generational set up. Including multiple proxy measures of parental background into a single estimate of status persistence, the authors find no evidence of bias in prior estimates of social intergenerational mobility in Sweden.

[4]For an overview of factors that might explain the excess persistence see, among others, Solon (2014a). A recent theoretical examination of multigenerational persistence based on *careers* can be found in Zylberberg (2016).

migration background and race of individuals.

Another approach is to use information on direct contact between grandparents and grandchildren – or on a higher likelihood of contact between them – and compare the regression coefficients of individuals with and without direct contact to their grandparents. This method allows to account for intergenerational effects from grandparents to grandchildren generated by direct contact abstracting from those direct links that should be the same for individuals with and without a direct contact to their grandparents, which includes the genetic transmission of traits or the role of family networks. When information on exposure or coresidence are directly available, the analysis is straightforward. For example, Zeng and Xie (2014) show for rural China that the effect of grandparental education on school dropout is significantly stronger for coresident grandparents than for those who are not living in the same household as their grandchildren. However, when this information is not available, a common procedure is to use information on the year of death of the grandparents and check if the grandparent died before the grandchild was born, which is the identification strategy adopted also in the present study. Braun and Stuhler (2016b) apply this strategy, too, and find no significant difference between the regression coefficients of grandparents who died before their grandchildren were born and grandparents who were still alive.[5]

2.2.3. *Universal law of social mobility and the role of institutions*

A remarkable difference between the *latent factor model* and the *grandparental effect model* is related to their implications about the role of institutions to affect intergenerational mobility and the persistence of inequality. While the former argues that social policy interventions can only change short run patterns of social mobility, without having any effect on the long run effects of dynasties, the latter stresses the importance of the environment. Mare (2011) argues, for example, that the effect of grandparents on their grandchildren might vary between and within countries, and depend on the historical and institutional context. Indeed, recent empirical findings for different countries seem to confirm this theory. For instance, while Zeng and Xie (2014)'s findings point at the existence of a direct effect of coresident grandparents on their grandchildren in rural China, the application of LaFave and Duncan (2014) to Indonesia shows no effect of grandparental resources on grandchildren's human capital.

To investigate the importance of the institutional context and to test the hypothesis of a "universal law" of social intergenerational mobility, we propose a novel approach. First, we analyse time trends in the intergenerational persistence of human capital over two and three generations for different cohorts. Then, we pool the samples of the three countries and allow for country-specific intercepts. Technically, this procedure should reduce the omitted variable bias deriving from differences in institutions and enable to evaluate whether a common

[5]Since Braun and Stuhler (2016b) find a significant correlation between year of death and the education of grandparents, they present further applications using World War II as an exogenous source of variation in the time of death. All tests on this behalf confirm their main results.

behaviour exists between societies in the transmission of inequality over two and three generations, while abstracting from characteristics which should be equally transmitted from grandparents and parents to children across countries. In addition, as mentioned above, our data allows us to control for migration or ethnic background. Thus, we are able to model potential between-group differences in intercepts (see Solon, 2014a).

2.3. Data

Our analysis is based on three very similar and nationally representative longitudinal household surveys: i) the *German Socio-Economic Panel* (SOEP) for Germany, ii) the *Panel Study of Income Dynamics* (PSID) for the US, and iii) the *British Household Panel Survey* (BHPS) for the UK which we extend by information from the follow up survey *Understanding Society* (UKHLS). Using these surveys has several advantages for our analysis: First, the data sets are highly comparable and they are designed upon similar schemes. Indeed, SOEP, PSID and BHPS/UKHLS are part of the Cross-National Equivalent File (CNEF) where different data sets are harmonized for cross-national comparisons (see Frick et al., 2007). Second, socio-economic conditions of respondents and their family members are carefully reported over time, even when children leave their initial household. Third, the three data sets entail retrospective questions on parental characteristics. These information allow us to reconstruct the educational history of families over three consecutive generations. Since important structural differences affected individuals living in East and West Germany before and after reunification we restrict our German sample to families residing in West Germany before reunification.

The main challenge is to find a measure for human capital and socio-economic status that is i) available for grandparents, parents and children, and ii) comparable across countries and generations. An ideal measure would account for generation-specific differences due to educational institutions as well as country- and time-specific differences in the capability to generate income in the labour market. We approximate these concepts with a widely accepted measure for the human capital stock of an individual: completed years of education.

Table 2.1.: *Descriptive statistics*

	Germany				USA				UK			
	Year of Birth	Education	s.d.	N	Year of Birth	Education	s.d.	N	Year of Birth	Education	s.d.	N
Children	1972	12.56	2.609	3210	1970	13.95	2.258	6303	1975	12.87	2.724	1532
Fathers	1942	11.53	2.445	2893	1942	12.88	3.226	5589	1946	10.84	4.066	1413
Mothers	1945	10.68	2.057	3135	1944	12.86	2.563	6268	1948	10.21	3.965	1516
GF-F	1917	10.71	3.450	2672	1927	11.06	3.962	5539	1920	9.74	3.922	964
GM-F	1913	9.08	3.133	2677	1925	11.64	3.355	5319	1917	8.14	3.651	960
GF-M	1913	10.73	3.305	2913	1924	11.01	4.005	6202	1918	9.72	4.008	1374
GM-M	1910	9.24	2.980	2948	1923	11.50	3.473	6068	1914	8.29	3.797	1368

Notes: Means, standard deviations, and number of observations. Education measured in completed years of education. GF/GM-F/M: Grandfather/Grandmother-Father's/Mother's side.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Completed years of education includes the regular years of schooling needed to obtain the indicated educational degree (measured in ISCED levels) and accounts for vocational training and tertiary education as well as for the skill level (measured in ISCO levels). Using education to measure socio-economic status reduces potential measurement error in intergenerational mobility estimates since individuals tend to be well informed about their own and their parents' highest obtained educational attainment (Black and Devereux, 2011a). Furthermore, in contrast to earnings, the highest educational attainment is obtained relatively early in life and is less volatile over the life-cycle. Detailed information on the data and the exact codification of completed years of education for children, parents, and grandparents can be found in the Additional Material.

For a matter of fact, due to the structure of the educational system, in the UK it might be less appropriate to adopt a continuous measure like years of education when measuring intergenerational mobility (Dearden et al., 1997). We address this issue measuring mobility also by correlation coefficients and by adopting an outcome variable that indicates the relative standing of individuals and their ancestors. To obtain this measure, which is conceptually even closer to the notion of human capital and comparable across countries and time periods, we perform a linear transformation of the relevant outcome variables for grandparents, parents, and children. The transformation yields the standard score (Z-Score) of educational achievements by cohorts:

$$z_{ijT} = \frac{y_{ijT} - \bar{y}_{jT}}{\sigma_{jT}}. \tag{2.3.1}$$

Here, $\bar{y}_{jT}$ and σ_{jT} are the mean and standard deviation of completed years of education of all individuals from generation $T \epsilon \{t, t-1, t-2\}$ in cohort j. The cohort refers to the cohort of the children's generation. This measurement gives the relative standing (in standard deviations) of an individual, his parents, and grandparents with respect to their reference groups, i.e. people competing with them in the labour market.

The main strength of this approach is the higher comparability between countries and time periods, accounting especially for the expansion of educational attainment in the second half of the 20th century that took place in all three countries under examination.[6] The Z-Score is adopted to built quantiles of children's, parents', and grandparents' relative educational position that are used to display transition matrices and mobility curves. As further robustness check, we also run the complete analysis using the Z-Score of educational attainment instead of the completed years of education. As usually done in the literature, we will refer to the parents' and grandparents' education (educational position) as the completed years of education (the Z-Score) of the parent and grandparent with the highest educational

[6]Standardizing the outcome variables by adopting Z-Scores yields regression estimates which are similar to the correlation coefficients (reported below the tables) with one important difference: The correlation coefficient is standardized by the variances of the entire sample, while our transformation compares individuals with their respective cohort. Furthermore, applying the transformation on the outcome variables instead of the estimated parameter allows us to test the coefficient of grandparents against zero, controlling for parents, within a simple regression.

attainment (educational position) within the family (Black and Devereux, 2011a). In further analyses we also disentangle this measurement and analyse the education (educational position) of fathers, mothers, and all four grandparents, separately.

We draw the same sample in each survey. For our analysis, we need families that participated in the respective survey for at least two generations and where the first participating generation (parents; generation *t-1*) has available retrospective information on their father's or mother's educational attainments and occupation. We integrate this information to a measure for grandparents' education (generation *t-2*) and associate it to adult children (generation *t*) with available information on educational attainment. Our samples consist of individuals born between 1960 and 1985 with available information on the educational attainment of at least one of their parents as well as grandparents. In addition, individuals have to be at least 28 years old at the time of their last interview. The age restriction helps us to reduce bias due to uncompleted educational biographies and is justified empirically by observing patterns in our data: the mean of completed years of education is stable from the age of 28 onwards.

Table 2.1 shows the weighted means and standard deviation of completed years of education observed in our samples over three generations. In all three countries, educational attainment has substantially increased over generations. The US sample shows the highest averages, while educational attainments are lower and rather similar in Germany and in the UK. These patterns match with the ones found in other data sets on cross-national educational achievements.[7]

2.4. Descriptive Evidence on Multigenerational Mobility

2.4.1. *Dynastic inequality*

First, we look at changes in the distribution of educational attainment over time. For this purpose, we measure the degree of inequality in the distribution of completed years of education for each generation and the degree of inequality in the distribution of family means across generations. The resulting analysis is close to the one proposed by Shorrocks (1978b) and mirrors the concept of dynastic inequality (Jäntti and Jenkins, 2015). Table 2.2 shows short and long-run (dynastic) inequality for each country, as well as two indices to account for multigenerational mobility as an equalizer of long term inequality. Three different inequality measures are applied that share the characteristic of strong Lorenz-dominance, but differ in their sensitivity towards changes along the distribution: i) Gini coefficient, which reacts stronger to changes at the middle of the distribution; i) Theil index, which is sensit-

[7] A comparison of mean years of schooling observed in the Barro-Lee data on educational attainment as well as an analysis of selectivity issues regarding the analysed sample are included in the Additional Material.

Table 2.2.: *Multigenerational mobility as an equalizer of dynastic inequality*
(a) Germany

	t	*t-1*	*t-2*	*Family Mean*	*M(S)*	*M(F)*
Gini	0.117	0.107	0.136	0.101	0.719	0.256
s.e.	*0.0011*	*0.0015*	*0.0033*	*0.0016*	*0.0033*	*0.0144*
Theil	0.022	0.020	0.047	0.017	0.811	0.642
s.e.	*0.0004*	*0.0005*	*0.0033*	*0.0005*	*0.0090*	*0.0134*
CV	0.209	0.204	0.276	0.182	0.736	0.339
s.e.	*0.0020*	*0.0023*	*0.0062*	*0.0029*	*0.0052*	*0.0113*

(b) USA

	t	*t-1*	*t-2*	*Family Mean*	*M(S)*	*M(F)*
Gini	0.089	0.100	0.144	0.090	0.711	0.376
s.e.	*0.0011*	*0.0013*	*0.0024*	*0.0012*	*0.0075*	*0.0069*
Theil	0.012	0.018	0.046	0.014	0.769	0.693
s.e.	*0.0003*	*0.0006*	*0.0013*	*0.0005*	*0.0160*	*0.0076*
CV	0.166	0.187	0.276	0.162	0.722	0.412
s.e.	*0.0035*	*0.0027*	*0.0038*	*0.0022*	*0.0087*	*0.0067*

(c) UK

	t	*t-1*	*t-2*	*Family Mean*	*M(S)*	*M(F)*
Gini	0.100	0.153	0.208	0.113	0.754	0.454
s.e.	*0.0029*	*0.0036*	*0.0032*	*0.0020*	*0.0163*	*0.0130*
Theil	0.024	0.049	0.073	0.021	0.854	0.707
s.e.	*0.0017*	*0.0020*	*0.0027*	*0.0010*	*0.0147*	*0.0154*
CV	0.202	0.291	0.375	0.201	0.768	0.463
s.e.	*0.0054*	*0.0054*	*0.0052*	*0.0042*	*0.0114*	*0.0125*

Notes: Gini, Theil and Coefficient of Variation. *t, t-1, t-2* are the generation of children, parents and grandparents, respectively. *Family mean* is the mean of completed years of education over three generations. *M(S)* is the mobility index proposed by Shorrocks: $M(S) = 1 - \frac{I(\sum_{T=t-2}^{t} y_T)}{\sum_{T=t-2}^{t} w_T I(y_T)}$ with $w_T = \bar{y}_T / \bar{y}_F$. *M(F)* is the mobility index proposed by Fields: $M(F) = 1 - \frac{I(\sum_{T=t-2}^{t} y_T)}{I(y_{t-2})}$. $I()$ denotes the inequality index, y_T is the outcome in generation T, and $\bar{y}_F$ the family mean. The closer the value is to one, the greater is mobility in both indeces. Bootstrapped s.e. with 100 replications.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

ive to changes at the lower middle of the distribution; and iii) Coefficient of Variation (CV), which is more sensitive to changes at the top of the distribution. The two computed mobility measures are the ones proposed by Shorrocks (1978a) and Fields (2010). The first relates dynastic inequality to the weighted inequality in all generations, the second evaluates mobility as equalizer of long term outcomes relative to the initial shape of the distribution.

In all countries, we find decreasing inequality in completed years of education from the grandparents' to the children's generation. The UK shows relatively high inequality of educational attainments in the grandparents' and parents' generation, but also the highest degree of mobility. Inequality in children's completed years of education tends to be the largest in Germany. The US tend to be the country with the lowest educational inequality. The evaluation of differences in mobility between Germany and the US depends on the applied measure. Measuring mobility relative to the initial level of inequality – i.e. in the grandparents generation – Germany is less mobile to a larger extent than measuring it with respect to the overall distribution.

It is expedient to compare short-run inequality with dynastic inequality. It has been argued that whenever dynastic inequality is less than inequality in any given generation there was some equalizing mobility between generations (Jäntti and Jenkins, 2015). In our analysis, Germany is the only country with dynastic inequality being lower than cross-sectional inequality in every generation and for all measures. In the US, inequality in the children's generation is lower than dynastic inequality if measured by the Gini and Theil index. In the UK, inequality in generation t is lower than dynastic inequality measured by the Gini index, but higher or equally large for the other two measures. In conclusion, mobility acts as an equalizer of dynastic inequality in all three countries, especially in Germany, although the impacts on the distribution are of distinct magnitude.

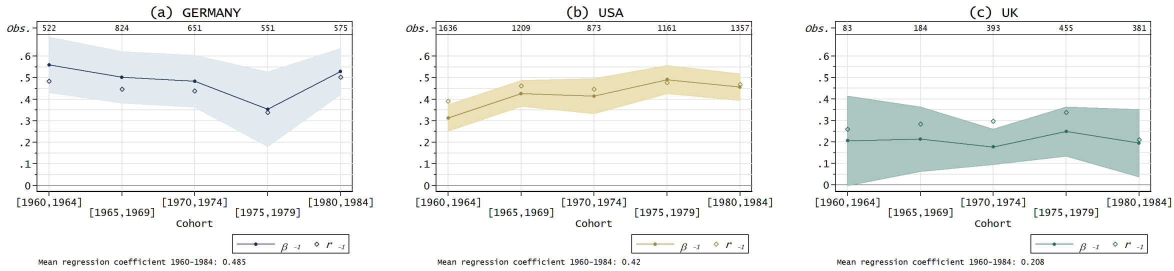
2.4.2. *Multigenerational mobility trends*

In this part, we show trends of multigenerational mobility. Figure 2.1 depicts two indicators which measure the degree of intergenerational mobility over two and three generations experienced by different cohorts: i) The regression coefficient, β_{-m}, obtained by regressing children's education on parents' ($m = 1$) or grandparents' ($m = 2$) education, measured in completed years of education; ii) The correlation coefficient, r_{-m}, which accounts for changes in the distribution of educational attainments ($r_{-m} = (\sigma_{-m}/\sigma_0)\beta_{-m}$). Here,$\sigma_0$ is the standard deviation of educational attainment in the children's generation.

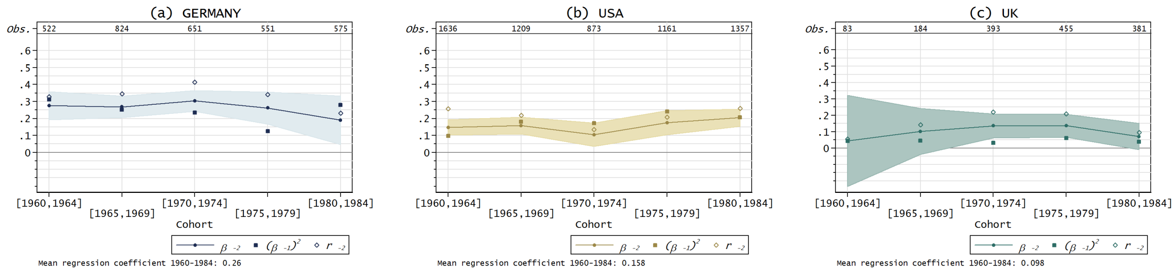
Mobility patterns generally differ between countries and confirm earlier findings on cross country comparisons of educational correlations (see e.g. Hertz et al., 2007). Panel A shows the two generation case, i.e. parents and children. Educational mobility is the lowest in Germany with an average regression coefficient of 0.49, and is higher in the US and the UK where coefficients are 0.42 and 0.21, respectively. The development of mobility rates is, however, different between the US and the UK. Older cohorts show a relatively high degree of mobility

Figure 2.1.: *Multigenerational Mobility Trends – Regression (β) and correlation (r) coefficients*

Panel A – Two Generations; Parents' on children's education



Panel B – Three Generations; Grandparents' on grandchildren's education



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

in both countries, but mobility decreased in the US by far more for younger cohorts than in the the UK where it remained almost unchanged. Correlation coefficients show similar patterns within countries. A major difference is that correlation coefficients tend to be smaller than regression coefficients in Germany while they tend to be higher in the US and the UK. This relates to changes in the variance of educational attainment over time.

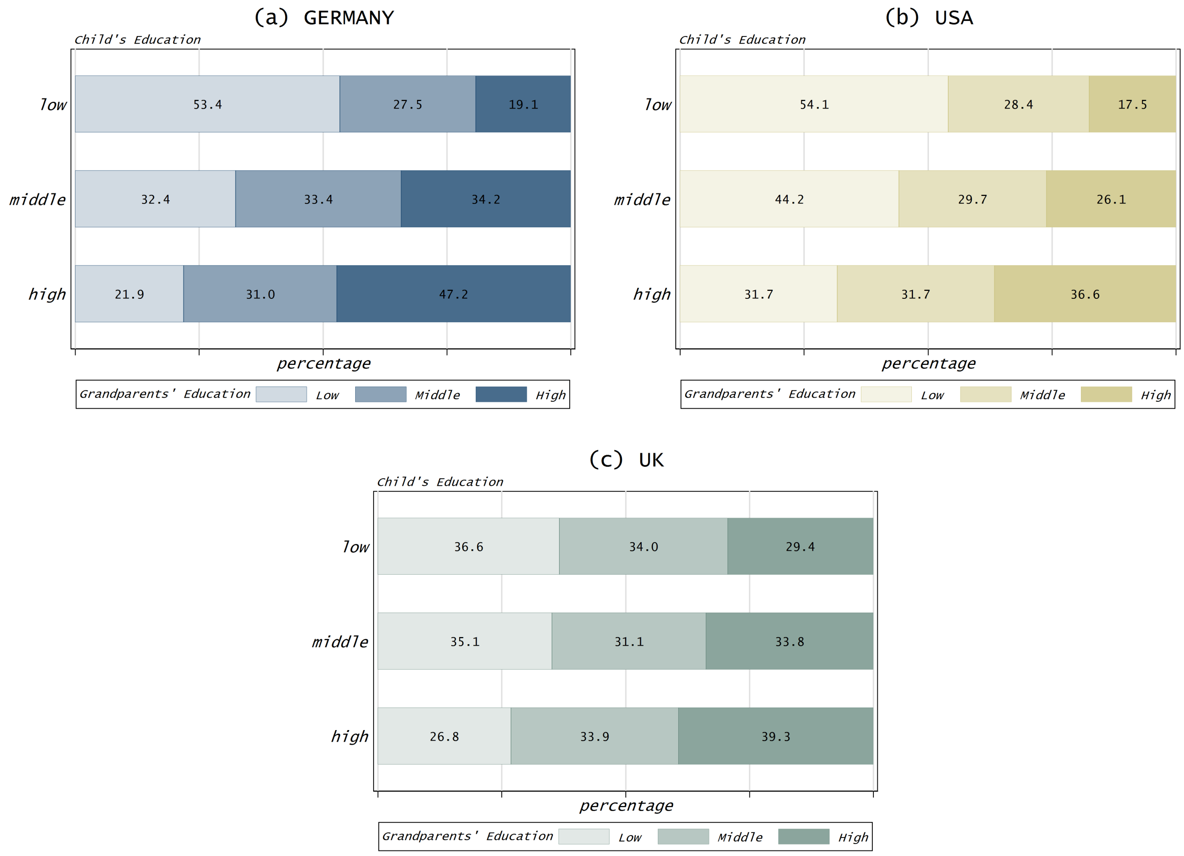
Panel B shows intergenerational mobility over three generations, i.e. grandparents and grandchildren. Although coefficients are substantially smaller and somewhat more stable within countries, the ranking between countries is basically unchanged. On average, ten years of grandparental education are associated to an increase in grandchildren's education of about three years in Germany, one and a half years in the US and less than one year in the UK.

2.4.3. *Transition matrices & mobility curves*

Deeper insights into intergenerational mobility in a cross-country analysis can be derived from non-parametric approaches (Corak et al., 2014). These give further insights on how structural mobility – e.g. because of educational expansion – affects intergenerational mobility in each country and in which parts of the distribution mobility takes place.

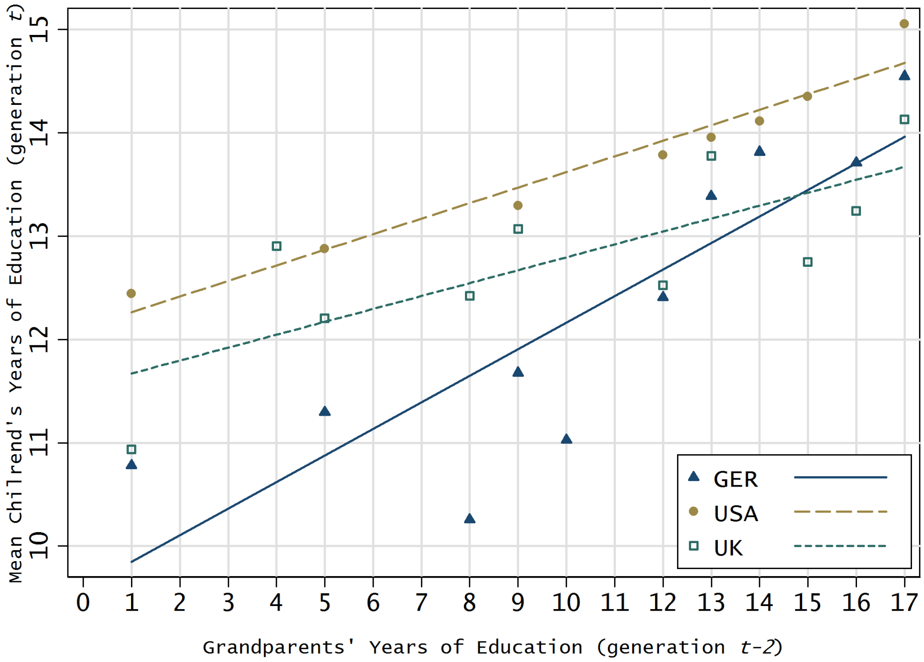
First, we construct mobility matrices which show the percentage of children with low, middle, and high educational attainment for each class of grandparents' educational position; depicted in Figure 2.2. Educational position is based on the Z-Scores of educational attainment by cohorts as explained in Section 2.3. The three quantiles – low, middle, and

Figure 2.2.: *Transition matrices by quantiles of the Z-Score of educational attainment*

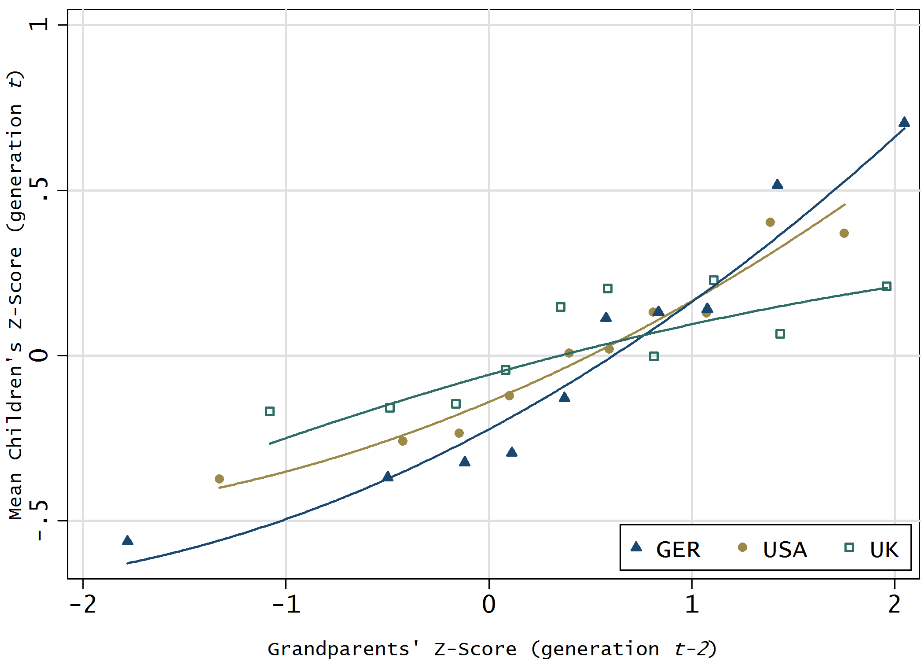


Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Figure 2.3.: *Mobility curves – Mean education of grandchildren by grandparents' education*



(a) *Completed years of education - Linear fit*



(b) *Educational position (Z-Score) - Quadratic fit*

Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

high – display the position within the respective distribution of the cohort's educational attainment. The highest upward mobility from the bottom to the top of the distribution is observed in the US, the lowest in Germany; 31.7 and 21.9 % of children with high education have grandparents with low education, respectively. Interestingly, both countries show a similar persistence at the bottom of the distribution. For instance, in our samples for Germany and the US about 53 and 54 percent of children with low educational position have grandparents in the bottom part of the distribution. In contrast, only 37 percent of the individuals in our UK sample show this pattern. Furthermore, Germany shows the highest persistence at the top of the distribution with 47 percent, while in the US and the UK it is about 37 and 39 percent, respectively.

Second, we compute *mobility curves* over three generations.[8] Figure 2.3 displays the average years of education and educational position of grandchildren for each level of grandparents' education and educational position. Hereby, the former accounts for absolute changes while relative changes within the distribution are registered in the second. This method has the advantage to show how absolute mobility differs over the distribution of grandparents' status. We find differences between countries – especially between Germany and the US – to be marked in the lower part of the distribution. For instance, the average education of grandchildren in the bottom part of the grandparents' distribution is substantially lower in Germany. In contrast, in the upper part of the distribution differences are smaller. Our sample for the UK shows a much flatter curve signalizing higher mobility within the distribution. Generally, differences between countries are less pronounced measuring social status by educational positions rather than years of education. For instance, for lower than average educational attainment of grandparents the mean educational position of the children is lower than the mean of their reference group in all three countries.

2.5. Testing Theories of Multigenerational Persistence

2.5.1. *Iterated regression fallacy*

Table 2.3 shows our estimates of equation (2.2.1) where we separately regress children's education on parents' and grandparents' education, and equation (2.2.2) where we regress children's education on both parents' and grandparents' education. As commonly done in the literature, we only consider the education of the parent and grandparent with the highest educational level within the family (Black and Devereux, 2011a). Estimates for Grandfather-Father-Son and Grandmother-Mother-Daughter lineages are included in the Additional Material (Tables 2.14-2.17) and discussed below. Intergenerational correlation coefficients are reported below the tables. The outcome variable is completed years of education.

The regression coefficients of parents' education in column (1) and grandparents' educa-

[8] Mobility curves are usually applied to measure the mean income rank of children for each rank of their parents (see e.g. Bratberg et al., 2016). See also Chetty et al. (2014a).

Table 2.3.: *Regression analysis - Outcome: Completed years of education*

(a) Germany

	(1)	(2)	(3)
Parents (β_{-1})	0.484***		0.413***
	(0.0295)		(0.0394)
Grandparents (β_{-2})		0.258***	0.101***
		(0.0243)	(0.0297)
Observations	3210	3210	3210

Correlation coefficients: $r_{-1} = 0.451$, $r_{-2} = 0.327$
Test $(\beta_{-1})^2 = \beta_{-2}$: F = 0.8984, Prob > F = 0.3433 ; $(\beta_{-1})^2 = 0.235$

(b) USA

	(1)	(2)	(3)
Parents (β_{-1})	0.400***		0.386***
	(0.0169)		(0.0195)
Grandparents (β_{-2})		0.167***	0.021
		(0.0137)	(0.0150)
Observations	6303	6303	6303

Correlation coefficients: $r_{-1} = 0.453$, $r_{-2} = 0.254$
Test $(\beta_{-1})^2 = \beta_{-2}$: F = 0.2221, Prob > F = 0.6375 ; $(\beta_{-1})^2 = 0.160$

(c) UK

	(1)	(2)	(3)
Parents (β_{-1})	0.208***		0.189***
	(0.0284)		(0.0288)
Grandparents (β_{-2})		0.111***	0.047**
		(0.0210)	(0.0197)
Observations	1532	1532	1532

Correlation coefficients: $r_{-1} = 0.279$, $r_{-2} = 0.163$
Test $(\beta_{-1})^2 = \beta_{-2}$: F = 10.4645, Prob > F = 0.0012 ; $(\beta_{-1})^2 = 0.043$

Notes: Tables show regressions of children's educational outcomes on the outcomes of the parent or grandparent with highest education within the family. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

tion in column (2) confirm the patterns observed before; the UK shows the highest degree of intergenerational mobility, Germany the lowest. In the regression analysis including both, parents and grandparents education, in column (3), the grandparental coefficient is positive in each application, but only significantly different from zero for Germany and the UK. According to these first results, we cannot reject the hypothesis for the US that the intergenerational transmission of human capital follows an AR(1) process, while we reject it for Germany and the UK.

Next, we test if the directly estimated coefficients of grandparents are equal to the ones predicted by the iterative regression procedure, i.e. squaring the coefficient of parents (H_0 : $\beta_{-2} = \beta^2_{-1}$). The tests are reported below the Tables. Although the estimated grandparental coefficients in columns (2) are always greater than the squared parental coefficient, we cannot reject the hypothesis that they are equal for Germany and the US. Performing the same analysis for each cohort separately, we find that the squared parental coefficient neither systematically over nor under predicts the directly estimated grandparental coefficient (see Panel B of Figure 2.1).

As further robustness check, we perform the same analysis adopting the Z-Score of educational attainment measured in comparison to individuals of the same cohort. The observed patterns are the same and results do not change qualitatively applying either measurement. Tables 2.8-2.11 show the main results with this alternative outcome variable, all other estimations applying the Z-Score can be found in the Additional Material. An insightful finding is that applying the Z-Score of educational attainment changes the country ranking between Germany and the US regarding the association between parents' and children's outcomes. Interestingly, our results as well as previous studies on educational mobility found the US to be more mobile than Germany (e.g. Chevalier et al., 2009; OECD, 2015a), while studies on income mobility over two generations mostly found the opposite or, at least, no significant differences between the two countries (e.g. Couch and Dunn, 1997; Schnitzlein, 2015). Thus, we interpret our finding in the sense that the Z-Score yields a better approximation of social status which, indeed, was our primary goal when applying this transformation.

So far, our cross-country results are mixed and show that the validity of the iterated regression procedure to extrapolate long-run mobility estimates varies by countries. The evidence for the US suggests that there is no direct effect of grandparents on grandchildren. However, such a clear statement cannot be made for Germany and the UK at this point of the analysis.

2.5.2. *Latent Factor Model*

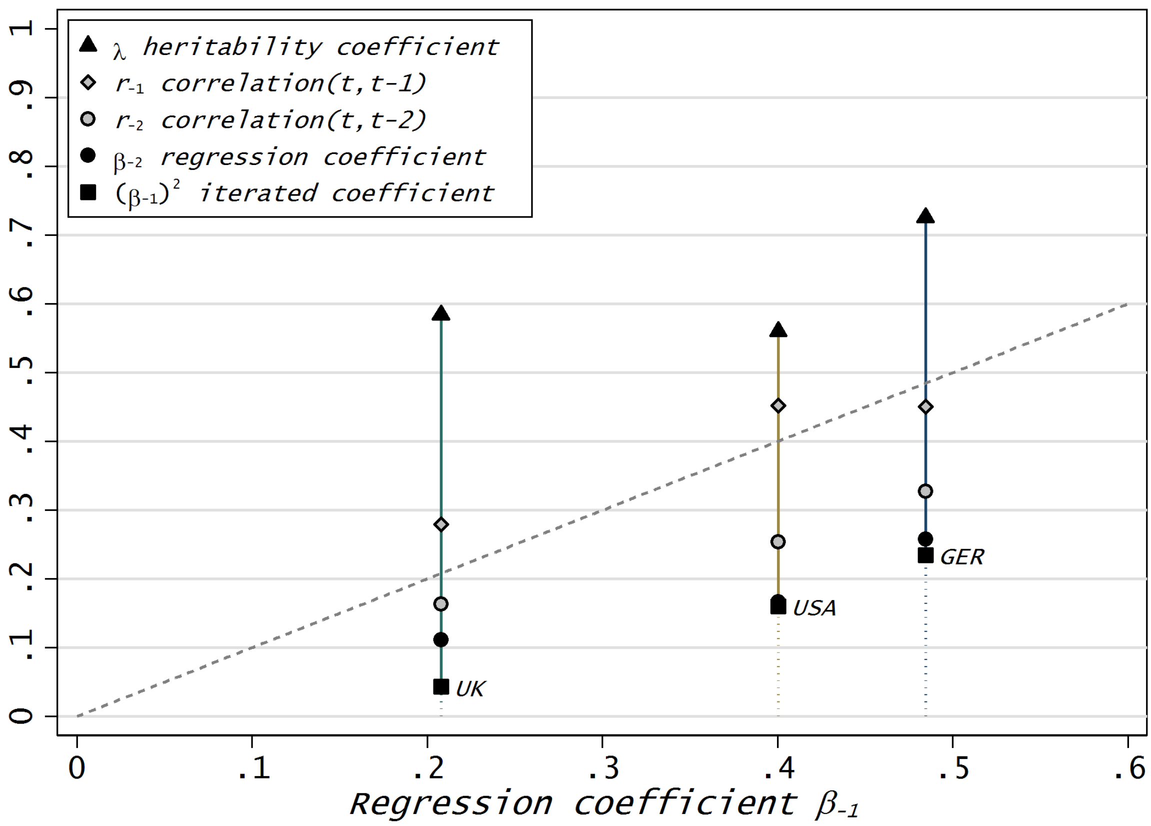
Table 2.4 entails the parameter estimates to test the hypotheses of Clark's latent factor model described in Section 2.2.1. Using the correlation coefficients between children and parents, and children and grandparents, we calculate the heritability coefficient λ and the transferability coefficient ρ as in equation (2.2.6) and (2.2.7). Figure 2.4 sums up the estimated coefficients for each country.

Table 2.4.: *Estimated correlation (r), heritability (λ), and transferability (ρ) coefficients*

	Years of Education		
	GER	*USA*	*UK*
r_{-1}	0.451	0.453	0.279
r_{-2}	0.327	0.254	0.163
λ	0.726	0.560	0.584
s.e.	*0.0602*	*0.0314*	*0.0937*
ρ	0.788	0.899	0.692
s.e.	*0.0464*	*0.0274*	*0.0832*

Notes: Bootstrapped s.e. (200 replications).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

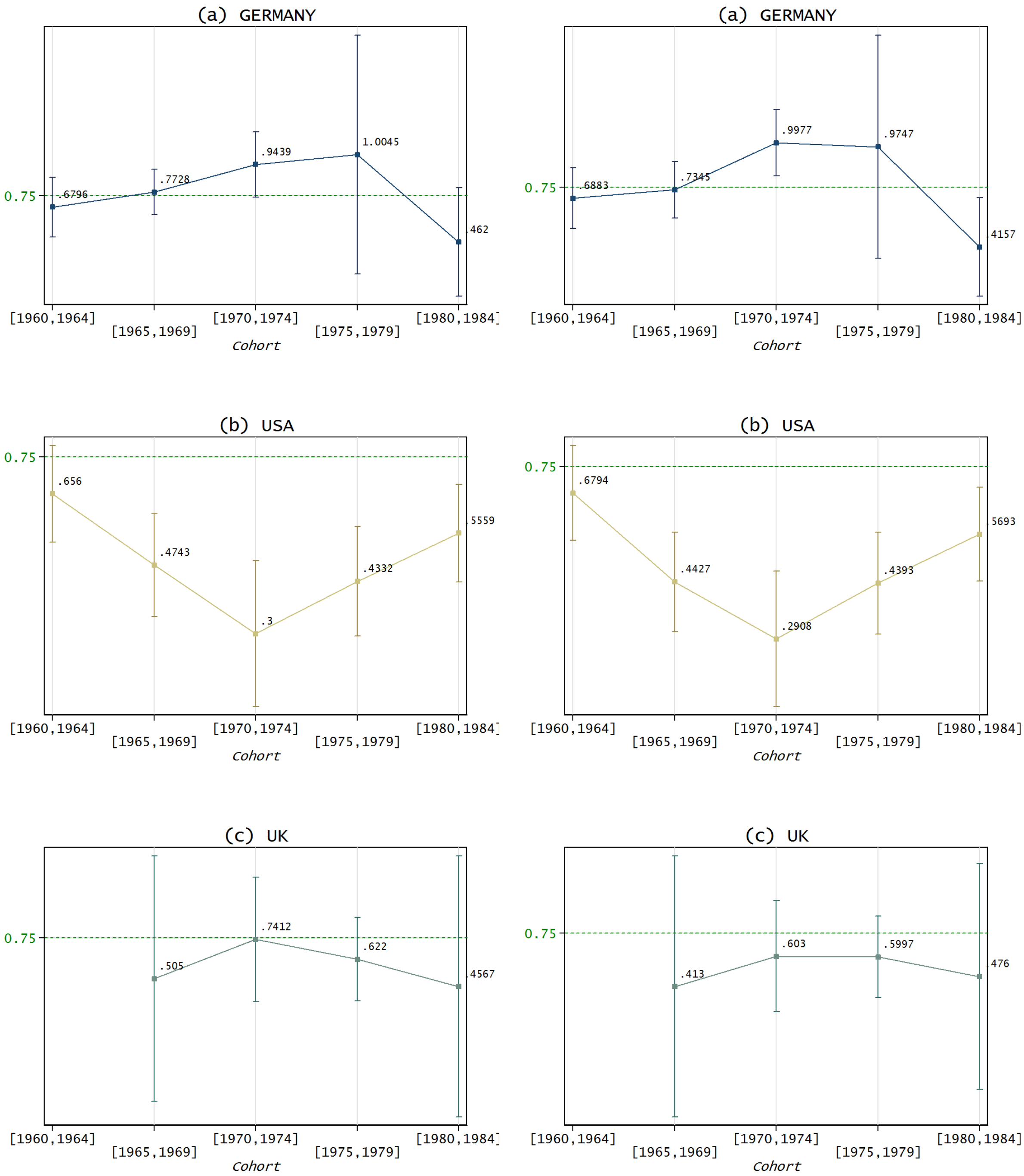
Figure 2.4.: *Summary and comparison of the estimated coefficients*



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Figure 2.5.: *Estimated heritability coefficient (λ) by cohorts*

Panel A – Outcome: Completed years of education *Panel B – Outcome: Z-Score of educational attainment*



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

In our application, λ varies between 0.560 and 0.726 and ρ between 0.692 and 0.899. Clark's hypothesis that λ is larger than the correlation in observed outcomes is confirmed. However, differences between countries are statistically significant: The difference between the estimates for Germany and the US is statistically significant at the 10 % level. The same is true applying the Z-Score instead of completed years of education as outcome variable; the range for the Z-Score is 0.506 to 0.725 for λ and 0.717 to 0.937 for ρ. Furthermore, the heritability coefficient varies also over time: Performing the analysis for different cohorts separately we obtain different values of λ. Figure 2.5 shows the heritability coefficient estimated for different cohorts. Hereby, in some of our estimations we cannot reject the hypothesis of a heritability coefficient being close, equal, or higher than 0.75. In Germany, for instance, some cohorts even display values of λ which are close to unity. However in the US, λ is constantly and significantly lower than 0.75 for the cohorts 1965-69 to 1980-84. The results for the UK also suggest λ to be smaller than 0.75. All in all, we find no clear evidence in favour of Clark's hypothesis that the historical and institutional context does not matter for the movements of families along the distribution in the long run.[9]

Extensions: Lineages, Assortative Mating and Sample Selectivity As further extensions, we account for lineages within families and estimate the rates of assortative mating. When we disentangle the intergenerational transmission in different lineages following son-father-grandfather and daughter-mother-grandmother triplets, the overall results basically do not change (see Tables 2.14-2.17). However, gender specific pathways in the transmission of social status across two and three generations are revealed to some degree. For instance, in all three countries the regression coefficient of maternal education on the education of the daughter is higher than the coefficient of paternal education on sons, while the coefficient of grandfathers on fathers is higher than the coefficient of grandmothers on mothers. Regarding the transmission over three generations, the size of the coefficients of grandfathers on sons and granddaughters on daughters is rather similar in all three countries.

In Germany the positive and significant effect of grandparents on grandchildren, controlling for parents, seems to be mainly driven by the influence of grandfathers on their grandsons. The coefficient of grandmothers on their granddaughter is not significant when controlling for mother's education. These diverging findings might be explained by progressive changes in gender roles, as well as women's educational attainment and labour market participation experienced in industrialized countries in the last decades that led to a decrease in the association in observed outcomes between grandmothers and granddaughters.

[9]As Braun and Stuhler (2016b) point out, large variation in ρ among generations might lead to bias in the estimation of λ. We find large variations in ρ among cohorts in the children's generation, but cannot determinate the direction of the bias, since we have no information on the magnitude of ρ in the parents' and grandparents' generation. For a clear identification of Clark's hypothesis of time varying λ, these information are necessary. Future research with more comprehensive data on three ore more generations over multiple cohorts should address this point.

The results on the US in this sense are even more pronounced. In our previous analysis, we did not find any significant positive effect of grandparents on grandchildren, controlling for the social status of parents. However, there is a significant positive effect of both, grandfathers on grandsons, and grandmothers on granddaughters, if analysed separately. These results indicate that there might be a direct, gender-specific grandparental effect on the educational attainment of grandchildren in the US. The fact that for both lineages we reject the hypothesis of an AR(1) process for the US gives further support to this hypothesis. Finally, in the UK the coefficients of grandfathers on grandsons and grandmothers on granddaughters are both not significant. This might however just be the result of relatively small sample sizes which result in larger standard errors. Finally, although some common behaviours of the intergenerational transmission exist, the country-specific differences found in the main analysis persist when disentangling by different lineages. Regarding the test of the latent factor model, the results point even stronger at different heritability coefficients between countries which are smaller than the hypothesized 0.75.[10]

The analysis of assortative mating – understood as non-random selection of individuals becoming parents – is relevant for the study of intergenerational persistence because the degree of spouse correlation in a society influences mobility parameters (Chadwick and Solon, 2002; Ermisch et al., 2006). Although the baseline model by Becker and Tomes assumes perfect assortative mating, the implications of the latent factor model crucially depend on this feature. Higher spouse correlations in endowments cause higher heritability coefficients. Therefore, large values of λ depend on high and constant rates of assortative mating (see Braun and Stuhler, 2016b). Since endowments are unobservable characteristics, in order to analyse assortative mating we focus on spouse correlations in observable outcomes, i.e. completed years of education and the Z-Score of educational attainment. However, since we mostly have information on both father's and mother's outcomes in our data, our intergenerational mobility parameters are estimated taking the parent with highest education, as usually done in the literature on educational mobility when the characteristics of both parents are available.[11] The highest observable outcome should be an useful approximation of the average unobservable endowment of the two parents. So, the issue of assortative mating in unobservable endowments should influence less our results in comparison to studies that only have information on one parent. Still, it is an interesting dimension to account for; especially its differences between countries and over time.

Indeed, we find substantial differences in assortative mating between countries and generations. The results discussed in this part of the analysis can be found in the Additional Material. Spouse correlations in the parents' and grandparents' generation are about 0.6 and 0.8 in Germany, about 0.4 and 0.8 in the UK, and about 0.6 in both generations in the US, respectively. Hence, assortative mating decreased in all three countries – with the UK

[10]The coefficient r_{-1} used to estimate the heritability coefficient λ is the average of the correlation coefficients of sons (daughters) on fathers (mothers) and of fathers (mothers) on grandfathers (grandmothers).

[11]Estimates of income mobility instead mostly focus on son-father pairs, because lower labour-force participation rates among women cause their earnings to be a unreliable indicator of social status.

showing the largest changes between the grandparents' and parents' generation – but is still a prevalent phenomenon, possibly fostering the intergenerational transmission of social status. These findings are in line with earlier studies on educational assortative mating (alias educational *homogamy*) for the cohorts included in our analysis. In the UK, past studies show a decreasing trend from the cohorts around 1925 to 1960 (Chan and Halpin, 2003). In the US, despite of a general rising trend, assortative mating decreased from 1940 to 1960, which should be exactly the time of marriage of the grandparents and parents in our sample (Schwartz and Mare, 2005). In Germany, assortative mating in education has been rising constantly among natives in the last decades (Grave and Schmidt, 2012). Excluding people with migration background from our analysis we come to the same result.

Interestingly, among the three countries under evaluation there seems to be a negative association between intergenerational mobility and assortative mating: In our analysis, the UK is the country with highest mobility and lowest assortative mating in the parents' generation, while Germany is the one with lowest mobility and highest assortative mating. Another interesting finding is the difference in correlation coefficient among both grandfathers and both grandmothers that is high in Germany and, particularly, in the US, and very low in the UK. A possible reason for the higher degree of intergenerational mobility found in our UK sample could therefore be the weaker intermarriage of elites in the grandparent's generation, which seems to be substantially stronger in the other two countries.

Finally, a sensitivity analysis shows that samples drawn from household surveys might be positively selected in educational attainments. We find that the average years of education of individuals in our samples – restricted by the condition of available information on parents' and grandparents' education – is higher than the mean of the unrestricted sample, weighted by the inverse probability of selection. Furthermore, restricting the sample on the condition to have just information on parental education yields lower regression coefficients. Therefore, our results might be understood as an upper bound for intergenerational persistence. Since the selectivity issue and the direction of a potential bias seem to be the same in the three surveys, the cross-country analysis should hold, as well as the following identification of mechanisms.

2.5.3. *Direct Grandparental Effect*

Next, we test for the presence of a direct and independent effect of grandparents following two different strategies. First, we include more variables capturing different features of parental background to test whether the positive significant coefficient of grandparental outcomes is just an artefact of omitted variable bias or not. Second, we test if the grandparental coefficient varies with the likelihood of grandchild's exposure to the respective grandparent. For this purpose, we use the time of death of the grandparent as exogenous source of variation.[12]

Omitted variables First, we test for the general existence of a grandparental effect. For this exercise, we pool all data sets and perform a similar analysis as before; results can be found in Table 2.5 Panel A. Our data is particularly suitable to control for omitted variable bias, since we mostly have information on both parents and all four grandparents. Furthermore, we can control for the influence of ethnic capital, an essential parental background characteristic, as a possible source of omitted variable bias.[13] In column (1), the coefficient of grandparental education is positive and significant, and gets slightly smaller when allowing country-specific intercepts and slopes as in column (2). To control for ethnic capital, in column (3) a dummy is included in the regression which is one if the individual is non-white in the US and the UK, or has migration background in Germany, and zero otherwise. This dummy is then interacted with the country fixed effects in column (4) to control for country-specific ethnic capital. The coefficient of grandparents decreases when controlling for ethnic capital and country-specific ethnic capital, but is still positive and significantly different from zero.

The next four columns (5) to (8) control successively for the same characteristics as above, but include the completed years of education of both father and mother, instead of only including information of the parent with the highest degree. The resulting coefficient of grandparental education in columns (5) is still positive and statistically significant, but rather small. The coefficient becomes not significantly different from zero when father's and mother's education is interacted with the country dummies in the subsequent estimations, shown in columns (6) to (8). The coefficients of the control variables are mostly significantly different from zero and their inclusion increases the adjusted R-squared of the regressions. So, the persistence of a positive and significant coefficient for grandparental education observed before seems to be mainly driven by omitted variables which cause bias in the estimation of the grandparental effect. We try to further reduce the bias caused by unobserved characteristics of parental social status performing the same analysis applying the Z-Scores of educational attainments. Indeed, in the joint analysis pooling the three samples, the coefficient of grandparental educational position measured by the Z-Score is not significantly different from zero as soon as we control for the education of both parents (see Table 2.10).

[12]As argued, for example, by Braun and Stuhler (2016b), time of death might be correlated with unobserved factors that influence the intergenerational transmission and, therefore, not suitable as exogenous source of variation. However, in our samples we do not find any clear association. The regression coefficient of time of death and grandparental education, measured in completed years of education and by the Z-Score, is mostly not significantly different from zero. Also, the association between year of death and educational attainment when controlling for year of birth is very weak and mostly not statistically significant.

[13]Borjas (1992) originally controls for ethnic capital in the regressions by including the average skill level (measured in earnings) of migrant groups, clustered by their national origin. We adopt a more general approach grouping individuals by their migration status in Germany or ethnicity in the US and the UK. As has been shown in previous studies, the intergenerational mobility of these groups differ significantly from the average mobility of the native population. Hence, controlling for these characteristics should reduce omitted variable bias substantially.

Table 2.5.: *Testing for a grandparental effect: Controlling for multiple features of parental background*

***Panel A – Full sample; Outcome**: Completed years of education*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grandparents	0.060***	0.046***	0.046***	0.042***	0.029**	0.016	0.018	0.014
	(0.0114)	(0.0116)	(0.0117)	(0.0117)	(0.0120)	(0.0122)	(0.0123)	(0.0124)
Parents	0.315***	0.369***	0.368***	0.369***				
	(0.0172)	(0.0186)	(0.0191)	(0.0195)				
GER (0/1) × Parents		0.083**	0.083**	0.077**				
		(0.0336)	(0.0336)	(0.0353)				
UK (0/1) × Parents		-0.180***	-0.179***	-0.176***				
		(0.0333)	(0.0335)	(0.0339)				
Father					0.170***	0.189***	0.192***	0.192***
					(0.0138)	(0.0179)	(0.0180)	(0.0182)
GER (0/1) × Father						0.128***	0.129***	0.122**
						(0.0472)	(0.0471)	(0.0477)
UK (0/1) × Father						-0.082***	-0.084***	-0.081***
						(0.0282)	(0.0284)	(0.0285)
Mother					0.188***	0.226***	0.227***	0.228***
					(0.0152)	(0.0237)	(0.0236)	(0.0238)
GER (0/1) × Mother						0.065	0.067	0.061
						(0.0489)	(0.0488)	(0.0490)
UK (0/1) × Mother						-0.109***	-0.110***	-0.110***
						(0.0313)	(0.0313)	(0.0313)
Country F.E.	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Non-white or Migrant	No	No	Yes	Yes	No	No	Yes	Yes
- (interacted with country f.e.)	No	No	No	Yes	No	No	No	Yes
Adj. R^2	.1788	.2069	.207	.2085	.1912	.2217	.222	.2237
Observations	11045	11045	11039	11039	9769	9769	9764	9764
Clusters	5768	5768	5762	5762	5168	5168	5163	5163

***Panel B – Country-wise; Outcome**: Completed years of education*

	(1) USA	(2) USA	(3) USA	(4) GER	(5) GER	(6) GER	(7) UK	(8) UK	(9) UK
Grandparents	0.020	0.001	0.002	0.096***	0.049*	0.048	0.044**	0.018	0.016
	(0.0152)	(0.0161)	(0.0162)	(0.0316)	(0.0296)	(0.0323)	(0.0198)	(0.0212)	(0.0211)
Parents	0.383***			0.414***			0.192***		
	(0.0202)			(0.0394)			(0.0290)		
Father		0.193***	0.195***		0.304***	0.304***		0.107***	0.110***
		(0.0177)	(0.0180)		(0.0463)	(0.0463)		(0.0223)	(0.0225)
Mother		0.233***	0.233***		0.270***	0.270***		0.117***	0.118***
		(0.0249)	(0.0249)		(0.0437)	(0.0438)		(0.0216)	(0.0215)
Non-white or Migrant (0/1)	-0.095		0.074	-0.081		-0.025	0.763*		0.984**
	(0.1040)		(0.1096)	(0.1724)		(0.1853)	(0.4097)		(0.3921)
Adj. R^2	.2055	.2267	.2267	.2149	.23	.2297	.08382	.08496	.09016
Observations	6303	5554	5554	3210	2818	2818	1526	1397	1392
Clusters	2065	1898	1898	2192	1890	1890	1505	1380	1375

Notes: Cluster adjusted s.e. at family level in parenthesis. Base category is the US. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

The evidence, so far, points therefore against the existence of an independent and direct effect of grandparents, once parental social status is accounted for properly.

However, the fact that a general rule regarding the direct effect of grandparents might not exist does not rule out specific differences caused by institutions. As argued, for instance, by Mare (2011), the effect of grandparents might vary by context and institutional characteristics could determine the magnitude of the effect. Indeed, we find heterogeneous profiles comparing the three countries. Table 2.5 Panel B reports the estimated coefficients country wise. For Germany, the coefficient of grandparents is significantly different from zero when controlling, first, for the parent with highest education, and, then, for the education of both parents. The last evidence seems initially to be in contrast with the findings of Braun and Stuhler (2016b) who find statistically insignificant coefficients in most of their applications controlling for both parents. However, Braun and Stuhler (2016b) find, indeed, a positive significant coefficient in two of their five samples which are closer to our sample in terms of the years of birth of individuals and their grandparents. In our analysis, the coefficient of grandparents for Germany is no longer significantly different from zero if we additionally control for ethnic capital, besides mother's and father's educational attainment. The results on the UK show a positive and significant coefficient of grandparents controlling for parents and ethnic capital. The coefficient is, however, substantially smaller and not significantly different from zero as soon as we control for the education of both parents. Our results, therefore, only partly confirm the findings of Chan and Boliver (2013) on the persistence of social status over three generations in the UK. For the US, the coefficient is persistently not significantly different from zero in all applications. This pattern confirms earlier findings on older cohorts for the US by Behrman and Taubman (1985); Peters (1992); Warren and Hauser (1997).

Our results are qualitatively similar for the three countries when the outcome variable is the Z-Score of educational attainment (see Table 2.11). Interestingly, the results adopting the Z-Score for the US show a negative coefficient of grandparents when controlling for both father and mother, as found by previous studies on income mobility over three generations (Peters, 1992; Behrman and Taubman, 1985) and hypothesized by Becker and Tomes (1979). We interpret this as further evidence in favour of our supposition that the Z-Score mirrors socio-economic status properly.

Death of grandparents For the second exercise, we test whether the coefficient of grandparental education varies with the likelihood of interaction between grandparents and grandchildren (following Braun and Stuhler, 2016b). Here, we use the information on the year of death of grandparents and the year of birth of grandchildren to check if a direct interaction was possible between the two or not. Since the information on parental year of death is only available in the SOEP and the PSID we restrict our analysis for this exercise to Germany and the US.

The estimation strategy is straightforward: Equation (2.2.2) is estimated interacting the

Table 2.6.: *Testing for a grandparental effect: Grandparents' death as exogenous source of variation in the likelihood of interaction*

***Outcome**: Completed years of education*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Father	0.368***	0.367***	0.330***	0.359***				
	(0.0250)	(0.0296)	(0.0266)	(0.0306)				
Mother					0.391***	0.373***	0.431***	0.430***
					(0.0290)	(0.0350)	(0.0328)	(0.0366)
GF-F	0.047**	0.029						
	(0.0186)	(0.0220)						
GM-F			0.055**	0.033				
			(0.0229)	(0.0236)				
GF-M					0.086***	0.106***		
					(0.0200)	(0.0241)		
GM-M							0.040	0.048
							(0.0278)	(0.0333)
Death=1 × GF-F		0.047						
		(0.0355)						
Death=1 × GM-F				0.075				
				(0.0521)				
Death=1 × GF-M						-0.067*		
						(0.0378)		
Death=1 × GM-M								-0.033
								(0.0571)
Death=1		-0.479						
		(0.5481)						
Death=1 × Father		0.003						
		(0.0462)						
Death=1				0.459				
				(0.7046)				
Death=1 × Father				-0.093*				
				(0.0518)				
Death=1						-0.084		
						(0.5402)		
Death=1 × Mother						0.064		
						(0.0463)		
Death=1								0.425
								(0.8073)
Death=1 × Mother								0.005
								(0.0770)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3360	3360	2241	2241	2973	2973	2147	2147
Clusters	1871	1871	1309	1309	1797	1797	1311	1311

Notes: GF/GM-F/M: Grandfather/Grandmother-Father's/Mother's side. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

education of the respective grandparent with a dummy variable which is one if there was no possibility of direct interaction – i.e. the grandparent died before the grandchild turned one year old – and zero otherwise. The results are shown in Table 2.6. If a direct interaction has a substantial effect, we would expect the coefficient of "dead grandparents" to be significantly lower than the coefficient of grandparents who were alive when the grandchild was born.

This hypothesis does not find a clear support in our findings. Only dead grandparents on the mother's side show the expected negative coefficient with respect to the coefficient of living grandparents. If we subdivide the analysis, it is evident that this result is completely driven by our German sample. Again, we find cross-country differences in the evaluation of a direct effect of grandparents. Identical patterns are observed when applying the Z-Score as outcome variable.[14] Of course, this strategy rules only those effects out that depend on direct interaction. There still might be important and persistent effects which derive from grandparents regardless of whether they were alive or not; for instance, family wealth, reputation, networks, as well as genetic traits that skip one generation. These cannot be clearly ruled out in this analysis. Our results show that direct interaction might only have a limited effect on grandchildren's human capital and confirm that these effects might vary with the cultural, historical, or institutional context.

Our findings for Germany regarding maternal grandparents seem, however, to confirm earlier findings and the hypotheses raised by family sociologists and human evolutionary scientists on differential effects of maternal and paternal grandparents on grandchildren. The former argue that the emotional closeness between mothers and their parents explains the stronger effect of maternal grandparents on grandchildren. Evolutionary explanations instead mostly focus on the degree of assumed genetic relatedness. One theory states, for example, that the bias in grandparental investment might depend on *paternity uncertainty*: maternal grandparents know for sure that their daughter is the mother of their grandchild (although in the case of the maternal grandfather there might still be some uncertainty about genetic relatedness), while the probability of relatedness on the father's side is usually smaller than one. However, to go deeper into the exact reasons and mechanisms of differences in grandparental effects would go beyond the scope of this work.[15]

2.6. Conclusions

This study evaluated multigenerational mobility in a cross-country setting using harmonized survey data sets. On grounds of highly comparable estimates we found some clear patterns: First, multigenerational mobility tends to vary with the historical and institutional context. We even find different effects of grandparental exposure on grandchildren's socio-economic status by country and gender. Second, our finding of different heritability para-

[14] These results are robust to the exclusion of people with migration background.

[15] For a recent review of theories and empirical findings on differential grandparental effects, see Danielsbacka et al. (2015).

meters across countries and time does not support the existence of a "universal law of social mobility". Third, the differences in long run mobility rates in the US, the UK, and Germany are in line with previous findings on cross-country differences over two generations (Blanden, 2013; Chevalier et al., 2009; Hertz et al., 2007; OECD, 2015a). Hence, our findings show that cross-country relationships, at least in this small sample of countries, hold aside from the timing of measurement, and short-run mobility (i.e. over two generations) does not seriously over nor under predict long-run mobility patterns.

A strength of our findings, apart from the cross-country perspective, lies in the adoption of measures which should be suitable as *omnibus measures* for latent socio-economic status with less measurement error (see Nybom and Vosters, 2016; Solon, 2014a). Especially, our analysis using the relative position of grandparents, parents, and children should be particularly useful in that sense, since it allows to compare individuals and their ancestors with the corresponding reference group, namely people competing in the labour market broadly at the same time. An issue challenging our findings, and generally the analysis of intergenerational mobility with household survey data, turned out to be sample selectivity. We find that higher educated people are more likely to have available information on parents' and grandparents' education. Especially, families with higher education (which tend to have lower intergenerational mobility) are more likely i) to participate in household surveys for more than one generation and ii) to answer retrospective questions about their parents' education. Our intergenerational persistence estimates over two and three generations might, thus, be understood as an upper bound. Even with these upper bound estimates we found no support for a strong unobserved intergenerational transmission of socio-economic status that is constant across time and space. Furthermore, since selectivity is the same in all three countries, the cross-country analysis should still be valid. On top of this, the identification of the mechanisms of multigenerational persistence should not be affected. Nevertheless, it might be important to address the issue of sample selectivity in future studies dealing with intergenerational transmission using survey data.

Other points worth mentioning are the uncovered different effects by gender and family lineages. Decomposing the analysis by the effect of (grand)fathers and (grand)mothers on (grand)sons and (grand)daughters we find that significant differences exist between correlations and even direct effects. Interestingly, we find these patterns to differ across countries, confirming that historical, institutional, and cultural features matter for the intergenerational transmission of socio-economic status.

Concluding, a relevant point is how our findings are related to income mobility. Previous studies covering two generations have shown that rates of intergenerational mobility in education and income show the same broad picture, but are less than perfectly correlated. Since data on permanent income over three generations is rare, we cross-checked our results adopting a transformation that yields an outcome measure which is intuitively closer to the concepts of human capital and socio-economic status than completed years of education. Our analysis showed that our results adopting this transformation mirror past findings on intergenerational income mobility. It might therefore be useful to deepen this methodological aspect in future.

2.7. Additional Material

2.7.1. DATA

The SOEP is an annually repeated longitudinal study of private households in Germany that was launched in 1984. Since 1991, it also includes a sample of the East German population.[16] For the current study we restrict our sample to people residing in West Germany. The PSID is a representative sample of the US population and was annually repeated between 1968 and 1995. Since 1995, it is repeated biennial only and was reduced in its scope.[17] The BHPS is an annually repeated longitudinal study of private households in Great Britain and was run between 1991 and 2008.[18] In 2009, the BHPS was detached by Understanding Society which is an annually repeated longitudinal study of private households in Great Britain and covers an even larger array of people's social and economic circumstances, attitudes, behaviours and health.[19] It builds on the BHPS and a large number of former BHPS respondents were incorporated into Understanding Society from the second wave of interviews onwards. We treat information collected from BHPS sample members in Understanding Society as if it were information collected in successive BHPS waves.[20]

2.7.1.1. Harmonization

We maximize the comparability of our educational measure by following the harmonization procedures adopted in the Cross-National Equivalent File (CNEF).[21]

PSID provides detailed information on completed years of education for each family unit member at the time of the interview. It encompasses information on primary, secondary, and tertiary education as well as vocational training. We use this information to construct both the variables on schooling and education for parents (generation t-1) and children (generation t). In addition, retrospective questions on parental education are available. In this case, the answer of the responding household head is categorized into one of eight possible grade categories. We use this information to attribute the completed years of education of grandparents (generation t-2) to their grandchildren. Since we can directly observe generation *t* and *t-1* in our samples, we use these retrospective information to compute the completed years of education for generation *t-2* (grandparents). Also, whenever individual

[16] See: Wagner, Gert G., Joachim R. Frick, and Jürgen Schupp (2007) The German Socio-Economic Panel Study (SOEP) - Scope, Evolution and Enhancements. *Journal of Applied Social Science Studies* 127 (1), 139-169.

[17] Panel Study of Income Dynamics, public use dataset. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI (2016).

[18] Since 2001, the BHPS is also representative of the United Kingdom. This was achieved by adding 1,500 additional households from Scotland and 1,500 households from Wales in 1999 and another 2,000 households from Northern Ireland in 2001. See: University of Essex. Institute for Social and Economic Research. (2010). British Household Panel Survey: Waves 1-18, 1991-2009. 7th Edition. UK Data Service. SN: 5151.

[19] See: University of Essex. Institute for Social and Economic Research, NatCen Social Research. (2015). Understanding Society: Waves 1-5, 2009-2014. [data collection]. 7th Edition. UK Data Service. SN: 6614.

[20] There is no information on BHPS sample members for 2009.

[21] The CNEF project provides a harmonized subset of the information included in various household surveys and suitable for international comparisons. For information on CNEF, see Frick et al. (2007).

response on completed years of education is not available for parents, we take the information given by retrospective questions.

SOEP provides a comparable measure of completed years of education for each household member at the time of the interview. In contrast to the PSID, the scale of completed years of education is restricted to values ranging from seven years of education to eighteen years of education. We limit the scale at the upper bound to be consistent with the scale from the PSID. Retrospective questions on the educational level of both mothers and fathers are also available, at which the respondents have to refer to school leaving degrees ranging from "secondary school degree" to "did not attend school". As described before, the available information on the respondent and its parents is, then, transformed to our common scale of years of education.

The panel surveys for the UK, BHPS and Understanding Society, can be combined with each other for longitudinal analyses. Both do not provide a direct measure of completed years of education, but information on the highest educational qualification of a respondent and its respective parents.[22] This variable combines both information on the highest school leaving degree as well as information on vocational training. Again, the information provided in the retrospective questions on parents are less detailed and contain only five different categories. By using additional information on parental occupation and skills, measured in ISCO levels, we are however able to construct comparable measures of schooling and education for children, parents and grandparents. Figure 2.6 shows the codification scheme applied in each survey, Figure 2.7 the mean completed years of education by age and a comparison with the Barro-Lee data on educational attainment.

Finally, the household surveys are non-random draws of the population and oversample certain groups, like PSID does with low-income households and SOEP with migrants. Sample design weights are therefore provided to represent the actual population. Computing descriptive statistics and performing regressions without using weighting factors would results in inconsistent estimates. Our estimates are, therefore, obtained by weighting each observation by its inverse probability of selection into the sample. Since we pool several waves of the surveys, we normalize these weights for every survey year to maintain its relative population share. To account for heteroscedasticity, standard errors are obtained by clustering observations within the household of origin. For comprehensive overviews on household survey design and weighting procedures, see Deaton (1997) and Solon et al. (2015).

2.7.1.2. Selectivity of sample

A sensitivity analysis shows that the samples might be positively selected in educational attainments. We find that the weighted mean years of education of individuals in our sample – restricted by the condition of available information on parents' and grandparents' education – is higher than the weighted mean of the unrestricted sample. Restricting the sample on

[22] Information on parents are provided in Wave 13 in the BHPS and in Wave 2 of Understanding Society.

Figure 2.6.: *Codification of completed years of education*

$$Years\,of\,Schooling = \begin{cases} 1 & if\,school\,not\,attended \\ 5 & if\,school\,dropout\,and\,no\,school\,degree \\ 9 & if\,secondary\,school\,degree \\ 10 & if\,intermediate\,school\,degree \\ 12 & if\,technical\,school\,degree \\ 13 & if\,upper\,secondary\,school\,degree \end{cases}$$

$$Years\,of\,Education = \begin{cases} 1 & if\,0-5\,grades \\ 5 & if\,6-8\,grades\,or\,"grade\,school" \\ 9 & if\,9-11\,grades\,(some\,high\,school)\,or\,junior\,high \\ 12 & if\,12\,grades\,(completed\,high\,school) \\ 13 & if\,12\,grades\,plus\,nonacademic\,training\,or\,R.N.\,(no\,further\,elaboration) \\ 14 & if\,some\,college,\,no\,degree\,or\,Associate's\,degree \\ 15 & if\,College\,BA\,and\,no\,advanced\,degree\,mentioned\,or\,normal\,school\,or\,R.N.\,with\,3\,years\,college \\ 17 & if\,College,\,advanced\,or\,professional\,degree,\,some\,graduate\,work\,or\,close\,to\,receiving\,degree \end{cases}$$

(a) PSID - USA

$$Years\,of\,Schooling = \begin{cases} 1 & if\,school\,not\,attended \\ 5 & if\,school\,dropout\,and\,no\,school\,degree \\ 9 & if\,secondary\,school\,degree \\ 10 & if\,intermediate\,school\,degree \\ 12 & if\,technical\,school\,degree \\ 13 & if\,upper\,secondary\,school\,degree \end{cases}$$

$$Years\,of\,Education = \begin{cases} Years\,of\,Schooling & if\,no\,vocational\,degree \\ Years\,of\,Schooling+3 & if\,vocational\,degree \\ Years\,of\,Schooling+4 & if\,Tech\,Engineer,\,Civil\,Service\,Training,\,Special\,Tech\,School \\ 17 & if\,College,\,University \end{cases}$$

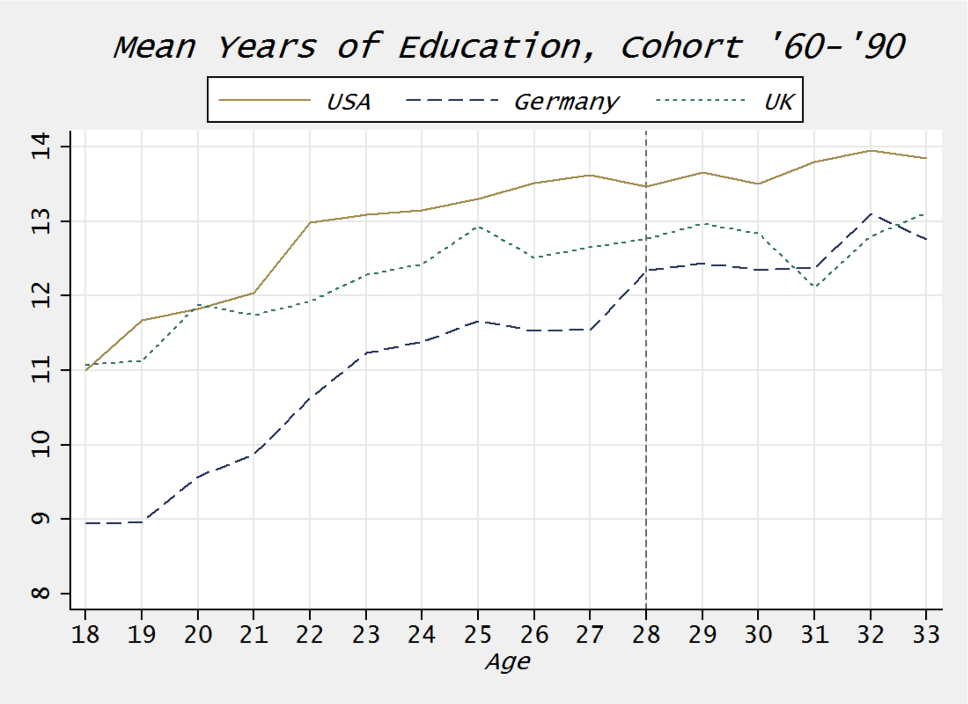
(b) SOEP - Germany

$$Years\,of\,Schooling = \begin{cases} 1 & if\,did\,not\,go\,to\,school\,at\,all \\ 5 & if\,left\,school\,with\,no\,qualifications\,or\,certificates \\ 9 & if\,left\,school\,with\,some\,qualifications\,or\,certificates \\ 12 & if\,post\,school\,quals\,or\,certs\,(e.g.\,city\,\&\,guilds) \\ 13 & if\,university\,degree\,or\,higher\,degree \end{cases}$$

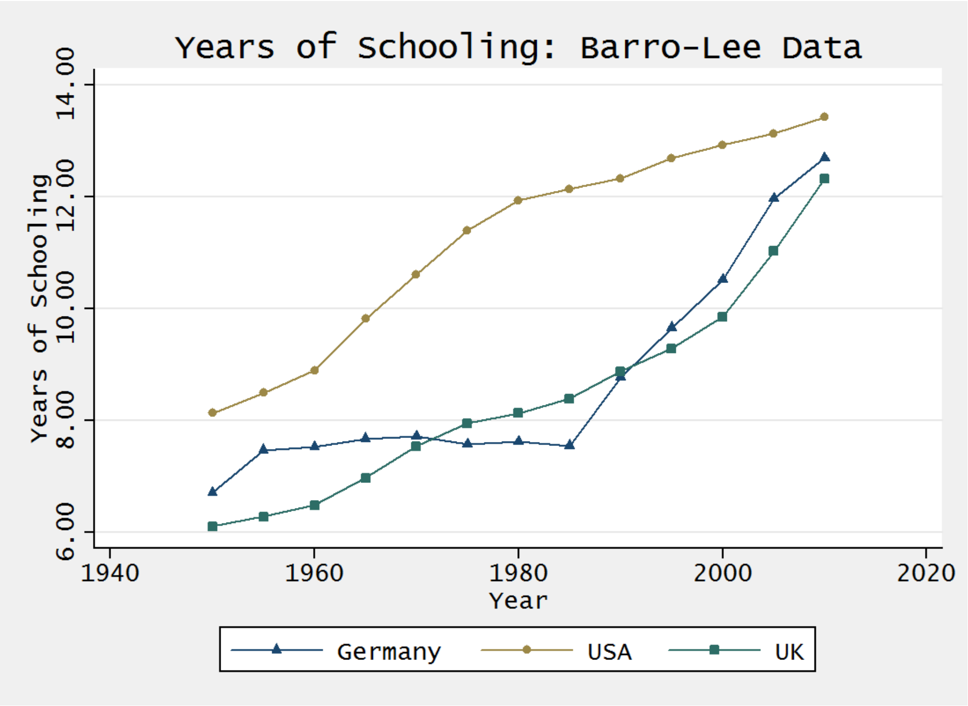
$$Years\,of\,Education = \begin{cases} Years\,of\,Schooling & if\,ISCO\,level\,9\,(skill\,level\,1) \\ Years\,of\,Schooling+3 & if\,ISCO\,levels\,4-8\,(skill\,level\,2) \\ Years\,of\,Schooling+4 & if\,ISCO\,level\,0,1\,and\,3\,(skill\,level\,3) \\ 17 & if\,ISCO\,levels\,2\,(skill\,level\,4) \end{cases}$$

(c) BHPS/UKHLS - UK

Figure 2.7.: *Mean education by age and comparison with other data sets on mean educational attainment*



(a) *Mean education by age*



(b) *Barro-Lee Data on years of schooling (see Barro and Lee, 2013)*

Table 2.7.: *Testing selection into sample (Cohort 1960-1985); Weighted statistics.*
Sample 1: Sample used in this study (parents and children in survey and information on grandparental education).
Sample 2: Parental information retrieved from retrospective questions; information on grandparental education not necessarily available.

Mean years of education	*Sample 1*	*Sample 2*	*p-value*	*Unrestricted*	*p-value*
GER	12.552	12.497	0.2261	12.141	0.0000
USA	13.660	13.181	0.0000	13.088	0.0000
UK	12.673	12.630	0.5094	12.008	0.0000

First p-value shows the probability that the weighted means of Sample 1 and Sample 2 are equal. Second p-values shows the probability that the weighted mean of Sample 1 and of the Unrestricted sample are equal.

Regression coefficient (β_-1)	*Sample 1*	*N*	*Sample 2*	*N*	*p-value*
GER	0.484	3,210	0.380	12,044	0.0004
USA	0.400	6,299	0.378	10,475	0.1931
UK	0.208	1,532	0.169	4,757	0.1774

P-value shows the probability that the weighted regression coefficient of Sample 1 and Sample 2 are equal.

the condition to have information on parental education retrieved from retrospective questions – and not necessarily grandparental education – yields lower regression coefficients. These differences are statistically significant at the 1 % level for SOEP, at the 5 % level for BHPS/UKHLS and not significant for PSID. The interpretations and consequences of this bias for our study are discussed in the paper.

2.7.2. *Analysis performed applying the Z-Score of educational attainment*

Table 2.8.: *Regression analysis - Outcome: Z-Score of educational attainment*
(a) Germany

	(1)	(2)	(3)
Parents (β_{-1})	0.423***		0.365***
	(0.0241)		(0.0329)
Grandparents (β_{-2})		0.331***	0.115***
		(0.0285)	(0.0366)
Observations	3210	3210	3210

Correlation coefficients: $r_{-1} = 0.444$, $r_{-2} = 0.322$
Test $(\beta_{-1})^2 = \beta_{-2}$: F = 28.4403, Prob > F = 0.0000 ; $(\beta_{-1})^2 = 0.179$

(b) USA

	(1)	(2)	(3)
Parents (β_{-1})	0.491***		0.480***
	(0.0197)		(0.0222)
Grandparents (β_{-2})		0.256***	0.024
		(0.0236)	(0.0237)
Observations	6303	6303	6303

Correlation coefficients: $r_{-1} = 0.445$, $r_{-2} = 0.225$
Test $(\beta_{-1})^2 = \beta_{-2}$: F = 0.4075, Prob > F = 0.5233 ; $(\beta_{-1})^2 = 0.241$

(c) UK

	(1)	(2)	(3)
Parents (β_{-1})	0.313***		0.290***
	(0.0421)		(0.0422)
Grandparents (β_{-2})		0.148***	0.056**
		(0.0303)	(0.0281)
Observations	1532	1532	1532

Correlation coefficients: $r_{-1} = 0.276$, $r_{-2} = 0.148$
Test $(\beta_{-1})^2 = \beta_{-2}$: F = 2.7467, Prob > F = 0.0977 ; $(\beta_{-1})^2 = 0.098$

Notes: Tables show regressions of children's educational outcomes on the outcomes of the parent or grandparent with highest education within the family. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 2.9.: *Z-Score - Estimated correlation (r), heritability (λ), and transferability (ρ) coefficients*

	Z-Score		
	GER	*USA*	*UK*
r_{-1}	0.444	0.445	0.276
r_{-2}	0.322	0.225	0.148
λ	0.725	0.506	0.537
s.e.	*0.0529*	*0.0298*	*0.1041*
ρ	0.783	0.937	0.717
s.e.	*0.0377*	*0.0375*	*0.0839*

Notes: Bootstrapped s.e. (200 replications).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 2.10.: *Z-Score - Testing for a grandparental effect: Controlling for multiple features of parental background*
***Outcome**: Z-Score of educational attainment*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grandparents	0.057***	0.056***	0.055***	0.050***	0.012	0.012	0.015	0.011
	(0.0163)	(0.0165)	(0.0168)	(0.0167)	(0.0171)	(0.0173)	(0.0177)	(0.0177)
Parents	0.395***	0.466***	0.465***	0.465***				
	(0.0176)	(0.0210)	(0.0216)	(0.0222)				
GER (0/1) × Parents		-0.071**	-0.071**	-0.076**				
		(0.0310)	(0.0311)	(0.0326)				
UK (0/1) × Parents		-0.176***	-0.173***	-0.169***				
		(0.0466)	(0.0466)	(0.0472)				
Father					0.253***	0.283***	0.286***	0.287***
					(0.0176)	(0.0233)	(0.0236)	(0.0238)
GER (0/1) × Father						0.028	0.028	0.021
						(0.0437)	(0.0437)	(0.0442)
UK (0/1) × Father						-0.113***	-0.116***	-0.112***
						(0.0414)	(0.0418)	(0.0418)
Mother					0.227***	0.249***	0.249***	0.250***
					(0.0166)	(0.0238)	(0.0237)	(0.0238)
GER (0/1) × Mother						-0.032	-0.030	-0.036
						(0.0401)	(0.0400)	(0.0402)
UK (0/1) × Mother						-0.068*	-0.070*	-0.069*
						(0.0386)	(0.0385)	(0.0386)
Country F.E.	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Non-white or Migrant	No	No	Yes	Yes	No	No	Yes	Yes
- (interacted with country f.e.)	No	No	No	Yes	No	No	No	Yes
Adj. R^2	.1563	.161	.1612	.1622	.1769	.1817	.1819	.183
Observations	11045	11045	11039	11039	9769	9769	9764	9764
Clusters	5768	5768	5762	5762	5168	5168	5163	5163

Notes: Cluster adjusted s.e. at family level in parenthesis. Base category is the US. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 2.12.: *Testing for a grandparental effect: Grandparents' death as exogenous source of variation in the likelihood of interaction*
***Outcome**: Z-Score of educational attainment*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Father	0.433***	0.450***	0.402***	0.440***				
	(0.0280)	(0.0346)	(0.0311)	(0.0369)				
Mother					0.381***	0.361***	0.409***	0.412***
					(0.0283)	(0.0356)	(0.0298)	(0.0339)
GF-F	0.079***	0.048						
	(0.0285)	(0.0367)						
GM-F			0.084***	0.076**				
			(0.0299)	(0.0337)				
GF-M					0.152***	0.183***		
					(0.0302)	(0.0371)		
GM-M							0.064*	0.076*
							(0.0377)	(0.0452)
Death=1 × GF-F		0.077						
		(0.0536)						
Death=1 × GM-F				0.023				
				(0.0667)				
Death=1 × GF-M						-0.105*		
						(0.0607)		
Death=1 × GM-M								-0.047
								(0.0757)
Death=1		0.042						
		(0.0455)						
Death=1 × Father		-0.039						
		(0.0553)						
Death=1				0.058				
				(0.0605)				
Death=1 × Father				-0.128**				
				(0.0640)				
Death=1						-0.014		
						(0.0493)		
Death=1 × Mother						0.064		
						(0.0527)		
Death=1								0.073
								(0.0707)
Death=1 × Mother								-0.013
								(0.0735)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3360	3360	2241	2241	2973	2973	2147	2147
Clusters	1871	1871	1309	1309	1797	1797	1311	1311

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP and PSID.
Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

	(1) USA	(2) USA	(3) USA	(4) USA	(5) GER	(6) GER	(7) GER	(8) GER
Father	0.501***	0.459***			0.394***	0.423***		
	(0.0503)	(0.0517)			(0.0482)	(0.0525)		
Mother			0.349***	0.395***			0.357***	0.420***
			(0.0551)	(0.0565)			(0.0464)	(0.0417)
GF-F	0.022				0.092			
	(0.0420)				(0.0737)			
GM-F		0.047				0.122*		
		(0.0394)				(0.0668)		
GF-M			0.131***				0.285***	
			(0.0474)				(0.0580)	
GM-M				0.038				0.135**
				(0.0647)				(0.0628)
Death=1 × GF-F	0.070				0.129			
	(0.0642)				(0.1049)			
Death=1 × GM-F		0.047				0.045		
		(0.0844)				(0.1154)		
Death=1 × GF-M			-0.036				-0.220**	
			(0.0780)				(0.1049)	
Death=1 × GM-M				0.029				-0.170
				(0.0935)				(0.1461)
Death=1	0.104*				-0.052			
	(0.0588)				(0.0740)			
Death=1 × Father	-0.034				-0.047			
	(0.0732)				(0.0838)			
Death=1		0.171**				-0.090		
		(0.0818)				(0.0861)		
Death=1 × Father		-0.097				-0.178*		
		(0.0905)				(0.0958)		
Death=1			0.034				-0.049	
			(0.0678)				(0.0753)	
Death=1 × Mother			0.083				0.057	
			(0.0817)				(0.0701)	
Death=1				0.110				0.057
				(0.0951)				(0.1110)
Death=1 × Mother				-0.015				-0.006
				(0.1106)				(0.1005)
Observations	1832	1105	1390	931	1528	1136	1583	1216
Clusters	811	501	646	434	1060	808	1151	877

Own estimations based on SOEP and PSID.
Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Table 2.11.: *Z-Score - Testing for a grandparental effect: Controlling for multiple features of parental background – country-wise*
***Outcome**: Z-Score of educational attainment*

	(1) USA	(2) USA	(3) USA	(4) GER	(5) GER	(6) GER	(7) UK	(8) UK	(9) UK
Grandparents	0.021	-0.006	-0.004	0.106***	0.057	0.055	0.053*	0.010	0.008
	(0.0241)	(0.0253)	(0.0256)	(0.0387)	(0.0348)	(0.0378)	(0.0280)	(0.0307)	(0.0306)
Parents	0.477***			0.365***			0.294***		
	(0.0230)			(0.0330)			(0.0423)		
Father		0.287***	0.290***		0.299***	0.299***		0.171***	0.175***
		(0.0231)	(0.0236)		(0.0387)	(0.0387)		(0.0351)	(0.0352)
Mother		0.253***	0.254***		0.199***	0.199***		0.181***	0.182***
		(0.0248)	(0.0247)		(0.0340)	(0.0340)		(0.0308)	(0.0307)
Non-white or Migrant (0/1)	-0.038		0.044	-0.044		-0.011	0.248		0.310*
	(0.0455)		(0.0464)	(0.0644)		(0.0689)	(0.1583)		(0.1621)
Adj. R^2	.198	.2208	.2209	.2056	.2258	.2256	.08014	.0876	.09126
Observations	6303	5554	5554	3210	2818	2818	1526	1397	1392
Clusters	2065	1898	1898	2192	1890	1890	1505	1380	1375

Notes: Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 2.13.: *Testing for a grandparental effect:*
Grandparents' death as exogenous source of variation in the likelihood of interaction – Effects estimated separately for USA and Germany
***Outcome**: Completed years of education*

	(1) USA	(2) USA	(3) USA	(4) USA	(5) GER	(6) GER	(7) GER	(8) GER
Father	0.341***	0.302***			0.440***	0.453***		
	(0.0357)	(0.0331)			(0.0547)	(0.0580)		
Mother			0.297***	0.339***			0.462***	0.520***
			(0.0485)	(0.0514)			(0.0547)	(0.0518)
GF-F	0.016				0.063			
	(0.0235)				(0.0557)			
GM-F		0.020				0.107*		
		(0.0246)				(0.0563)		
GF-M			0.070**				0.240***	
			(0.0283)				(0.0469)	
GM-M				0.025				0.137**
				(0.0409)				(0.0595)
Death=1 × GF-F	0.040				0.139			
	(0.0403)				(0.0875)			
Death=1 × GM-F		0.044				0.102		
		(0.0640)				(0.1113)		
Death=1 × GF-M			-0.020				-0.187**	
			(0.0457)				(0.0842)	
Death=1 × GM-M				0.041				-0.200
				(0.0663)				(0.1218)
Death=1	-0.185				-0.698			
	(0.6549)				(0.9900)			
Death=1 × Father	-0.002				-0.084			
	(0.0555)				(0.0962)			
Death=1		0.534				1.168		
		(0.9010)				(1.2223)		
Death=1 × Father		-0.049				-0.208**		
		(0.0639)				(0.1012)		
Death=1			-0.712				1.535	
			(0.7458)				(0.9382)	
Death=1 × Mother			0.078				0.036	
			(0.0703)				(0.0833)	
Death=1				0.062				1.607
				(1.0757)				(1.3930)
Death=1 × Mother				-0.024				0.042
				(0.1004)				(0.1137)
Observations	1832	1105	1390	931	1528	1136	1583	1216
Clusters	811	501	646	434	1060	808	1151	877

2.7.3. *Testing for a grandparental effect*

2.7.4. *Lineages*

Table 2.14.: *Lineages - Regression analysis by son/daughter – father/mother – grandfather/grandmother*
Outcome: Completed years of education

(a) Germany

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.486***		0.439***	
	(0.0355)		(0.0455)	
Grandfather		0.225***	0.076**	0.338***
		(0.0314)	(0.0342)	(0.0233)
Observations	1625	1503	1497	1497

Test $\beta^f_{-1} \cdot \beta^s_{-1} = \beta^f_{-2}$: F = 3.6893, Prob > F = 0.0550 ; $\beta^f_{-1} \cdot \beta^s_{-1} = 0.164$

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.539***		0.513***	
	(0.0421)		(0.0506)	
Grandmother		0.215***	0.051	0.321***
		(0.0345)	(0.0359)	(0.0250)
Observations	1391	1311	1310	1310

Test $\beta^m_{-1} \cdot \beta^d_{-1} = \beta^m_{-2}$: F = 1.5214, Prob > F = 0.2177 ; $\beta^m_{-1} \cdot \beta^d_{-1} = 0.173$

(b) USA

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.281***		0.262***	
	(0.0220)		(0.0268)	
Grandfather		0.147***	0.039**	0.412***
		(0.0158)	(0.0184)	(0.0238)
Observations	2705	2681	2681	2681

Test $\beta^f_{-1} \cdot \beta^s_{-1} = \beta^f_{-2}$: F = 3.8558, Prob > F = 0.0498 ; $\beta^f_{-1} \cdot \beta^s_{-1} = 0.116$

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.363***		0.335***	
	(0.0187)		(0.0241)	
Grandmother		0.168***	0.056***	0.333***
		(0.0172)	(0.0184)	(0.0275)
Observations	3250	3153	3153	3153

Test $\beta^m_{-1} \cdot \beta^d_{-1} = \beta^m_{-2}$: F = 7.3774, Prob > F = 0.0067 ; $\beta^m_{-1} \cdot \beta^d_{-1} = 0.121$

(c) UK

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.145***		0.084**	
	(0.0304)		(0.0356)	
Grandfather		0.076**	0.046	0.357***
		(0.0306)	(0.0332)	(0.0481)
Observations	734	506	506	506

Test $\beta^f_{-1} \cdot \beta^s_{-1} = \beta^f_{-2}$: F = 0.6329, Prob > F = 0.4267 ; $\beta^f_{-1} \cdot \beta^s_{-1} = 0.052$

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.157***		0.147***	
	(0.0318)		(0.0343)	
Grandmother		0.085***	0.046	0.265***
		(0.0312)	(0.0299)	(0.0475)
Observations	721	651	651	651

Test $\beta^m_{-1} \cdot \beta^d_{-1} = \beta^m_{-2}$: F = 1.9852, Prob > F = 0.1593 ; $\beta^m_{-1} \cdot \beta^d_{-1} = 0.041$

Notes: Tables show regressions of sons'/daughters' educational outcomes on the outcomes of father/mother and grandfather/grandmother. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01. $\beta^{s/d}$ regression coefficient of the education of fathers/mothers on sons/daughters. $\beta^{f/m}$ regression coefficient of the education of grandfathers/grandmothers on fathers/mothers.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 2.15.: *Lineages - Estimated correlation (r), heritability (λ) and transferability (ρ) coefficients*
Outcome: Completed years of education

	GER		*USA*		*UK*	
	Sons	*Daughters*	*Sons*	*Daughters*	*Sons*	*Daughters*
r_{-1}	0.456	0.455	0.451	0.451	0.286	0.240
r_{-2}	0.286	0.256	0.251	0.275	0.121	0.118
λ	0.627	0.563	0.557	0.609	0.424	0.491
s.e.	*0.0712*	*0.0770*	*0.0457*	*0.0472*	*0.1613*	*0.1508*
ρ	0.853	0.899	0.900	0.861	0.821	0.699
s.e.	*0.0506*	*0.0635*	*0.0425*	*0.0348*	*0.5916*	*0.4914*

Notes: Bootstrapped s.e. (200 replications). r_{-1} is here the average of the correlation coefficients of son (daughter) on father (mother) and of father (mother) on grandfather (grandmother).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 2.16.: *Lineages - Regression analysis by son/daughter – father/mother – grandfather/grandmother*
Outcome: Z-Score of educational attainment

(a) Germany

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.444***		0.399***	
	(0.0331)		(0.0410)	
Grandfather		0.302***	0.108***	0.486***
		(0.0365)	(0.0402)	(0.0297)
Observations	1625	1503	1497	1497

Test $\beta^f_{-1} \cdot \beta^s_{-1}=\beta^f_{-2}$: F = 5.6279, Prob > F = 0.0178 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.216

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.396***		0.374***	
	(0.0356)		(0.0421)	
Grandmother		0.232***	0.064	0.451***
		(0.0384)	(0.0401)	(0.0339)
Observations	1391	1311	1310	1310

Test $\beta^m_{-1} \cdot \beta^d_{-1}=\beta^m_{-2}$: F = 1.9480, Prob > F = 0.1631 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.179

(b) USA

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.410***		0.391***	
	(0.0290)		(0.0335)	
Grandfather		0.232***	0.056*	0.450***
		(0.0291)	(0.0302)	(0.0282)
Observations	2705	2681	2681	2681

Test $\beta^f_{-1} \cdot \beta^s_{-1}=\beta^f_{-2}$: F = 2.6858, Prob > F = 0.1015 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.184

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.396***		0.371***	
	(0.0210)		(0.0259)	
Grandmother		0.229***	0.078***	0.409***
		(0.0257)	(0.0257)	(0.0348)
Observations	3250	3153	3153	3153

Test $\beta^m_{-1} \cdot \beta^d_{-1}=\beta^m_{-2}$: F = 6.8630, Prob > F = 0.0089 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.162

(c) UK

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.233***		0.137**	
	(0.0501)		(0.0575)	
Grandfather		0.124***	0.080	0.320***
		(0.0451)	(0.0502)	(0.0482)
Observations	734	506	506	506

Test $\beta^f_{-1} \cdot \beta^s_{-1}=\beta^f_{-2}$: F = 1.1846, Prob > F = 0.2769 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.075

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.209***		0.197***	
	(0.0424)		(0.0455)	
Grandmother		0.105**	0.057	0.245***
		(0.0431)	(0.0417)	(0.0455)
Observations	721	651	651	651

Test $\beta^m_{-1} \cdot \beta^d_{-1}=\beta^m_{-2}$: F = 1.5634, Prob > F = 0.2116 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.051

Notes: Tables show regressions of sons'/daughters' educational outcomes on the outcomes of father/mother and grandfather/grandmother. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01. $\beta^{s/d}$ regression coefficient of the education of fathers/mothers on sons/daughters. $\beta^{f/m}$ regression coefficient of the education of grandfathers/grandmothers on fathers/mothers.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 2.17.: *Lineages - Estimated correlation (r), heritability (λ) and transferability (ρ) coefficients*
Outcome: Completed years of education

	GER		*USA*		*UK*	
	Sons	*Daughters*	*Sons*	*Daughters*	*Sons*	*Daughters*
r_{-1}	0.456	0.433	0.428	0.418	0.276	0.227
r_{-2}	0.292	0.240	0.227	0.243	0.131	0.105
λ	0.641	0.555	0.531	0.581	0.476	0.464
s.e.	*0.0631*	*0.0776*	*0.0496*	*0.0506*	*0.1668*	*0.1676*
ρ	0.844	0.883	0.897	0.849	0.761	0.699
s.e.	*0.0419*	*0.0650*	*0.0468*	*0.0388*	*0.2216*	*0.3099*

Notes: Bootstrapped s.e. (200 replications). r_{-1} is here the average of the correlation coefficients of son (daughter) on father (mother) and of father (mother) on grandfather (grandmother).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 2.18.: *Lineages - Pooled sample*
Outcome: Completed years of education

Sons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.212***	0.212***			0.203***		0.132***
	(0.0203)	(0.0212)			(0.0219)		(0.0239)
Mother			0.246***	0.253***		0.244***	0.182***
			(0.0230)	(0.0230)		(0.0237)	(0.0264)
GF-F	0.061***				0.045***		0.027
	(0.0149)				(0.0173)		(0.0276)
GM-F		0.067***			0.034		0.019
		(0.0179)			(0.0213)		(0.0345)
GF-M			0.070***			0.055***	0.011
			(0.0143)			(0.0179)	(0.0281)
GM-M				0.067***		0.027	-0.003
				(0.0160)		(0.0199)	(0.0335)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4684	4559	5318	5263	4507	5180	4216
Clusters	3123	3061	3533	3508	3027	3457	2789

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Daughters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.237***	0.251***			0.243***		0.184***
	(0.0182)	(0.0187)			(0.0193)		(0.0206)
Mother			0.233***	0.239***		0.230***	0.154***
			(0.0222)	(0.0224)		(0.0231)	(0.0229)
GF-F	0.066***				0.046***		0.016
	(0.0140)				(0.0172)		(0.0244)
GM-F		0.064***			0.030		0.014
		(0.0150)			(0.0188)		(0.0262)
GF-M			0.080***			0.062***	0.028
			(0.0138)			(0.0176)	(0.0238)
GM-M				0.074***		0.027	0.010
				(0.0148)		(0.0189)	(0.0259)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4480	4386	5164	5114	4328	5039	4095
Clusters	2831	2790	3244	3228	2752	3174	2572

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Table 2.19.: *Lineages - Pooled sample*
Outcome: Z-Score of educational attainment

Sons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.329***	0.332***			0.323***		0.209***
	(0.0232)	(0.0236)			(0.0246)		(0.0270)
Mother			0.328***	0.338***		0.329***	0.251***
			(0.0221)	(0.0220)		(0.0227)	(0.0264)
GF-F	0.078***				0.062**		0.044
	(0.0211)				(0.0253)		(0.0353)
GM-F		0.069***			0.031		0.001
		(0.0219)			(0.0265)		(0.0392)
GF-M			0.098***			0.087***	0.003
			(0.0211)			(0.0256)	(0.0363)
GM-M				0.077***		0.021	-0.003
				(0.0201)		(0.0243)	(0.0383)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4683	4557	5318	5263	4505	5180	4214
Clusters	3122	3059	3533	3508	3025	3457	2787

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID, and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Daughters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.361***	0.379***			0.372***		0.283***
	(0.0224)	(0.0225)			(0.0233)		(0.0257)
Mother			0.316***	0.321***		0.312***	0.194***
			(0.0218)	(0.0217)		(0.0226)	(0.0246)
GF-F	0.079***				0.048*		0.008
	(0.0209)				(0.0267)		(0.0347)
GM-F		0.069***			0.039		0.010
		(0.0204)			(0.0261)		(0.0356)
GF-M			0.102***			0.076***	0.034
			(0.0201)			(0.0256)	(0.0331)
GM-M				0.088***		0.038	0.018
				(0.0204)		(0.0259)	(0.0362)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4475	4379	5164	5113	4321	5038	4090
Clusters	2826	2784	3244	3228	2746	3174	2568

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID, and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

2.7.5. *Assortative Mating*

Assortative mating is an important characteristic to account for studying the intergenerational persistence of socio-economic status. Higher spouse correlations in endowments cause higher heritability coefficients and large values of λ depend on high and constant rates of assortative mating. Here, we report spouse correlations in observable outcomes.

Table 2.20.: *Correlation of parents' and grandparents' education.*
*Spouse correlations (**assortative mating**) are Father/Mother, GF-F/GM-F and GF-M/GM-M.*

Panel A – Outcome: Completed years of education

(a) GER	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.598*	*0.469*	*0.416*	*0.440*	*0.404*
Mother	*0.598*	*1.000*	*0.484*	*0.428*	*0.520*	*0.486*
GF-F	*0.469*	*0.484*	*1.000*	*0.792*	*0.686*	*0.659*
GM-F	*0.416*	*0.428*	*0.792*	*1.000*	*0.665*	*0.706*
GF-M	*0.440*	*0.520*	*0.686*	*0.665*	*1.000*	*0.783*
GM-M	*0.404*	*0.486*	*0.659*	*0.706*	*0.783*	*1.000*

(b) USA	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.559*	*0.481*	*0.450*	*0.429*	*0.407*
Mother	*0.559*	*1.000*	*0.449*	*0.437*	*0.479*	*0.477*
GF-F	*0.481*	*0.449*	*1.000*	*0.637*	*0.877*	*0.585*
GM-F	*0.450*	*0.437*	*0.637*	*1.000*	*0.565*	*0.870*
GF-M	*0.429*	*0.479*	*0.877*	*0.565*	*1.000*	*0.636*
GM-M	*0.407*	*0.477*	*0.585*	*0.870*	*0.636*	*1.000*

(c) UK	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.409*	*0.332*	*0.302*	*0.302*	*0.280*
Mother	*0.409*	*1.000*	*0.253*	*0.228*	*0.306*	*0.284*
GF-F	*0.332*	*0.253*	*1.000*	*0.839*	*0.293*	*0.295*
GM-F	*0.302*	*0.228*	*0.839*	*1.000*	*0.290*	*0.278*
GF-M	*0.302*	*0.306*	*0.293*	*0.290*	*1.000*	*0.823*
GM-M	*0.280*	*0.284*	*0.295*	*0.278*	*0.823*	*1.000*

Panel B – Outcome: Z-Score of educational attainment

(a) GER	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.577*	*0.468*	*0.410*	*0.443*	*0.390*
Mother	*0.577*	*1.000*	*0.502*	*0.443*	*0.539*	*0.490*
GF-F	*0.468*	*0.502*	*1.000*	*0.776*	*0.674*	*0.643*
GM-F	*0.410*	*0.443*	*0.776*	*1.000*	*0.641*	*0.693*
GF-M	*0.443*	*0.539*	*0.674*	*0.641*	*1.000*	*0.760*
GM-M	*0.390*	*0.490*	*0.643*	*0.693*	*0.760*	*1.000*

(b) USA	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.540*	*0.439*	*0.412*	*0.380*	*0.359*
Mother	*0.540*	*1.000*	*0.389*	*0.384*	*0.421*	*0.424*
GF-F	*0.439*	*0.389*	*1.000*	*0.587*	*0.860*	*0.525*
GM-F	*0.412*	*0.384*	*0.587*	*1.000*	*0.507*	*0.847*
GF-M	*0.380*	*0.421*	*0.860*	*0.507*	*1.000*	*0.582*
GM-M	*0.359*	*0.424*	*0.525*	*0.847*	*0.582*	*1.000*

(c) UK	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.384*	*0.316*	*0.299*	*0.295*	*0.269*
Mother	*0.384*	*1.000*	*0.228*	*0.210*	*0.287*	*0.266*
GF-F	*0.316*	*0.228*	*1.000*	*0.837*	*0.271*	*0.264*
GM-F	*0.299*	*0.210*	*0.837*	*1.000*	*0.269*	*0.253*
GF-M	*0.295*	*0.287*	*0.271*	*0.269*	*1.000*	*0.815*
GM-M	*0.269*	*0.266*	*0.264*	*0.253*	*0.815*	*1.000*

3. Intergenerational Mobility and the Rise and Fall of Income Inequality

3.1. Introduction

The view of researchers and the public on inequality has been changing over the course of time. While the classical approach suggested that inequality might be beneficial because of its motivating nature (Keynes, 1920), it was subsequently seen as simply part of the process of economic development with no direct causal interrelation (Kuznets, 1955). Later, economists theorized that the shape of income distribution had a significant impact on growth rates and that, for instance, higher levels of inequality had a negative impact on economic performance (Alesina and Rodrik, 1994; Atkinson, 1997; Bénabou, 1996; Corneo and Jeanne, 2001; Galor and Zeira, 1993; Persson and Tabellini, 1994).[1] Finally, empirical studies evidenced a strong association between inequality and clearly detrimental patterns for a society, such as higher levels of crime, drug use, and persistent poverty (Wilkinson and Pickett, 2009), and recently an OECD report was even titled *"Why Less Inequality Benefits All"* (OECD, 2015b). Indeed, egalitarian theories of justice since the influential works of Rawls (1971) and Sen (1980) have suggested that, from a normative point of view, the key to understanding whether it is worth caring more or less about income distribution within a society - i.e. about (in)equality of outcomes - is the evaluation of (in)equality of opportunities.

Equality of opportunity is a long studied subject and for the most part one of the primary goals of policy makers. The fundamental discussion in this respect concerns the distinction between inequality of outcomes resulting from *individual efforts* and inequality of resources arising from *given circumstances* (Roemer, 2000). Recently, the topic has been extensively debated because of an alarming finding: in countries where income inequality is high, there is also a strong association between parents' and children's economic well-being (i.e. low intergenerational mobility).[2] The graph visualizing this phenomenon across countries is the well-known *Great Gatsby Curve*.[3] Indeed, the negative relationship between income inequal-

[1] A stimulating survey on researcher's view on inequality can be found in Galor (2009). See also Furman and Stiglitz (1998) for an overview of the consequences of inequality for economic growth.

[2] The concepts of equality of opportunity and social intergenerational mobility are arguably very close to each other. Brunori et al. (2013) find even a strong correlation between common indices of inequality of opportunity and measures of intergenerational mobility. For some viewpoints, and a discussion on similarities and differences of the two constructs, see Roemer (2004, 2012) and Corak (2013a).

[3] The *Great Gatsby Curve* was addressed by Alan Kruger as chairman of the council of economic advisers in

ity and intergenerational mobility was already hypothesized in the past in some influential theoretical contributions, starting from the seminal studies of Becker and Tomes (1979) and Loury (1981) to macroeconomic models of, among others, Galor and Zeira (1993), Owen and Weil (1998), Maoz and Moav (1999) and Hassler et al. (2007). The presence of such a relationship would mean, in simple terms, that when inequality is high, the same families persist at the top or bottom of the income distribution over (two or more) generations.

Finding a clear link between an unequal distribution of income, low social mobility, and the persistence of economic inequality would probably be the strongest motivation, especially for policy makers, for caring about income inequality. However, most empirical studies on the relationship between income inequality and intergenerational mobility focus on comparisons between countries. Hence, the existing evidence so far does not allow us to rule out that the association might merely be driven by cross-country heterogeneity, for instance in institutions. Only few recent studies investigate the relationship but restrict the analysis to one single country (e.g. Chetty et al., 2014c,b; Güell et al., 2015). Therefore, more research with comparable data on multiple countries and cohorts is crucial for our understanding of the interplay between income inequality and intergenerational mobility (as pointed out for example by Jäntti and Jenkins, 2013). The purpose of the present study is to deepen our understanding of this relationship, applying a profound empirical analysis on harmonized survey data for 18 distinct countries and spanning multiple cohorts. Its main contribution is to test whether a negative relationship exists in a between-country *and* within-country set up.

The laboratory for this exercise is Latin America. Two different sources of harmonized household survey data allow such a comparative analysis that controls for cross country heterogeneity to be performed there. An interesting fact is that while worldwide inequality has constantly been rising and Latin American countries have been following this trend for some time, many of them seem to have experienced a significant decrease in inequality in the last decade (Gasparini et al., 2011; Cord et al., 2013). Sufficient variation of the explanatory mechanisms should therefore be given in cross-country comparisons as well as in within countries comparisons over time. Furthermore, the usual limitation that only information on educational attainment is available is overcome by constructing a measure for individual relative educational position, which is identified as a better proxy for well-being across countries and over time.

The main findings are as follows. Estimations performed on two different data sets confirm the link portrayed by the Great Gatsby Curve and hypothesized by economic theory. Individuals who experienced higher (lower) income inequality in childhood or adolescence – i.e. when parental investment in human capital is crucial – show significantly lower (higher) intergenerational mobility as adults. This negative relationship is driven by the lower upward mobility of individuals at the bottom of the distribution. These results are robust and

a speech titled “The Rise and Consequences of Inequality in the United States” on January 12, 2012, at the Center for American Progress. The original analysis and a discussion can be found in Corak (2013b,a).

do not change when different specifications are adopted. Further analyses show that one of the driving forces behind this relationship might be economic growth and that public expenditures on education show the expected positive association with intergenerational mobility. Altogether, the crucial importance of private and public investment in children's human capital is confirmed, with the latter being a channel to support higher intergenerational mobility. This last finding has important implications for public policies that aim to enhance equality of opportunity in a society.

The remainder of the paper is organized as follows. Section 3.2 reviews the empirical literature on the relationship between inequality and intergenerational mobility and explains the theoretical mechanisms behind this association. Section 3.3 describes the data and presents the applied measurements. In Section 3.4 the main results are presented as follows. First, 3.4.1 focuses on the descriptive findings showing the estimated degree of intergenerational mobility of an older and a younger cohort in 18 Latin American countries and provides a stylized analysis on inequality and mobility in Latin America. Then, 3.4.2 displays the estimated association between inequality experienced in childhood and intergenerational mobility as adults. Finally, 3.4.3 visualizes the magnitude of the factors associated with the intergenerational persistence of socioeconomic status. Section 3.5 concludes.

3.2. Inequality and Intergenerational Mobility: The State of the Art

The relationship between inequality and intergenerational mobility as a broad measure of equality of opportunity is of crucial importance for various dimensions of economic development.[4] Indeed, recent studies on the relationship between income inequality and growth found opposite effects when the distribution of income is determined by inequality of opportunities, on the one hand, or by inequality of efforts, on the other, being negative in the former and positive in the latter (Marrero and Rodríguez, 2013). Similar results have been found by authors dedicated to the study of inequality of educational attainments. They confirm that rising human capital enhances growth and economic development, but is only conditional on the degree of educational inequality (Cuaresma et al., 2013; Sauer and Zagler, 2014). Education takes place early in life and strongly shapes individual opportunities. The choice of certain educational tracks and first educational attainments are strongly determined by circumstances beyond the influence of the individual (for a recent survey, see Heckman and Mosso, 2014). Hence, these findings can be interpreted as further evidence of the detrimental impact of inequality of opportunities and the crucial role they play in a comprehensive analysis of income inequality.

In the past, this subject was analyzed in some influential theoretical contributions which

[4]The conceptual discussion on equality of opportunity has its origins in Philosophy (see among others Dworkin, 1981b,a). For a recent review, see Roemer and Trannoy (2015).

conceptualized the mechanisms behind the intergenerational transmission of inequality.[5] The main intuition used is that *family endowments* inherited by children from parents play a crucial role in the mechanisms underlying the transmission. Moreover, rising income inequality between families leads to higher inequality of investment in children's human capital and thus to lower upward mobility of children coming from poorer households. These implications arose from the seminal models of Becker and Tomes (1979, 1986)and Loury (1981) and the adaptations conducted by Solon (1992b).[6] Subsequent models built mainly on this framework (e.g. Owen and Weil, 1998; Maoz and Moav, 1999; Galor and Zeira, 1993; Hassler et al., 2007). In this last branch of studies in particular, an important weight is attributed both to credit market constraints that limit private investment in human capital and to public investment in human capital as one of the major contrasting forces of this dynamic.

These theoretical models are basically built on the assumption that parents derive utility not only from their present consumption level, but also from the future utility of their children. Therefore, parents invest mainly in the human capital of their children to raise their future income and, thus, utility. If the investment is exclusively private, budget constraints limit the investment choices of families and lead - especially in presence of credit market imperfections - to the persistence of inequality from one generation to the next, i.e. poor parents are unable to invest in the human capital of their children, who are therefore unable to afford better income opportunities for themselves and to climb up the social ladder. Consequently, when income becomes more unequally distributed, inequality of investment in children's human capital rises, causing low intergenerational mobility, social stratification, and even higher income inequality in the following generation.

Empirically, the question of whether parental income and credit constraints are determinants of disparities in human capital investments is far from being resolved, as pointed out, for example, by Piketty (2000) in an older review about intergenerational mobility and Black and Devereux (2011b) in a more recent one. Actually, the association might be even stronger if altruism and the propensity to invest in children's human capital are positively associated with (relative and absolute) income. Furthermore, other direct and indirect effects of certain parental background features play an important role, such as parental education or cognitive abilities (e.g. being able to support children in their educational career and the informational advantage of the value of certain degrees on the labor market), as well as so-called network and neighborhood effects (Benabou, 1996; Durlauf, 1996). Genetic transmission of abilities might also be a significant channel, as explained in some of the above-mentioned models, although it may be relatively weak in comparison with other family endowments, as recent research has shown (Black et al., 2015).[7] What is certain is that even though credit

[5]Actually, the idea that in Capitalist societies class reproduction and the persistence of inequality depend mainly on the initial distribution of wealth is the core of Marx's analysis and finds space in even older thoughts.

[6]Extensions to Gary Solon's first contribution are Solon (1999, 2002, 2004, 2014b).

[7]For a review on so-called "Nature and Nurture" effects, see Sacerdote (2011).

constraints are only one of many factors determining the formation of human capital, and simply providing income transfers to poor families would certainly not solve the problem of inequality in children's opportunities (as pointed out e.g. by Heckman and Mosso, 2014), the cross-country relationship between inequality and mobility shows that it is still a factor to be taken seriously.

Observing the dynamics of this process within society, as a logical consequence of the mechanisms explained above we would expect rising income inequality to cause lower intergenerational mobility. However, whereas the cross-country association between income inequality and intergenerational mobility has been investigated extensively (e.g. Aizer, 2014; Andrews and Leigh, 2009; Björklund and Jäntti, 2012; Blanden, 2013; Brunori et al., 2013; Checchi et al., 1999; Corak, 2013b,a; Holter, 2015; Jerrim and Macmillan, 2015), within-country evidence on this point is still rare. The influential works of Chetty et al. (2014c,b) use administrative data on income to estimate intergenerational mobility trends across geographical areas in the US. Their results show that mobility varies significantly across areas and that areas with high inequality display low rates of mobility, as predicted by the theoretical models and evidenced by the Great Gatsby Curve. This is confirmed by the analysis of Güell et al. (2015) on a sample of 103 Italian provinces using a novel measurement of intergenerational mobility based on the correlation of economic well-being with rare surnames.[8] However, observing time trends, Chetty et al. (2014c) find that intergenerational mobility - measured as the conditional correlation of parents' and childrens' rank in the income distribution, children's college attendance and other measures - has not fallen in the US despite rising inequality, confirming earlier findings by Lee and Solon (2009). The authors explain this by the fact that the rise in inequality in the US was mainly driven by top incomes (Piketty and Saez, 2003), while mobility depends to a larger extent on "middle class" inequality (i.e. among the bottom 99 % of the income distribution), as their own findings highlight. One of the very few studies analyzing cross-sectional inequality and intergenerational mobility trends in a developing country is the paper of Fan et al. (2015) on China. They find evidence for the existence of a Great Gatsby Curve within China, observing declining mobility rates along with rising inequality during the economic transition. Similar approaches to the one applied in the present study are recent analyses by Cingano (2014) on OECD countries using PIACC data, and by Kerney and Levine (2016) on the association between inequality and the probability of dropping out from school in the US. Both confirm the negative relationship between inequality and intergenerational mobility.

Finally, what also needs to be taken into account is that the interplay between three institutions determines the degree of intergenerational mobility in a society (Corak, 2013b). The first institution is the family, mainly due to the inheritance of endowments from parents to children, for example through investments in human capital (e.g. determining quantity, quality, and pertinence of educational attainments), genetic transmission of abilities, or the

[8]This measure of intergenerational mobility was first proposed by Guell et al. (2015).

passing down of certain values.[9] Concerning the last-mentioned point, empirical research found, for example, a positive association between income inequality and a stronger work ethic (Corneo and Neher, 2013), which might lead to higher intergenerational mobility. The second institution is the market, since higher returns to investment in human capital might act as an incentive for families to invest more and, thus, raise mobility (Solon, 2014b). The third is the state, which provides public investment in human capital for families that cannot afford an efficient level of investment due to budget constraints (Davies et al., 2005). Additionally on this last point, Ichino et al. (2011) argue that political institutions strongly influence the degree of persistence of socioeconomic status in a society and are one of the main explanations for cross-country differences in intergenerational mobility estimates. Another important aspect might be the timing of the investment in human capital. As pointed out, among others, by Heckman and Mosso (2014), investments are more effective at earlier ages, while interventions in adolescence may have only short-run effects. In any case, as various branches of research have shown, the role of parental background in children's outcomes is important over various stages of life (Ermisch et al., 2012).

3.3. Data & Measurement

3.3.1. *Data*

Studies on intergenerational mobility are always methodologically and conceptually constrained by the available data.[10] Ideally, the requirement for an empirical analysis of intergenerational mobility is the availability of valid measures (or good proxies) for permanent income of parents and children. Furthermore, for cross-country comparisons to be meaningful, the data must be as comparable as possible between countries. Research on intergenerational mobility in developing countries faces a further complication. Since panels are an absolute rarity in developing countries, there are only two ways to obtain information on the economic outcomes (e.g. educational attainment, occupation) of both parents and children. The first is to restrict the analysis to children and parents still living in the same household. The second is to use the information given by retrospective questions on parental characteristics. Estimates derived from the first would be biased by the truncation and non-representativeness of the sample since adult children which left the household because of marriage, college or other reasons are not taken into account.[11] The second alter-

[9] Some authors also related different fertility choices of poor and rich households to the persistence of poverty (e.g. Moav, 2005).

[10] The three "Ws" of mobility analysis, as termed by Jäntti and Jenkins (2013): mobility of *What*, among *Whom*, and *When*. See also Björklund and Jäntti (2012) for an overview.

[11] Although intuitively the problem is clear enough, research on the actual degree of the bias is rare. Only recently, a study by Emran et al. (2017) has shown that the bias is severe on measures of mobility that do not take into account the variances of the dependent and independent variable, such as the intergenerational regression coefficient, and not as strong for normalized measurements, such as the standardized intergenerational correlation.

Table 3.1.: Latinobarometro; Databases 1998, 2000-2011, 2013.

Country	Year of birth	(sd)	(min)	(max)	Age	(sd)	(min)	(max)	Male
Argentina	1980	5.97	1970	1995	26.26	5.92	18	43	0.49
Bolivia	1980	6.20	1970	1995	26.11	6.10	18	43	0.49
Brazil	1980	6.08	1970	1995	26.64	6.16	18	43	0.49
Chile	1979	6.20	1970	1995	26.75	6.18	18	43	0.49
Colombia	1980	6.09	1970	1995	26.45	6.04	18	43	0.49
Costa Rica	1980	6.16	1970	1995	26.31	6.12	18	43	0.49
Dominican Rep.	1981	6.33	1970	1995	27.02	6.32	18	43	0.49
Ecuador	1980	6.20	1970	1995	26.30	6.00	18	43	0.49
El Salvador	1980	5.97	1970	1995	26.04	5.75	18	43	0.48
Guatemala	1980	6.16	1970	1995	25.83	5.90	18	43	0.48
Honduras	1980	6.12	1970	1995	25.85	5.88	18	43	0.49
Mexico	1979	6.02	1970	1995	26.67	6.03	18	43	0.47
Nicaragua	1980	6.00	1970	1995	25.74	5.79	18	43	0.48
Panama	1980	6.20	1970	1995	26.58	6.10	18	43	0.48
Paraguay	1981	6.40	1970	1995	26.48	6.33	18	43	0.50
Peru	1980	6.20	1970	1995	26.33	6.10	18	43	0.49
Uruguay	1980	6.22	1970	1995	26.76	6.11	18	43	0.50
Venezuela	1980	6.02	1970	1995	26.28	5.93	18	43	0.50

Weighted Sample Statistics: Means and Standard Deviations by Country.

Table 3.2.: Harmonized Household Surveys

Country	Year of birth	(sd)	(min)	(max)	Age	(sd)	(min)	(max)	Male
Brazil	1976	5.17	1970	1990	27.75	5.67	18	38	0.42
Chile	1979	6.22	1970	1995	31.04	6.23	18	43	0.36
Colombia	1981	6.73	1970	1995	29.38	6.73	18	43	0.46
Ecuador	1976	4.90	1970	1988	24.89	4.96	18	36	0.45
Guatemala	1980	6.15	1970	1993	27.61	6.05	18	41	0.43
Mexico	1978	5.94	1970	1991	28.67	6.16	18	39	0.42
Nicaragua	1975	3.17	1970	1980	22.95	3.17	18	28	0.44
Panama	1978	5.46	1970	1990	26.75	5.54	18	38	0.46
Peru	1976	4.98	1970	1995	31.35	5.57	18	43	0.78

Weighted Sample Statistics: Means and Standard Deviations by Country. Brazil: PNAD 1982, 1988, 1996; PDSD 2008. Chile: CASEN 2006, 2009, 2011, 2013. Colombia: ECV 2003, 2008, 2010-2013. Ecuador: ECV 1994, 1995, 1998, 2006. Guatemala: ENCOVI 2000, 2006, 2011. Mexico: MXFLS 2002, 2005, 2006, 2009-2012. Nicaragua: EMNV 1998. Panama: ENV 1997, 2003, 2009. Peru: ENAHO 2001-2012.

Table 3.3.: Latinobarometro; Databases 1998, 2000-2011, 2013.

Country	Education	(sd)	(min)	(max)	Parental education	(sd)	(min)	(max)	N
Argentina	11.05	2.62	0	15	9.00	3.67	0	15	6634
Bolivia	9.62	4.10	0	15	6.13	5.39	0	15	7881
Brazil	8.79	3.69	0	15	5.81	4.36	0	15	6822
Chile	10.70	3.06	0	15	8.99	4.04	0	15	5986
Colombia	9.84	3.96	0	15	7.05	4.86	0	15	7461
Costa Rica	8.67	3.58	0	15	7.03	4.43	0	15	6030
Dominican Rep.	9.18	4.05	0	15	6.66	5.06	0	15	3926
Ecuador	9.71	3.74	0	15	6.93	4.47	0	15	7843
El Salvador	8.17	4.41	0	15	4.79	5.02	0	15	6635
Guatemala	6.19	4.68	0	15	4.28	4.68	0	15	6757
Honduras	6.33	4.31	0	15	4.11	4.39	0	15	6953
Mexico	9.39	3.69	0	15	7.02	4.70	0	15	8035
Nicaragua	7.46	4.44	0	15	5.28	5.26	0	15	6540
Panama	9.82	3.98	0	15	7.40	4.91	0	15	5634
Paraguay	9.31	3.46	0	15	6.02	3.93	0	15	6245
Peru	10.68	3.49	0	15	8.30	4.92	0	15	7800
Uruguay	9.66	2.97	0	15	8.23	3.62	0	15	5793
Venezuela	9.93	3.34	0	15	7.22	4.34	0	15	7191

Years of education. Weighted Sample Statistics: Means and Standard Deviations by Country.

Table 3.4.: Harmonized Household Surveys

Country	Education	(sd)	(min)	(max)	Parental education	(sd)	(min)	(max)	N
Brazil	8.40	4.49	0	22	5.30	4.42	0	22	18219
Chile	12.03	3.16	0	22	9.22	4.40	0	25	130750
Colombia	9.51	4.27	0	23	5.75	4.29	0	17	101040
Ecuador	9.02	3.87	0	22	6.54	4.41	0	20	17212
Guatemala	5.52	4.55	0	20	3.12	3.99	0	20	33517
Mexico	9.31	3.55	0	18	5.70	4.68	0	18	5883
Nicaragua	6.15	3.97	0	17	3.94	3.99	0	17	2360
Panama	9.97	4.23	0	24	7.57	4.96	0	17	12308
Peru	9.86	3.86	0	19	6.20	4.96	0	17	66175

Years of education. Weighted Sample Statistics: Means and Standard Deviations by Country. Brazil: PNAD 1982, 1988, 1996; PDSD 2008. Chile: CASEN 2006, 2009, 2011, 2013. Colombia: ECV 2003, 2008, 2010-2013. Ecuador: ECV 1994, 1995, 1998, 2006. Guatemala: ENCOVI 2000, 2006, 2011. Mexico: MXFLS 2002, 2005, 2006, 2009-2012. Nicaragua: EMNV 1998. Panama: ENV 1997, 2003, 2009. Peru: ENAHO 2001-2012.

native should, therefore, be more appropriate to study intergenerational mobility. However, not all surveys work with retrospective questions to obtain information on parental characteristics.

The data sources used in this study fulfill all the required prerequisites. First, the public opinion survey *Latinobarometro*, which since 1995 has recorded individual and household characteristics of a nationally representative sample of adult respondents in 18 Latin American countries, including questions about one's own and parental education (since 1998).[12] Second, a micro data set which pools several household surveys for 9 Latin American countries, all ofs which could be identified as asking directly with retrospective questions about the educational attainments of parents.[13] While the *Latinobarometro* data is harmonized ex-ante, the data set which comprises different household surveys is harmonized ex-post. The countries included in the latter are Brazil, Chile, Colombia, Ecuador, Guatemala, Mexico, Nicaragua, Panama, and Peru. Tables 3.1 to 3.4 show some weighted descriptive statistics of the samples, which comprise 120,166 (*Latinobarometro*) and 390,404 (*Harmonized Household Surveys*) individuals who were born after 1970 and were at least 18 years old when the survey was conducted, with available information on their own and parental education.[14] The number of observations by country is much more balanced in the Latinobarometro, ranging from 3,926 in the Dominican Republic to 8,035 in Mexico, while in the second data set it varies from the 2,360 observations of Nicaragua to the 130,750 of Chile.

Since the Latinobarometro is a survey created appositely for cross-country comparisons, the means of year of birth, age, and sex are rather uniform across countries, while in the data set constructed from various household surveys there are notable differences. Also, the codification of completed years of education of parents and children is uniform in the Latinobarometro, but diverges between countries in the other sample. This is due to the fact that in some countries the definition of education was expanded to include higher order degrees in some survey years, for example a doctoral degree in Panama, and thus coded with 24 years of education. In order to make use of all the available information, the main analysis with the household survey data is performed while maintaining the different specifications

[12]The Latinobarómetro survey comprises a sample of 1000 to 1200 individuals per country every year. It is carried out by local firms under the technical supervision of the Latinobarómetro Corporation, a private non-profit organization based in Santiago (Chile). The study receives financing from Latin American and non-Latin American governments, the private sector, and international organizations, including the IADB (Inter-American Development Bank), UNDP (United Nations Development Programme), 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. The Dominican Republic was included for the first time in 2004, raising the country total to 18.

[13]The data presented here is used in a parallel project to compute a new macro panel data set of educational mobility trends over a span of more than 50 years (Neidhöfer et al., 2017).

[14]A priori, the analysis could be sensitive to the chosen age restriction because some individuals might not have yet completed their educational career at this age. A question on this that was included in the 2013 wave of the Latinobarometro survey shows that the mean age of completion of education in Latin America is 17.7, ranging from a mean age of approximately 15 in Honduras to approximately 20 in Brazil. Suitable robustness checks imposing different age restrictions (e.g. older than 21) have been performed, with no significant changes in the main analysis. The results can be found in the Online Appendix.

across countries and surveys. However, suitable robustness checks are performed, coding years of education uniformly across countries, based on levels of education indicated in all the surveys according to the same standard, and following the definition made by the Latinobarometro.[15] As can be seen clearly, the two data sets are fundamentally different from each other, and the samples of single countries are not necessarily comparable between data sets. For instance, while the samples of Chile and Colombia seem to be rather similar between the Latinobarometro and the harmonized household survey data set, in other countries, especially in Ecuador and Nicaragua, fewer cohorts are available in the latter. Also, after excluding individuals without information on parental education, the distribution of males and females is unbalanced in the pooled survey data of some countries.[16] For all these reasons, it is not possible to compare the two data sets in a descriptive analysis, while the within-sample analysis maintains its validity and is particularly useful.

Information on income inequality is extracted from the *Socio-Economic Database for Latin America and the Caribbean* (SEDLAC, CEDLAS and the World Bank), which is the main source of information regarding inequality, poverty, and other labor market or social indicators for Latin America.[17] The SEDLAC data relies on harmonized micro data from over 300 household surveys carried out in 24 Latin American and Caribbean countries and represents in each period more than 97 % of the total population in the region.[18] For the main analysis, use is made of the Gini coefficient of disposable household per capita income, for which the first spells vary from 1974 (in Argentina) to 2001 (in Colombia).[19] Information on economic growth, measured by GDP per capita in USD (constant at 2005 market prices), and on public expenditures in education, measured as percentage of GDP, are derived from World Bank data and are reported yearly since 1970.[20] All thedata sources used share the great advantage of assuring the best possible comparability between different countries and over time.[21]

[15]As usual in the literature, the highest parental degree – or in the case of missing information of one parent, the only one available – is used to measure parental education. The codification of completed years of education in the Latinobarometro and the alternative specification in the household survey sample are shown in the Online Appendix. The specification used in the main analysis with the latter follows the actually indicated completed years of education in the respective household survey.

[16]This is especially evident in Peru, where nearly 80 % of the sample are men. The reason in this case is that from 2002 on in the ENAHO household survey the question on education of parents is asked only of household heads, who are, in most cases, male.

[17]The date of the statistics used in this version of the paper is *November 2014*.

[18]Most household surveys included in SEDLAC are nationally representative. However, in some countries surveys which cover only urban areas (in Argentina, Bolivia, Colombia, Paraguay, and Uruguay) are also used. Still, in these countries the urban population represents the vast majority of the national population (e.g. 85 % in Argentina). Further computations make the data comparable if derived from different surveys for the same country and fill missing data points by interpolation; estimates obtained without interpolation are, however, not significantly different to the main results in this study. For further information on methodological issues, see "A guide to the SEDLAC: Socio-Economic Database for Latin America and the Caribbean." (CEDLAS and The World Bank, 2012). For an exhaustive discussion of the SEDLAC data also see Bourguignon (2015).

[19]Results do not change when using the Gini coefficient of equivalised household income instead.

[20]In the estimations concerning the early childhood period, the starting age of compulsory education is used instead of public expenditures on education.

[21]While the Latinobarometro survey is designed for comparable analyses between countries and over time, household surveys are not uniform across Latin American countries and differ significantly in geographical

3.3.2. *Measurement*

The established way to measure intergenerational mobility in a society is to estimate the following equation:

$$Y^t = \alpha + \beta Y^{t-1} + X + \varepsilon, \qquad (3.3.1)$$

where Y is a measure of permanent income or lifetime earnings for two subsequent generations within a family and X is a vector of controls. The coefficient β, thus, measures the degree of persistence in socioeconomic status from parents $(t-1)$ to children (t). Higher values of β display a higher association between parents' and children's well being, and therefore a lower intergenerational mobility, and vice versa.

Outcome variables The information which is most likely to be available in household surveys for both parents and children is completed years of education. In the absence of accurate information on long-run earnings, using education is arguably the best way to identify (lifetime) socioeconomic status since the use of income "snapshots" to approximate (*log*) lifetime earnings leads to serious bias in the intergenerational mobility estimates (Nybom and Stuhler, 2016).[22] Furthermore, retrospective information on educational attainment is less affected by measurement error than information on income or earnings. As Blanden (2013) shows with a small sample of countries, intergenerational mobility estimates obtained using educational attainment are highly correlated across countries with the best available estimates using income.

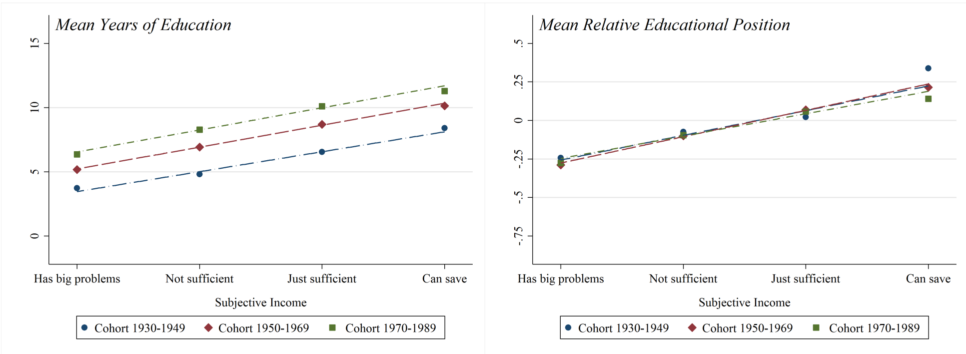
A comparable measure of intergenerational mobility across different countries and over different time periods is obtained through a linear transformation of parents' and children's educational attainments. The new outcome variable is centered around 0, which displays the mean years of education of even-aged people, born in the same year, of the same sex, and living in the same country. The obtained regression coefficient is thus a measurement which is close to the well-known intergenerational correlation, but has the main advantage of taking into account the inequality transmission of human capital, a dimension which gets lost if the latter is applied.[23]

coverage and questionnaires, sometimes also within countries over time. Although important improvements have been made by Latin American governments in the last few years – thanks also to programs like the Regional Program for Improvement of the Surveys and Measurement of the Living Conditions in Latin America and the Caribbean, MECOVI, launched in 1996 as a joint initiative of the Inter-American Development Bank (IDB), the World Bank, and the United Nations Economic Commission for Latin America and the Caribbean (UN-ECLAC) – the issue of comparability is still of great concern. However, the SEDLAC data is compiled with the greatest possible effort to make statistics comparable across countries and over time by using similar definitions of variables and by applying consistent methods. The same applies for World Bank data.

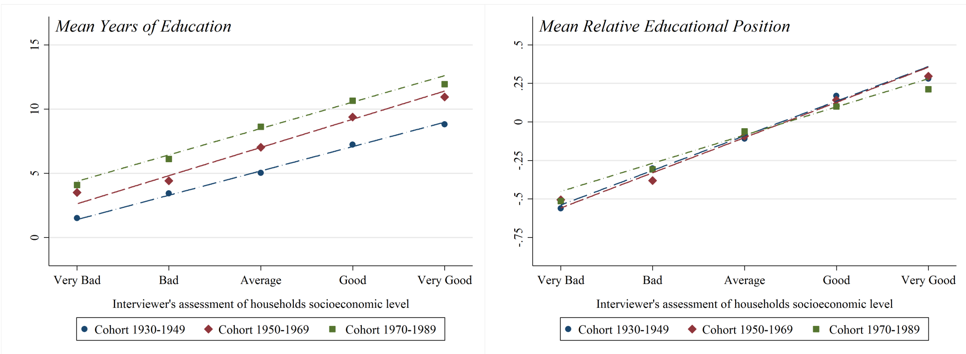
[22] Studies for the US have shown that proper measurements of intergenerational persistence of income can only be obtained with more than ten years of income spells for both parents and children (Solon, 1992b).

[23] The intergenerational correlation is obtained by multiplying the regression coefficient by the ratio of the standard deviations of parents' and children's outcome and, thus, adjusts for differences in inequality between generations. This is intentionally avoided here since the inequality of human capital is an interesting dimension which should not be taken out of the evaluation. In any case, to provide a comparison to the previous literature, estimates have also been computed i) without any normalization of completed years of

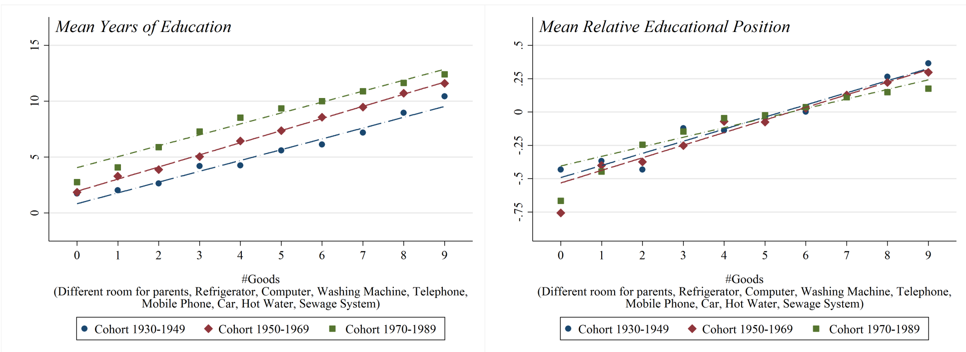
Figure 3.1.: Educational attainment as a proxy for well being: Years of Education *vs.* Relative Educational Position.



(a) Subjective Income



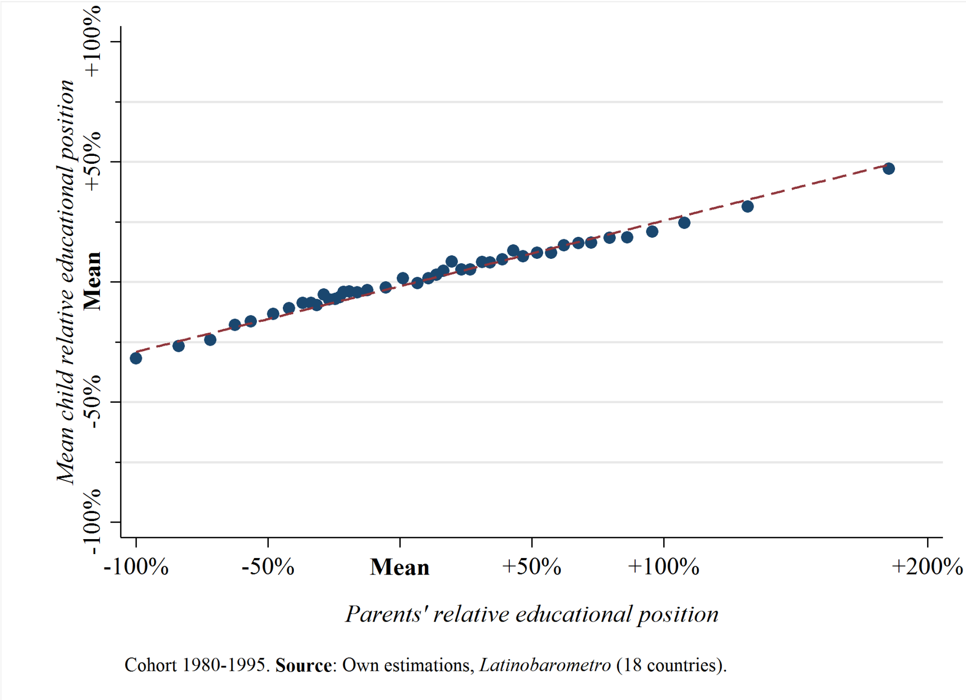
(b) Interviewer's assessment of socioeconomic status



(c) Number of goods

Notes: The graphs show the association between completed years of schooling and the relative educational position – i.e. the relative distance of an individual from the educational attainments of his or her reference group, defined as people of the same sex, born in the same year and in the same country – with different variables included in the Latinobaromtero survey indicating well-being or socio-economic status. Source: Latinobarometro 2013, own estimations.

Figure 3.2.: Intergenerational Mobility - Binned scatter plot of mean child position by parental background.



Notes: The graph shows a binned scatter plot of the average relative educational position of children for each category of parents' relative educational position. All Latin America (Graphs for each country in Online Appendix). Source: Latinobarometro, own estimates.

The above transformation of completed years of education has several further advantages. First, it offers an intuitive way to evaluate the relative position of parents and children with regard to their reference group, yielding an outcome variable which is more indicative of socioeconomic status than educational attainment alone. Indeed, the sensitivity analysis displayed in Figure 3.1 shows that the relative educational position obtained through a linear transformation is a more suitable indicator for well-being and relative socioeconomic status across time than simply evaluating completed years of education. Second, the assumption of linearity is less strong than using completed years of education and the relative educational position is closer to a normal distribution.[24] Furthermore, the transformation yields outcome variables that might be considered continuous, such as income or earnings, instead of ordinal, such as educational attainment. Third, the obtained variable is a measurement of relative standing and thus conceptually closer to rank-based measures, which in the case of income have been proved to be more robust and less affected by bias (Chetty et al., 2014b; Nybom and Stuhler, 2015). It should therefore be the appropriate measure to compare individuals from different countries and cohorts consistently.

Figure 3.2 shows the mean relative educational position of children against their parents'

education and ii) using the Z-Score of parental education. All estimations confirm the main results and can be found in the Online Appendix.

[24]The exploration of non-linearities in the relationship is addressed in section 3.4.3. Further analysis on the normality assumption can be found in the Online Appendix.

position in the pooled sample of Latin American countries using the Latinobarometro data. To construct this figure, parents' relative educational position is subdivided into bins of equal population size. The dots show the mean of the children's position for each bin.

Baseline Estimation In the first part of the analysis, equation (3.3.2) is estimated for the pooled sample of people born between 1980 and 1995, then separately for people born between 1980 and 1987 (older cohort) and 1988 and 1995 (younger cohort).

$$y_{ic} = \alpha + \sum_{k=1}^{18} \beta_k \cdot y_{ic}^p \cdot C_{ic} + \sum_{k=1}^{18} \xi_k \cdot C_{ic} + \sum_{k=1}^{18} \delta'_k (X_{ic} \cdot C_{ic}) + \varepsilon_{ic} \tag{3.3.2}$$

As explained above, the two outcome variables $y_{ic} = (Y_{ic} - \overline{Y})/\overline{Y}$ and $y_{ic}^p = (Y_{ic}^p - \overline{Y^p})/\overline{Y^p}$ indicate the *relative educational position* with respect to the reference group, with Y_{ic} being the completed years of education of individual i in country c, Y_{ic}^p that of her parents, and $\overline{Y}$ ($\overline{Y^p}$) the mean years of education of her (her parents') reference group, i.e. people of the same age, sex, country, and cohort.[25] C is a dummy variable that equals one if i lives in country $c = k$ and zero otherwise; ξ_k thus captures the country fixed effect of country k. X comprises individual controls for sex, age (polynomial), and survey year fixed effects. Estimating equation (3.3.2) is, thus, equivalent to estimating equation (3.3.1) for each country separately and yields β coefficients for the 18 Latin American countries under evaluation.

Interactions In the second part, the macro-level characteristics inequality, economic growth, and public investment in human capital are included in the regressions to analyze their association with individual outcomes. For this purpose, the variable for parental educational position is interacted with the relevant macro-level variables. What is of crucial importance here is how the macro-level characteristics are associated with individuals. For instance, measuring inequality and intergenerational mobility at the same time (e.g. in the same year) would imply the strong assumption that countries are in a steady-state, and within country differences would not be captured properly. The applied strategy takes these aspects into account and evaluates the macro-level characteristics when the individual was in a period of life when investments in human capital were essential.[26]

Three lifetime periods are identified when parental (or public) investment in human capital is essential: (A) *Early childhood,* defined as the age interval from 0 to 6, (B) *Primary school age*, from age 6 to 12, and (C) *Adolescence*, from age 12 to 18. Then, the mean of the relevant macro characteristics are matched to individuals according to the country where they live

[25]Since it would make no sense to compare the parents of people of different sex and age distinctly, the measure for parental education is normalized only by country and year of birth.

[26]Of course, investment in human capital may be made at every stage of life and up to older ages. However, as shown by many studies, human capital investments are more effective and have a longer lasting effect, the earlier they take place. See, among others, Ermisch et al. (2012); Heckman and Mosso (2014) for an overview of the importance of investment in human capital at different moments of children's lifetimes. Recently, Hufe et al. (2017) even argue that all achievements and behaviors of children are due to circumstances they should not be held responsible for.

and the respective age intervals mentioned before.[27] This method permits sufficient variation in the independent variables, not only between but also within countries.

Formally, the following equation is estimated separately for the three specifications (A), (B), and (C) mentioned above

$$y_{ijc} = \alpha+\beta y^{p}_{ijc}+\delta' X_{ijc}+\gamma_1\cdot y^{p}_{ijc}\cdot Q_{jc}+\tau_1 Q_{jc}+\gamma_2\cdot y^{p}_{ijc}\cdot G_{jc}+\tau_2 G_{jc}+\gamma_3\cdot y^{p}_{ijc}\cdot Z_{jc}+\tau_3 Z_{jc}+\sum_{k=1}^{18}\xi_k\cdot C_{ic}+\varepsilon_{ijc}, \quad (3.3.3)$$

restricting some of the coefficients to zero in different estimations. Subscript j is added and denotes i's birth cohort. Equation (3.3.3) enables us to evaluate how the relationship between y_{ijc} and y^{p}_{ijc} varies at different levels of the macro characteristics under evaluation. Q_{jc} indicates the level of income inequality in country c associated with cohort j (i.e. the average value of this characteristic in the years matching the specified age interval, as explained above), measured by the Gini coefficient of household per capita income retrieved from SEDLAC data. G_{jc} indicates economic growth, measured by GDP per capita (World Bank Data). Z_{jc} stands for public investment in human capital, measured by public expenditures on education as a percentage of GDP or by the starting age of compulsory education in one of the specifications (World Bank data).[28] Q, G and Z are centered on the sample mean and vary at the country c and cohort j level.[29]

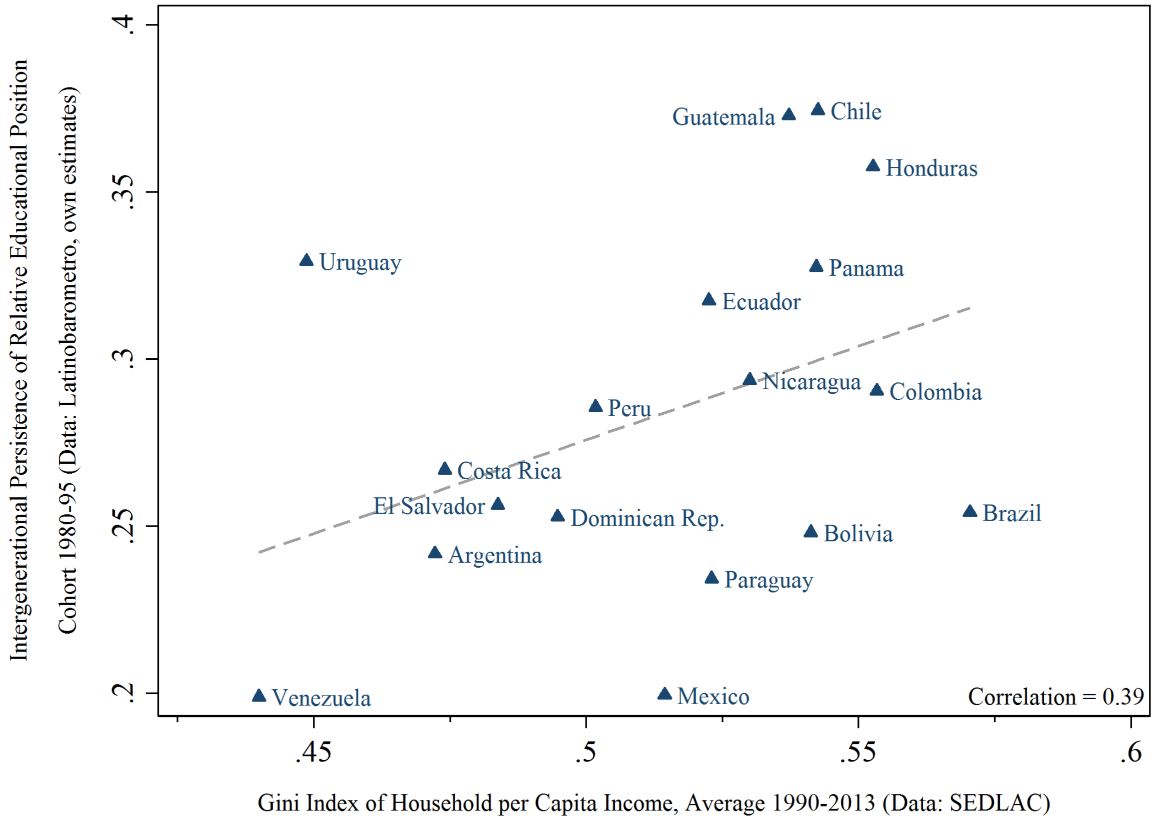
Since parental income is widely accepted as a useful approximation for parental investment in children, income inequality experienced in childhood can be understood as a proxy for inequality of parental investment in children's human capital, growth as an indicator for increasing parental resources, and public expenditures on education as a proxy for public investment in human capital (see Mayer and Lopoo, 2008).[30] The γ-coefficients thus signal a positive or negative change in the slope of the association of parents' and children's socioeconomic status according to the mentioned characteristics experienced in childhood by the individuals.[31] Standard errors are clustered by country and year of birth.

Table 3.5.: Intergenerational Mobility in Latin America: Regression Coefficients (β) for each Country (Data: Latinobarometro, own estimates)

	(1) Cohort 1980-1995		(2) 1980-1987		(3) 1988-1995	
Argentina	0.242***	(0.0069)	0.243***	(0.0075)	0.237***	(0.0170)
Bolivia	0.248***	(0.0137)	0.255***	(0.0171)	0.224***	(0.0073)
Brazil	0.254***	(0.0082)	0.257***	(0.0094)	0.244***	(0.0179)
Chile	0.374***	(0.0196)	0.382***	(0.0212)	0.346***	(0.0470)
Colombia	0.291***	(0.0131)	0.289***	(0.0154)	0.303***	(0.0175)
Costa Rica	0.267***	(0.0145)	0.287***	(0.0143)	0.204***	(0.0140)
Dominican Rep.	0.253***	(0.0150)	0.257***	(0.0187)	0.242***	(0.0226)
Ecuador	0.318***	(0.0097)	0.319***	(0.0115)	0.318***	(0.0165)
El Salvador	0.256***	(0.0110)	0.263***	(0.0120)	0.239***	(0.0163)
Guatemala	0.373***	(0.0147)	0.398***	(0.0157)	0.312***	(0.0198)
Honduras	0.358***	(0.0201)	0.334***	(0.0204)	0.441***	(0.0115)
Mexico	0.200***	(0.0110)	0.199***	(0.0136)	0.205***	(0.0131)
Nicaragua	0.294***	(0.0118)	0.280***	(0.0110)	0.340***	(0.0218)
Panama	0.328***	(0.0120)	0.323***	(0.0120)	0.348***	(0.0365)
Paraguay	0.234***	(0.0228)	0.289***	(0.0154)	0.128***	(0.0385)
Peru	0.286***	(0.0071)	0.281***	(0.0060)	0.305***	(0.0237)
Uruguay	0.329***	(0.0086)	0.338***	(0.0087)	0.310***	(0.0233)
Venezuela	0.199***	(0.0127)	0.212***	(0.0123)	0.141***	(0.0241)
Demographic controls	Yes		Yes		Yes	
Country fixed effects	Yes		Yes		Yes	
Observations	62729		46849		15880	
R^2	0.226		0.230		0.227	

Regression coefficients (β) of equation 2.2.1: own *vs.* parental relative educational position (see Section 3.3.2 and Figure 3.1). Demographic controls comprise *sex*, *age (polynomial)*, and *survey year*. Data: Latinobarometro 1998-2013. Statistical significance level * 0.1 ** 0.05 *** 0.01. Benchmark for Cohort 1980-1995: USA (PSID, own estimates) 0.158, Germany (SOEP v30, own estimates) 0.334.

Figure 3.3.: Inequality and Intergenerational Mobility in Latin America - The Great Gatsby Curve



Notes: The graph shows the relationship between income inequality and intergenerational mobility. Inequality is measured by the average Gini index of household per capita income from 1990 to 2013 (retrieved from SEDLAC Data). Intergenerational mobility is measured by the association between parents' and children's relative educational position of people born between 1980 and 1995 (see Section 3.3) on Latinobarometro data. Table 3.5 shows these estimates.

3.4. Results

3.4.1. Stylized Analysis

Latin America is an interesting laboratory to analyze inequality and intergenerational mobility. On the one hand, the region is still characterized by high levels of inequality which are among the highest from a global perspective (Alvaredo and Gasparini, 2015; Lustig et al., 2013). On the other hand, while worldwide inequality has been rising, most Latin American countries experienced a significant decrease in inequality in the last decade (Gasparini et al., 2011; Gasparini and Lustig, 2011; Cord et al., 2013).

Many studies in the past were dedicated to the study of intergenerational mobility in one or more countries in Latin America. The literature has recently been reviewed by Torche (2014) and includes, among others, Azevedo and Bouillon (2010); Binder and Woodruff (2002); Castellani and Lora (2014); Dahan and Gaviria (2001); Daude and Robano (2015); Ferreira et al. (2013); Gaviria et al. (2007). All basically confirm that mobility in Latin America is very low, as would typically be expected for countries with high levels of income inequality. These results are confirmed by the influential work of Hertz et al. (2008), which compares intergenerational mobility trends across countries. Unsurprisingly, the only four Latin American countries included in the original Great Gatsby Curve - Argentina, Brazil, Chile, and Peru - are situated in the upper right-hand corner of the curve.

Although the different countries in Latin American all have similar levels of inequality and intergenerational mobility when compared to developed countries – i.e. they would be situated in the same area of the graph showing a global analysis – significant differences can be registered between them. Table 3.5 shows the estimated regression coefficients of equation (3.3.2) to measure intergenerational mobility using the normalized measures for parents' and children's relative educational position as explained in Section 3.3.2. In the first column, the results are displayed for people born between 1980 and 1995, with the period then subdivided in the older cohort and younger cohort as above.[32] The rates of intergenerational mobility for the two cohorts are displayed separately in columns two and three of Table 3.5. In a ranking of the countries by their rates of intergenerational mobility, not all the

[27]A very simple example taking inequality measured by the Gini coefficient as a macro-level variable: For an individual born in 1986 in Argentina, the average Gini coefficient in Argentina from 1986 to 1992 (0.454) is associated with *early childhood*, the average from 1992 to 1998 (0.469) with *primary school age*, and the average from 1998 to 2004 (0.509) with *adolescence*.

[28]The estimation procedure is further explained in the notes of Table 3.9.

[29]Running estimations of equation (3.3.3) including cohort fixed effects do not change the results significantly.

[30]The limitations of this approach to identify a causal relationship are discussed in the conclusions.

[31]A similar methodology was adopted by Mayer and Lopoo (2008) to evaluate the relationship between government spending and intergenerational mobility and by Schütz et al. (2008) to analyze the effect of certain characteristics of the education system on equality of opportunity. In a recent study, Cingano (2014) similarly compares the mean effect of inequality experienced at the age of 14 on years of schooling, literacy, and numeracy of people with different parental educational background (low, middle, high) using PIACC data.

[32]Regression coefficients obtained without normalization as well as the intergenerational correlation and different age restrictions can be found in the Online Appendix.

differences between the countries are statistically significant, especially in the middle of the ranking. However, countries at the top of the ranking have significantly higher mobility than countries at the bottom; a pattern also found in earlier studies. Furthermore, in countries where one cohort experienced low (high) levels of mobility in comparison to the mean, the subsequent cohort also experienced low (high) intergenerational mobility. The range of the intergenerational mobility estimates varies from Venezuela and Mexico, where an increase of 10 percent in parental education relative to the mean of their reference group is associated with a 2 percent increase in the children's generation, to Chile and Guatemala, where it is associated with an increase of 3.7 percent. As a benchmark, our own estimates for the US (PSID data) and Germany (SOEP data) using the same restrictions (at least 18 years old and born between 1980 and 1995) and the applied linear transformation of completed years of education yield regression coefficients of 0.158 and 0.334, respectively.[33]

The average level of intergenerational mobility in Latin America is higher in the younger cohort, and the estimated regression coefficients for the older cohort are greater than the ones for the younger cohort in 12 out of 18 countries. In Mexico, Nicaragua, Peru, Colombia, Panama, and Honduras the younger cohort experienced lower intergenerational mobility than their older peers. However, these changes are sometimes very small in both directions and in most cases not statistically significant.[34]

The Great Gatsby Curve for Latin America is constructed using the intergenerational persistence estimates displayed in Table 3.5 and the Gini index of disposable household per capita income, retrieved from SEDLAC data. Figure 3.3 shows the relationship between the intergenerational persistence for people born between 1980 to 1995, estimated with the Latinobarometro, and the average level of income inequality between 1990 and 2013, retrieved fromSEDLAC. We observe that the expected relationship and the cross-country correlation between these two variables is 0.39.

[33] An alternative measurement of intergenerational mobility, called the Social Mobility Index (SMI) and proposed by Andersen (2003), is included in the SEDLAC data for each year and country in which survey data is available. This index, as well as its strength and limitations, are discussed in the Online Appendix. Since the limitations for an analysis of intergenerational mobility probably outweigh the advantages, in the present study our own measurements of intergenerational mobility are estimated. In the Online Appendix, the SMI-1 and SMI-2 are reported for the sake of completeness, and generally confirm the pattern of rising social intergenerational mobility in most Latin American countries. A comparison of the SMI with the intergenerational mobility measure estimated in the present study can be also found in the Online Appendix.

[34] Statistical significance is calculated using the pooled sample of the 1980-1995 cohort for each country separately and interacting the variable for parental educational position with a dummy signalizing the younger cohort. The changes in mobility are significant at the 0.05 level in only six countries, and at the 0.01 level in four. However, the sample is relatively small in the younger cohort, varying from 660 observations in Panama to 1,448 in Nicaragua. Since the Latinobarometro sample includes individuals who are 16 and 17 years old only in Bolivia and Brazil, in the main analysis the sample is restricted to individuals who are at least 18 years old. The estimates change slightly when different age restrictions are imposed, which also reduces the samples, however. Nevertheless, as can be seen in the Online Appendix, the changes in estimates are not too serious. A comparison of estimates obtained from the Latinobarometro data with ones obtained from the seven countries where the harmonized household survey data is available shows that the estimates are mainly consistent across countries, but sometimes differ regarding the two cohorts (See the Online Appendix). The main reason for this is likely to be the different composition of the samples in the Latinobarometro and the harmonized household survey data as stated above, especially in the younger cohort (See Tables 3.1 to 3.4 for descriptive statistics).

Table 3.6.: Baseline Estimates of Intergenerational Mobility for All Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	Latinobarometro (18 countries)			*Harmonized Household Surveys (9 countries)*		
Specification	(A)	(B)	(C)	(A)	(B)	(C)
Parental Background (PB)	0.260***	0.256***	0.259***	0.243***	0.254***	0.273***
	(0.0073)	(0.0045)	(0.0043)	(0.0073)	(0.0060)	(0.0059)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33007	62911	87937	63843	139610	203787
R^2	0.192	0.185	0.188	0.206	0.224	0.240
#Clusters(Country/Cohort)	193	290	365	54	97	134

Please, see the notes under Table 3.9.

This stylized analysis of the relationship between inequality and intergenerational mobility provides a first intuitive overview of the problem, but certainly not a solution. Indeed, these first findings do not allow a rejection of the hypothesis that cross-country heterogeneity is the main force behind the observed differences in inequality and intergenerational mobility, as some authors point out (e.g. Acemoglu and Robinson, 2012; Ichino et al., 2011). Hence, the main analysis in the following sections will evaluate the effect of income inequality on intergenerational mobility adopting a different approach that allows us to control for cross-country heterogeneity.

3.4.2. Interactions

In the previous section, the analysis was merely descriptive and restricted to a stylized analysis. Now, a detailed microeconometric set up is adopted which enables us to test the hypothesis of a negative relationship between inequality and intergenerational mobility. The methodology applied here and the underlying equations are described in detail in Section 3.3.2. Table 3.6, 3.7, 3.8, and 3.9 show the main results of estimating equation (3.3.3) with both data sets for the three specifications (A) *Early childhood,* (B) *Primary school age,* and (C) *Adolescence*, respectively. First, Table 3.6 shows the baseline estimates of equation (3.3.3) restricting the coefficients of all the macro-level variables to zero. Then, in Tables 3.7, 3.8, and 3.9 each specification comprises four different estimations. The 4th rows show the intergenerational mobility parameter β at the mean of all the interacted variables with parental educational position, i.e. inequality, growth, and public investment in human capital. The coefficients that display the interaction effect between parental educational position and the characteristics of interest can be found in the first three rows. Generally, different slopes in the conditional correlation of parents' and children's educational position related to the macro-level characteristics are observed.[35]

[35]Full Tables can be found in the Online Appendix.

Table 3.7.: Specification (A) Early Childhood: Interaction of inequality, growth, and public educational expenditures experienced in age interval from 0 to 6 with intergenerational mobility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Latinobarometro (18 countries)				*Harmonized Household Surveys (9 countries)*			
PB×$\overline{Gini}(0 \le age \le 6)$	0.192***	0.192***	0.142**	0.363**	1.217***	1.251***	0.246	-1.189
	(0.0667)	(0.0667)	(0.0719)	(0.1639)	(0.2699)	(0.2725)	(0.4435)	(1.6530)
PB×$\overline{GDPp.c.}(0 \le age \le 6)$			-0.014***	-0.013*			-0.027***	-0.016*
			(0.0039)	(0.0072)			(0.0072)	(0.0082)
PB×$\overline{Compulsory}(0 \le age \le 6)$				-0.000				0.027
				(0.0113)				(0.0255)
Parental Background (PB)	0.256***	0.256***	0.257***	0.243***	0.240***	0.241***	0.274***	0.204***
	(0.0073)	(0.0073)	(0.0069)	(0.0099)	(0.0063)	(0.0064)	(0.0108)	(0.0223)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	33007	33007	33007	15777	63843	63843	63843	22362
R^2	0.193	0.193	0.194	0.192	0.207	0.208	0.209	0.150
#Clusters(Country/Cohort)	193	193	193	138	54	54	54	28

Please, see the notes under Table 3.9.

Table 3.8.: Specification (B) Primary School Age: Interaction of inequality, growth, and public educational expenditures experienced in age interval from 6 to 12 with intergenerational mobility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Latinobarometro (18 countries)				*Harmonized Household Surveys (9 countries)*			
PB×$\overline{Gini}(6 \le age \le 12)$	0.130**	0.130**	0.048	0.107	0.826***	0.877***	0.734***	0.833**
	(0.0651)	(0.0651)	(0.0609)	(0.0745)	(0.2157)	(0.2124)	(0.2140)	(0.4030)
PB×$\overline{GDPp.c.}(6 \le age \le 12)$			-0.010***	-0.010***			-0.010***	-0.010***
			(0.0022)	(0.0026)			(0.0033)	(0.0035)
PB×$\overline{Pub.Educ}(6 \le age \le 12)$				-0.009**				-0.016*
				(0.0039)				(0.0090)
Parental Background (PB)	0.254***	0.254***	0.252***	0.250***	0.253***	0.253***	0.259***	0.259***
	(0.0044)	(0.0044)	(0.0039)	(0.0048)	(0.0059)	(0.0059)	(0.0070)	(0.0080)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	62911	62911	62911	53912	139610	139610	139610	130915
R^2	0.185	0.185	0.185	0.179	0.225	0.225	0.226	0.225
#Clusters(Country/Cohort)	290	290	290	255	97	97	97	85

Please, see the notes under Table 3.9.

Table 3.9.: Specification (C) Adolescence: Interaction of inequality, growth, and public educational expenditures experienced in age interval from 12 to18 with intergenerational mobility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Latinobarometro (18 countries)				*Harmonized Household Surveys (9 countries)*			
PB×$\overline{Gini}(12 \leq age \leq 18)$	0.221***	0.221***	0.101	0.109	0.832***	0.873***	0.797***	1.681***
	(0.0701)	(0.0701)	(0.0637)	(0.0673)	(0.2708)	(0.2619)	(0.2215)	(0.2491)
PB×$\overline{GDPp.c.}(12 \leq age \leq 18)$			-0.009***	-0.006***			-0.014***	-0.008***
			(0.0017)	(0.0018)			(0.0028)	(0.0018)
PB×$\overline{Pub.Educ}(12 \leq age \leq 18)$				-0.014***				-0.030***
				(0.0030)				(0.0064)
Parental Background (PB)	0.257***	0.257***	0.253***	0.248***	0.271***	0.271***	0.271***	0.272***
	(0.0040)	(0.0040)	(0.0036)	(0.0033)	(0.0061)	(0.0061)	(0.0056)	(0.0042)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	87937	87937	87907	78845	203787	203787	203787	195320
R^2	0.189	0.189	0.189	0.181	0.240	0.241	0.242	0.241
#Clusters(Country/Cohort)	365	365	364	329	134	134	134	128

Notes: Tables 3.7, 3.8 and 3.9 show the coefficients of linear regressions with the individual relative educational position as dependent variable (see Section 3.3.2 and Figure 3.1) for three different specifications. Table 3.6 shows the baseline estimates for the three specifications without inclusion of the macro-level variables. The specifications reflect three different choices for the age interval ($t_0 \leq age \leq t_1$) when the macroeconomic characteristics are matched to the individual: Specification (A) is the age interval from 0 to 6 years ($0 \leq age \leq 6$); Specification (B) from 6 to 12 ($6 \leq age \leq 12$); Specification (C) from 12 to 18 ($12 \leq age \leq 18$). The macroeconomic characteristics are measured as mean values from year $x + t_0$ to year $x + t_1$ and vary at the country and cohort level. Individual level data: *Latinobarometro* columns 1-4, *Harmonized household surveys* columns 5-8 (see Section 3.3.1). Demographic controls comprise *sex, age (polynomial),* and *survey year.* PB = Parental Relative Educational Position (see Section 3.3.2). Macroeconomic characteristics (interaction terms): $\overline{Gini}(t_0 \leq age \leq t_1)$ = Mean of the Gini coefficient of household per capita income measured in home country in the years corresponding to the age interval (SEDLAC Data). $\overline{GDPp.c.}(t_0 \leq age \leq t_1)$ = GDP per capita measured in home country in the years corresponding to the age interval (World Bank Data). $\overline{Compulsory}(t_0 \leq age \leq t_1)$ = Starting age of compulsory education measured in home country in the years corresponding to the age interval (World Bank Data). $\overline{Pub.Educ}(t_0 \leq age \leq t_1)$ = Public expenditures in education as percentage of GDP measured in home country in the years corresponding to the age interval (World Bank Data). Cluster adjusted s.e. by country and cohort (in parentheses). Statistical significance level * 0.1 ** 0.05 *** 0.01.

Income Inequality Inequality, as measured by the Gini coefficient of household per capita income (retrieved from SEDLAC data), significantly changes the slope in all three specifications, with only slight changes when country fixed effects are included. This is strong evidence for a negative relationship between inequality and intergenerational mobility, which goes beyond cross-country heterogeneity.[36] Furthermore, it might indicate an important role of budget constraints limiting parental investment in children's human capital in Latin America, since one of the main reasons for the decline in inequality in the region has been the provision of cash transfer programs to poor families and generally more exhaustive social spending (Gasparini and Lustig, 2011). In addition, it also provides contrasting evidence to the hypothesis of higher intergenerational mobility caused by higher returns to human capital investment, since the increase in inequality in Latin America was driven by a downfall in the skill premium, too.

Economic Growth & Public Expenditures on Education It has been theorized in economics that growth increases intergenerational mobility and, furthermore, drives income inequality (among others, Galor and Tsiddon, 1997; Galor and Moav, 2004; Hassler and Mora, 2000). On the other hand, many authors have highlighted the key role of public investment in human capital (among others Benabou, 1996; Davies et al., 2005; Solon, 2002) and empirically confirmed a positive association with intergenerational mobility (e.g. Mayer and Lopoo, 2008). To test these hypotheses, the two features are included in this analysis. When growth, measured by GDP per capita, is included, the interaction effect of inequality and parental background is still positive, but not significant in all specifications. The same pattern arises when public expenditure on education, measured as percentage of GDP, is interacted with parental education.[37]

On the one hand, this highlights one important channel which might be the main driver of the relationship, and, on the other, it confirms the power of public investment in human capital to outweigh the lack of private investment. Indeed, the coefficients of economic growth and public expenditures on education have the expected negative sign, showing an enhancing effect on intergenerational mobility. The former might be related to the large decrease in poverty in Latin America of the last decades.[38] Since growth has been mainly pro-poor in Latin America, allowing a substantial middle class to arise and hence lowering income inequality (Ferreira et al., 2013), it provides further evidence for the important role of budget constraints. The positive effect of public educational expenditures is confirmed by the lat-

[36] It is not surprising that including country fixed effects does not change the coefficients significantly, since the outcome variables for parents and children have been normalized at the country level. In a robustness check keeping the simply evaluated completed years of education as an outcome variable without any normalization, the coefficients indeed vary after the inclusion of country fixed effects, but are still positive and significant in all specifications. This robustness check confirms the presence of a negative relationship between inequality and intergenerational mobility when controlling for cross-country heterogeneity.

[37] Conducting the analysis with public expenditure per pupil as percentage of GDP per capita does not change the results significantly.

[38] The fraction of people in Latin America living under the poverty line fell from about 28 percent to 13 percent from the middle of the 1990s to 2011 (Levy and Schady, 2013).

est findings, among others, by Aizer (2014); Jerrim and Macmillan (2015); Herrington (2015); Holter (2015) on the importance of public investment in human capital for intergenerational mobility and equality of opportunity. The starting age of compulsory education does not seem to be associated with mobility.[39]

Robustness These results are robust to different specifications. First, in the main analysis using the harmonized household survey data, all the available information on educational attainment of parents and children is used to compute the relative educational position. A robustness check with the same specification as in the Latinobarometro data yields the same patterns. Second, if we restrict the analysis with the Latinobarometro data to the countries for which household survey data is available, the results are very similar in specifications (A) and (B), and differ slightly in (C).[40] Third, since the underlying sample is derived by pooling data from different waves of the survey in one case and different waves and countries in the other, the main results displayed above are obtained without using sampling weights. In any case, results obtained using inverse probability weights do not differ significantly.[41] Fourth, as a further robustness check, the estimations are performed using both the simply evaluated completed years of education of parents and children and the Z-Score of one's own and parental education. Using these measures, the evidence of a negative relationship between inequality and mobility is even more striking. Finally, different age restrictions imposed on the sample yield very similar and consistent results.[42]

3.4.3. Marginal Effects

The main results of the analysis so far are that income inequality experienced in childhood is negatively associated with intergenerational mobility. In contrast, the effects of economic growth and public expenditures on education are positive. These effects turn out to be statistically significant. Now, the question is how economically significant these results are and how to interpret them. Since both the parental relative educational position and the macro-level variables – inequality (Q, measured by the Gini coefficient of household per capita income), growth (G, measured by GDP per capita), and public investment in human capital (Z, measured by public expenditures on education as percentage of GDP) – are continuous, the coefficient of parental education measures the average effect of those variables at value 0, which is by construction the sample mean.

[39]However, the starting age of compulsory education also lacks substantial within country variation in the observation period.

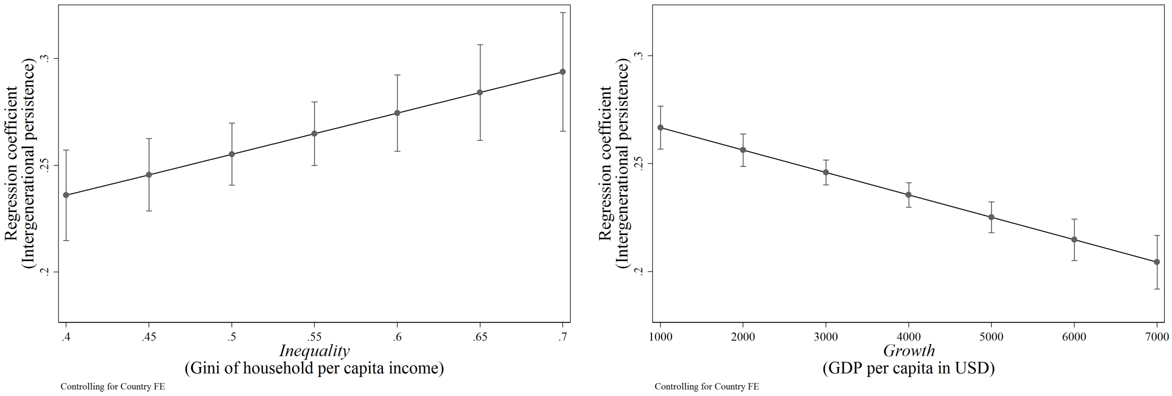
[40]Performing this robustness check, the only estimation which does not confirm the results of the main analysis is obtained in specification (C) when including economic growth in the regression. Here, the interaction effect of inequality on parental educational position becomes negatively significant (at the 0.05 level). A sensitivity analysis shows that this result is driven by Guatemala, which in fact has the more dispersed distribution of educational attainments in both samples.

[41]For a recent overview on sampling weights, see Solon et al. (2015).

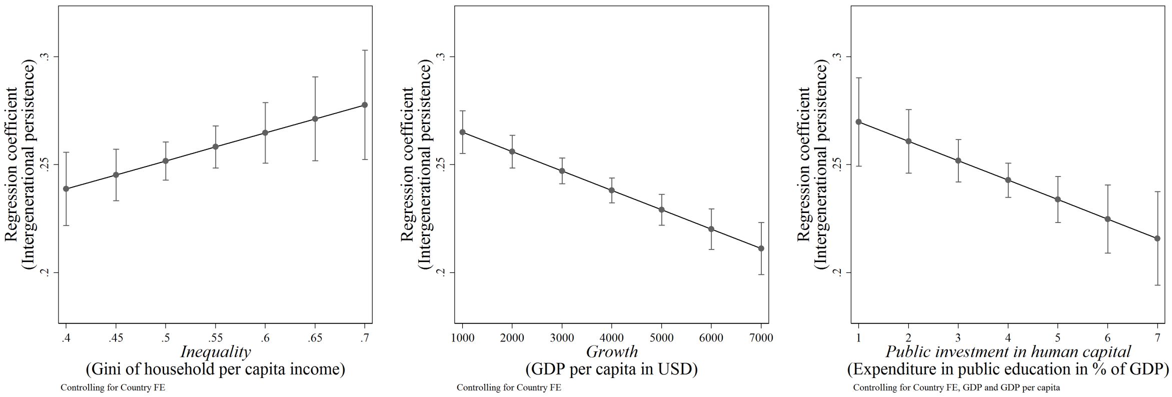
[42]These and other robustness checks can be found in the Online Appendix.

Figure 3.4.: Determinants of intergenerational mobility - Marginal effects; See Section 3.4.3

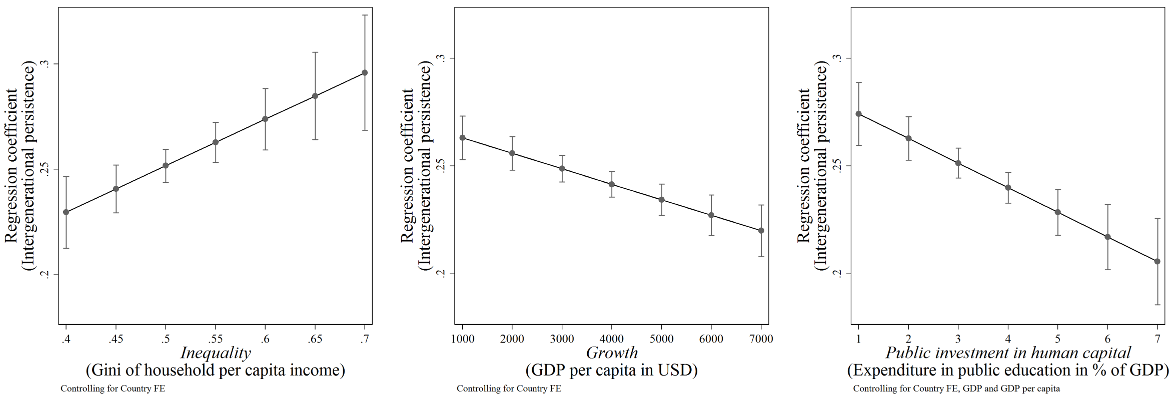
(A) Early childhood



(B) Primary school age



(C) Adolescence



Notes: The graphs show the marginal effects of the interaction terms estimated in equation 3.3.3 and their confidence interval (95 %) for the three distinct specifications.

Figure 3.4 shows the marginal effects of the interaction with parental educational background measured at different levels of inequality, economic growth, and public investment in human capital. The estimations control for country fixed effects. Additionally, GDP and GDP per capita are included in the estimation when the effect of public expenditures on education is measured. A statistically significant effect at economically plausible levels of inequality, growth, and public expenditure on education is found in all three specifications, (A) Early childhood, (B) Primary school age, and (C) Adolescence. As for the magnitude of the effect, intergenerational mobility - i.e. the gradient of parental educational background - varies significantly with relatively sharp shifts in inequality and growth and with moderate changes in public expenditure on education.[43]

When the Gini coefficient changes by 0.15, intergenerational mobility varies from 9 to 12 percent depending on the specification of the period of life under evaluation. The sharpest change in the slope can be observed when measuring inequality in early childhood (specification A). A change in inequality of similar magnitude has actually been experienced by Bolivia and Ecuador where inequality fell from a Gini coefficient of about 0.6 at the end of the nineties to 0.45 in the late 2000s. In the other Latin American countries where inequality was falling, the change was within a range of 0.02 to 0.1 Gini points in this period.

Changes in economic growth affect intergenerational mobility significantly between 5 and 8 percent of the gradient when GDP per capita changes by 2000 USD. The most remarkable change in the slope is observed, again, for growth in early childhood. In the case of economic growth measured by GDP per capita, the interpretation is more complex because of some contrasting facts. On the one hand, an increase of 2000 USD in GDP per capita is mostly a long-run process for a developing country and has never actually occurred in some Latin American countries, such as Bolivia, Guatemala, Honduras, and Nicaragua, since 1970. For some countries, for instance Brazil and Colombia, this has been a process lasting 30 and 40 years. However, in other countries, such as Chile, Costa Rica, and Panama, GDP per capita rose by 2000 USD or more within a decade. On the other hand, since year of birth varies in the sample from 1970 to 1995, the time horizon comprises 25 years, which might be enough for such a development to take place. Hence, the results of this study point to an overall significant influence of economic growth on intergenerational mobility. As a last remark, the relatively higher importance of economic growth (and inequality) experienced in early childhood seems to confirm that investment in human capital is especially important in the early periods of life.

The most important factor besides private investment in children's human capital has been theorized to be public investment through the provision of access to education. In the present study, public investment in human capital is measured by public expenditure on education as a percentage of GDP.[44] Holding GDP and GDP per capita constant, a change

[43] The full table displaying all marginal effects can be found in the Online Appendix.

[44] And also by the starting age of compulsory education, which, however, seems to have no significant effect on intergenerational mobility and is therefore not further evaluated in this part of the analysis.

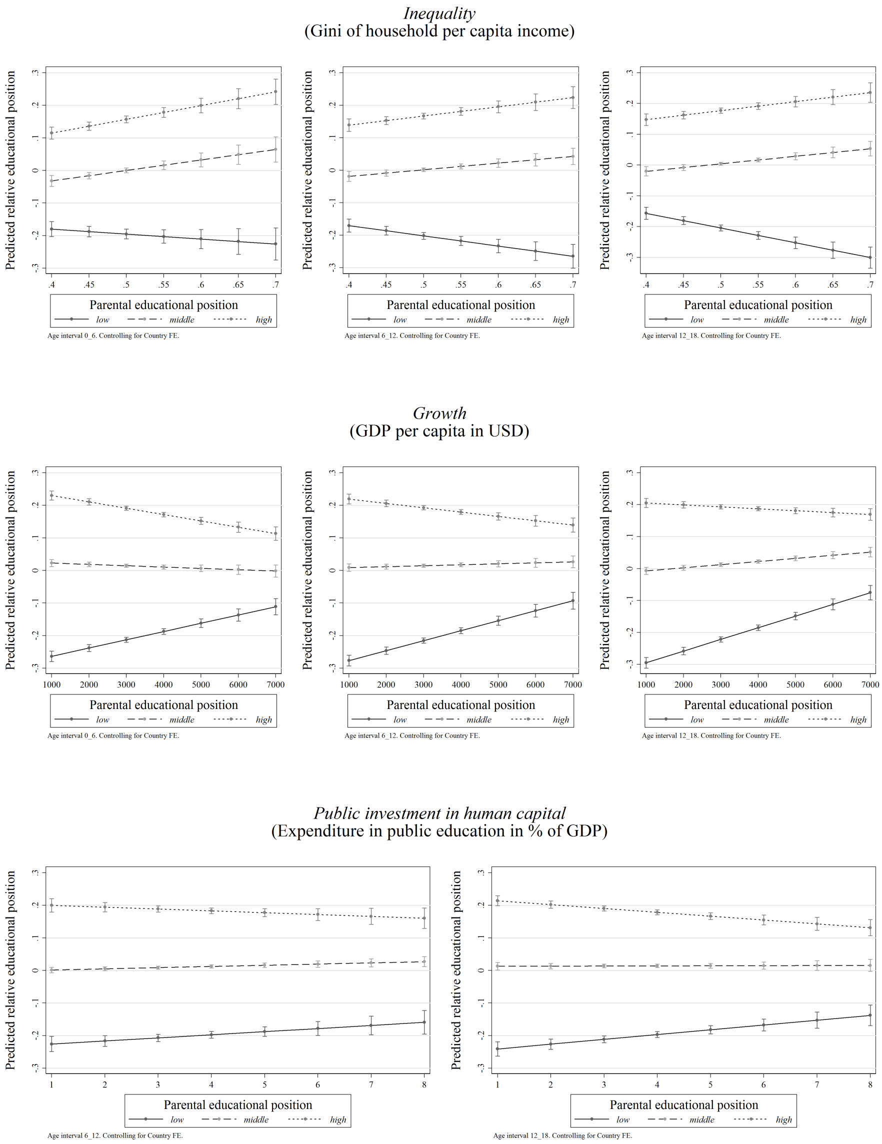
in public expenditures on education of two percentage points significantly changes intergenerational mobility estimates by 7 to 9 percent.[45] At the relatively low levels of public expenditures on education in Latin America, an increase of two percentage points can mean a doubling of the efforts in absolute terms; for example, in Ecuador, Nicaragua, and Uruguay public expenditures on education were around two percent of GDP in the early 2000s. Nevertheless, most countries indeed experienced such a change, especially in the period from 2000 to 2010. Public investment in human capital is thus confirmedas an important channel to replace private investment and, therefore, to increase intergenerational mobility.

Non-linearities An analysis of non-linear patterns in the relationships shows an even more striking picture. Figure 3.5 shows the predicted relative educational position of children from different parental educational backgrounds with rising levels of inequality, growth, and public education expenditures. In the process, parental educational background is subdivided into three categories of equal population size: *low*, comprising parents with 100 to 30 percent less completed years of education than their reference group; *middle*, comprising parents around the average of their reference group; *high*, comprising parents whose educational attainment is more than about 30 percent higher than their reference group.

The patterns of the interaction are clear and consistent in all specifications. The negative interaction of income inequality with intergenerational mobility is particularly strong for families with lower educational positions, while children from higher educated parents increase their relative educational position with rising inequality. The same patterns have been found by Cingano (2014) for OECD countries and by Kerney and Levine (2016) for high school dropout rates in the US. The reverse applies to growth and public education: low educated families profit most in terms of upward mobility from rising GDP per capita and public expenditures on education.

[45]The results do not change significantly if the duration of compulsory education in included as a further control variable in the estimations.

Figure 3.5.: Non-linearities in the determinants of intergenerational mobility - Marginal effects by parental educational position



Notes: The graphs show the predicted relative educational position of children from different parental educational background with rising levels of inequality, growth and public educational expenditures, as well as the confidence interval (95 %). Equation 3.3.3 is estimated subdividing parental educational background into three categories of equal population size: *Low*, comprising parents with 100 to 30 percent less completed years of education than their reference group. *Middle*, comprising parents around the average of their reference group. *High*, comprising parents whose educational attainment are more than about 30 percent higher than their reference group.

3.5. Conclusions

The aim of this study was to test the relationship between income inequality and intergenerational mobility while controlling for cross-country heterogeneity, thus contributing to filling the gap on multi-country and multi-period evidence on this relationship. Using two different sets of harmonized household survey data for 18 Latin American countries, this analysis confirms the negative relationship hypothesized by economic theory and suggested by cross-country evaluations, with the most compelling evidence being the link found between income inequality experienced in childhood and the level of intergenerational mobility in adulthood. The analysis of different patterns across the distribution shows that the upward mobility of individuals with low parental educational background in particular is seriously limited by higher levels of inequality, while individuals with high parental educational background even improve their relative educational position. In further analyses, economic growth could be established as one of the main channels behind the relationship in Latin America, while public expenditures on education are an important contrasting force. Since the two sets of micro data include the same countries but are derived from completely different sources – one from official public institutions and the other from non-governmental sources – obtaining the same patterns with both is strong evidence for the robustness of these results. It can, therefore, be concluded that (private and public) investment in human capital is a determinant for intergenerational mobility, and a strongly dispersed distribution of this feature seriously challenges equality of opportunity in a society.

The present analysis shows that even if institutional background and other heterogeneous effects at the country level are held constant, the negative relationship between income inequality and intergenerational mobility still persists. As argued above, if parental income is a good approximation for parental investment in children, as is usually assumed in the literature, income inequality experienced in childhood should be a valid proxy for the dispersion of parental investment. At the same time, economic growth should measure rising parental resources and the same should be true for public expenditures on education as a proxy for public investment in human capital (see Mayer and Lopoo, 2008). Still, these proxies are imperfect and the exact identification of a causal effect would require an exogenous source of variation in private and public investment in children's human capital. At the same time, although school enrollment and attendance (as well as health outcomes) increased especially among the poor in consequence of the widespread social programs in Latin America, educational systems still lag behind in quality, and the evidence on the long-run effectiveness on human capital and well-being is still mixed (e.g. Cruces et al., 2014; Levy and Schady, 2013). Identifying the exact mechanisms behind this relationship goes beyond the scope of this study, which is to test if the relationship between income inequality and intergenerational mobility is an artifact of cross-country heterogeneity or not. These mechanisms, and especially the channels of intergenerational transmission within families, remain a topic of great research interest with ample space for future research (see e.g. the discussion in Black and Devereux, 2011a).

A methodological contribution of this study is the adoption of a novel way to measure intergenerational mobility of socioeconomic status using a transformation of educational attainment. The sensitivity analyses show that the constructed measure for the relative educational position is highly correlated with income and well-being, performing as a more precise indicator of socioeconomic status than educational attainment. Neidhöfer and Stockhausen (2016) adopt a similar methodological approach and show that in a cross-country comparison of developed countries, intergenerational mobility measures applying the transformation of parents' and children's educational outcomes indeed mirror past findings on intergenerational income mobility better than measures of educational mobility. Future research will address these points in more detail using data sets that enable us to construct directly observed measures of intergenerational mobility in income, education, and educational positions, as well as in counterfactual scenarios.

In conclusion, this is one of very few studies analyzing the relationship between inequality and intergenerational mobility in developing countries. The implications should be applicable to developed countries as well, if no other differing mechanisms play a fundamental role. It is left for future research to empirically verify this last question.

3.6. Additional Material

3.6.1. Comparison of intergenerational mobility indices with both data sets

Table 3.13.: Intergenerational Mobility in Latin America - Linear Transformation by Mean

	(1) LB 1980-1987		(2) LB 1988-1995		(3) HS 1980-1987		(4) HS 1988-1995	
Argentina	0.243***	(0.0075)	0.237***	(0.0170)				
Bolivia	0.255***	(0.0171)	0.224***	(0.0073)				
Brazil	0.257***	(0.0094)	0.244***	(0.0179)	0.254***	(0.0228)	0.232**	(0.1095)
Chile	0.382***	(0.0212)	0.346***	(0.0470)	0.221***	(0.0070)	0.186***	(0.0045)
Colombia	0.289***	(0.0154)	0.303***	(0.0175)	0.251***	(0.0064)	0.192***	(0.0063)
Costa Rica	0.287***	(0.0143)	0.204***	(0.0140)				
Dominican Rep.	0.257***	(0.0187)	0.242***	(0.0226)				
Ecuador	0.319***	(0.0115)	0.318***	(0.0165)	0.343***	(0.0124)	0.339***	(0.0000)
El Salvador	0.263***	(0.0120)	0.239***	(0.0163)				
Guatemala	0.398***	(0.0157)	0.312***	(0.0198)	0.365***	(0.0074)	0.280***	(0.0167)
Honduras	0.334***	(0.0204)	0.441***	(0.0115)				
Mexico	0.199***	(0.0136)	0.205***	(0.0131)	0.219***	(0.0147)	0.184***	(0.0286)
Nicaragua	0.280***	(0.0110)	0.340***	(0.0218)	0.259***	(0.0000)		
Panama	0.323***	(0.0120)	0.348***	(0.0365)	0.328***	(0.0085)	0.265***	(0.0139)
Paraguay	0.289***	(0.0154)	0.128***	(0.0385)				
Peru	0.281***	(0.0060)	0.305***	(0.0237)	0.222***	(0.0046)	0.194***	(0.0073)
Uruguay	0.338***	(0.0087)	0.310***	(0.0233)				
Venezuela	0.212***	(0.0123)	0.141***	(0.0241)				
Demographic controls	Yes		Yes		Yes		Yes	
Country fixed effects	Yes		Yes		Yes		Yes	
Observations	46849		15880		114850		42201	
R^2	0.230		0.227		0.245		0.183	

Outcome variables measured as relative distance from the mean by age, sex, country and cohort.
Data: LB) Latinobarometro 1998-2013. HS) Household surveys.
Statistical significance level * 0.1 ** 0.05 *** 0.01.

Figure 3.6.: Intergenerational mobility in Latin America - Point estimates and confidence intervals (Data: Latinobarometro, own estimates)

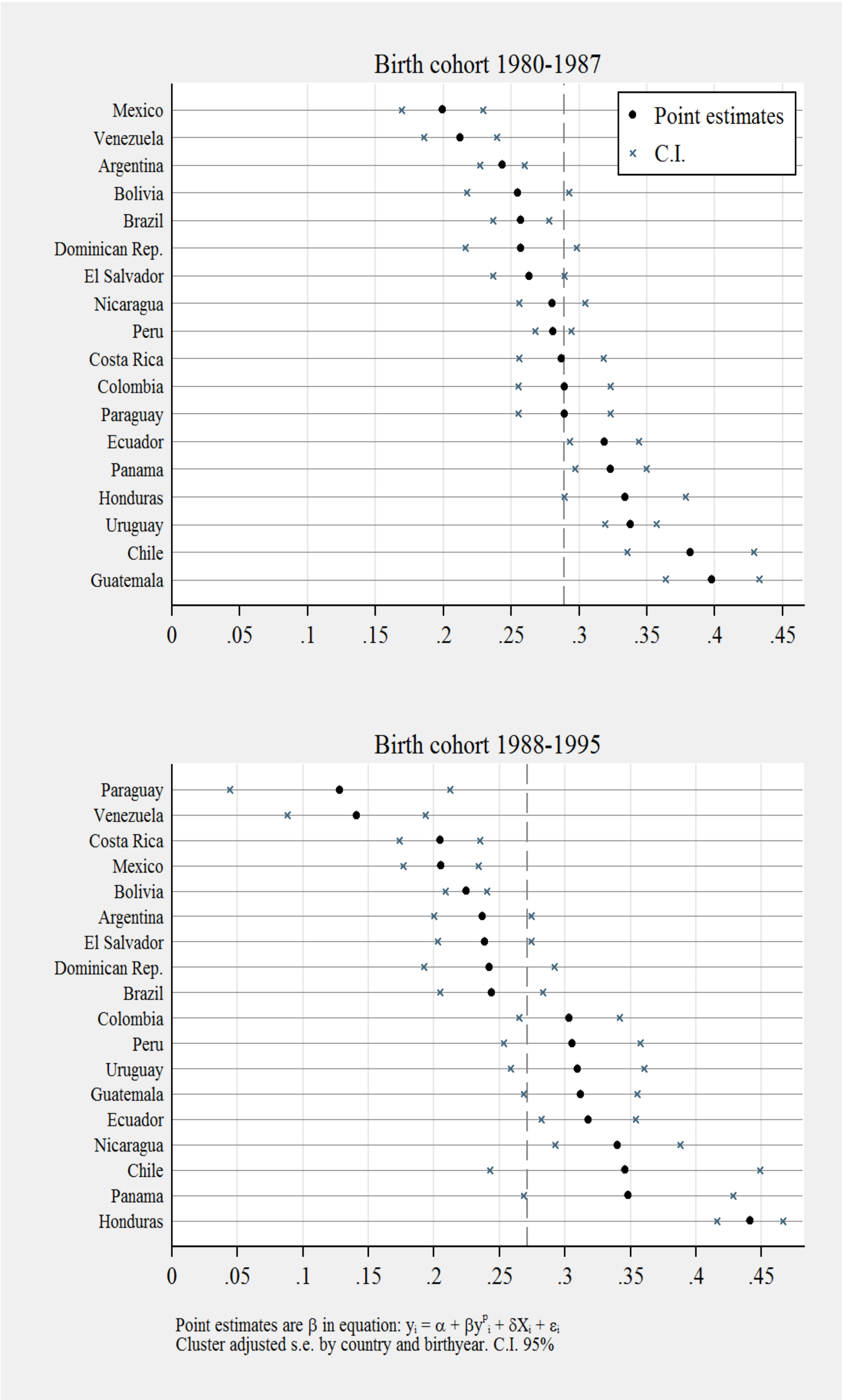
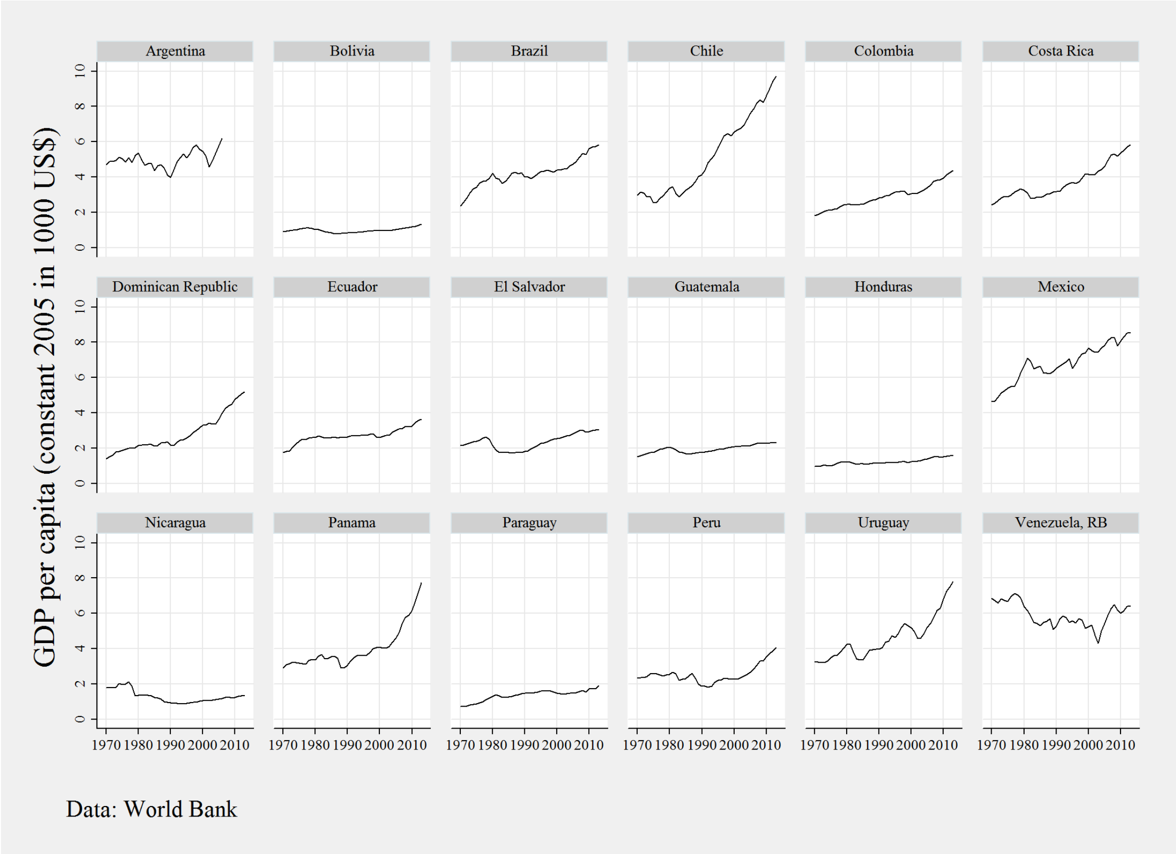
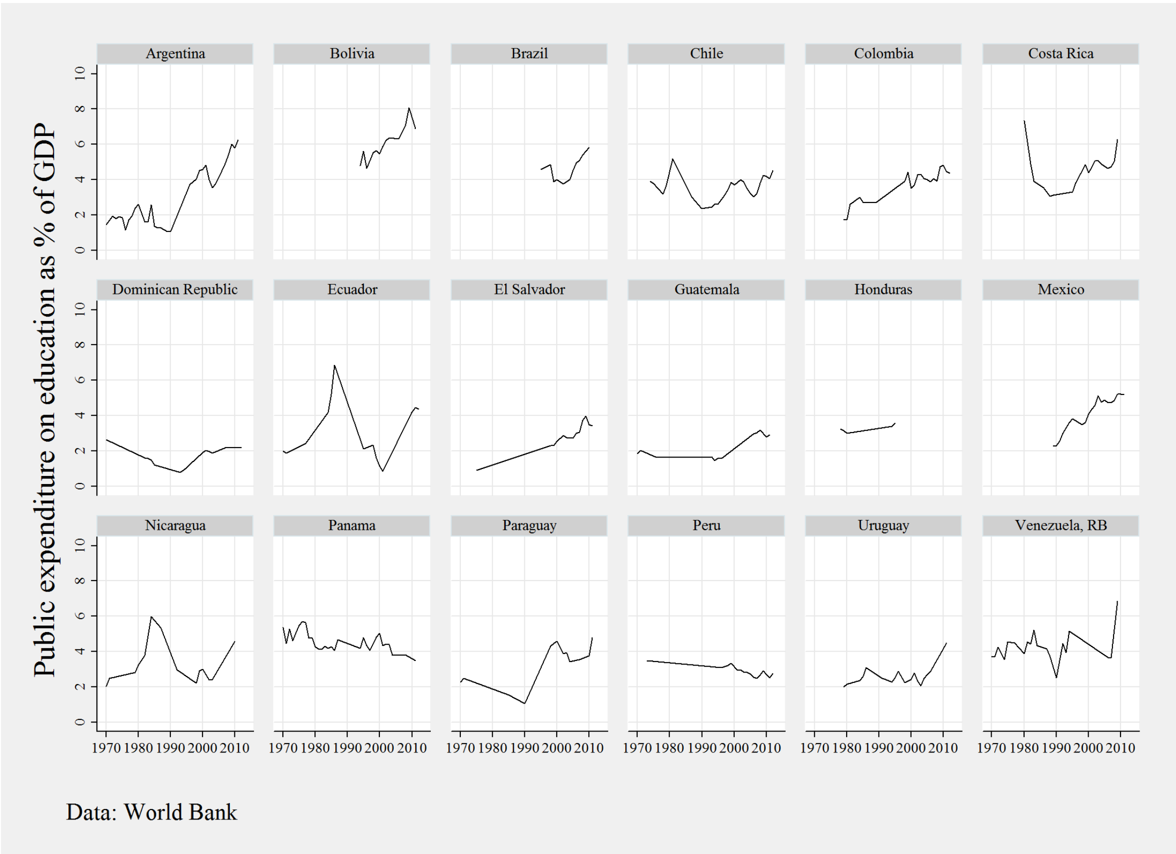


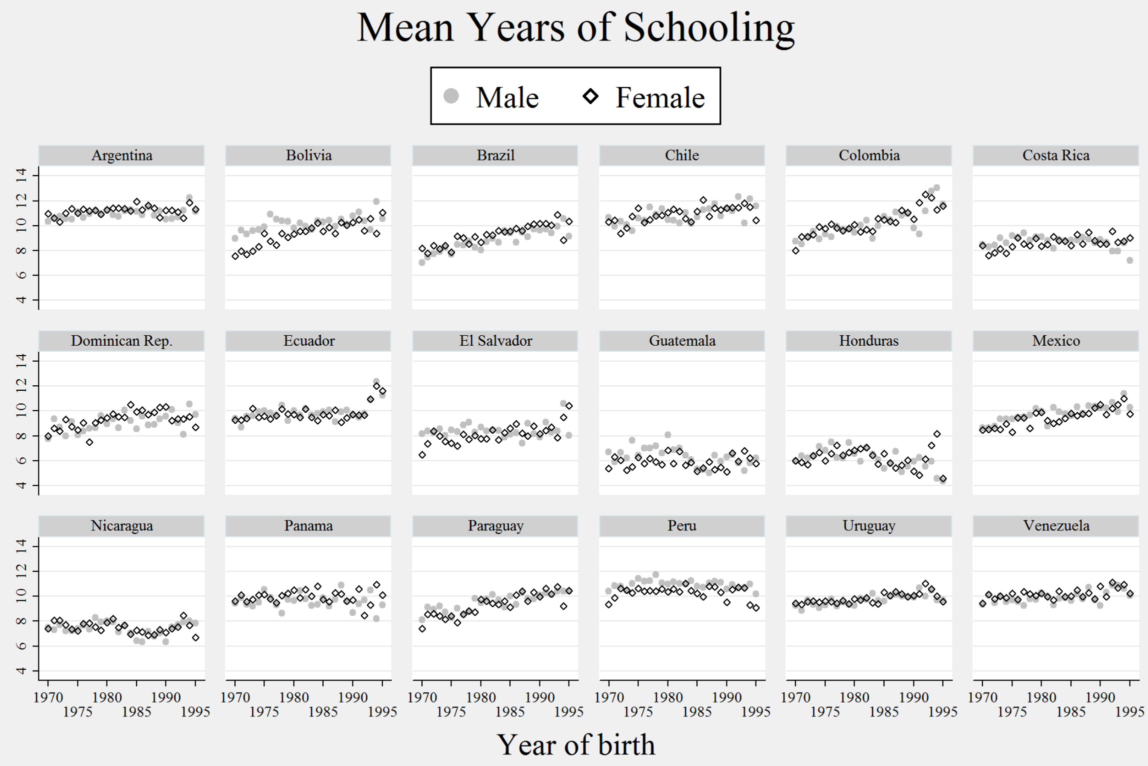
Figure 3.7.: Trends in Latin America



(a) GDP per capita



(b) Public expenditures in education



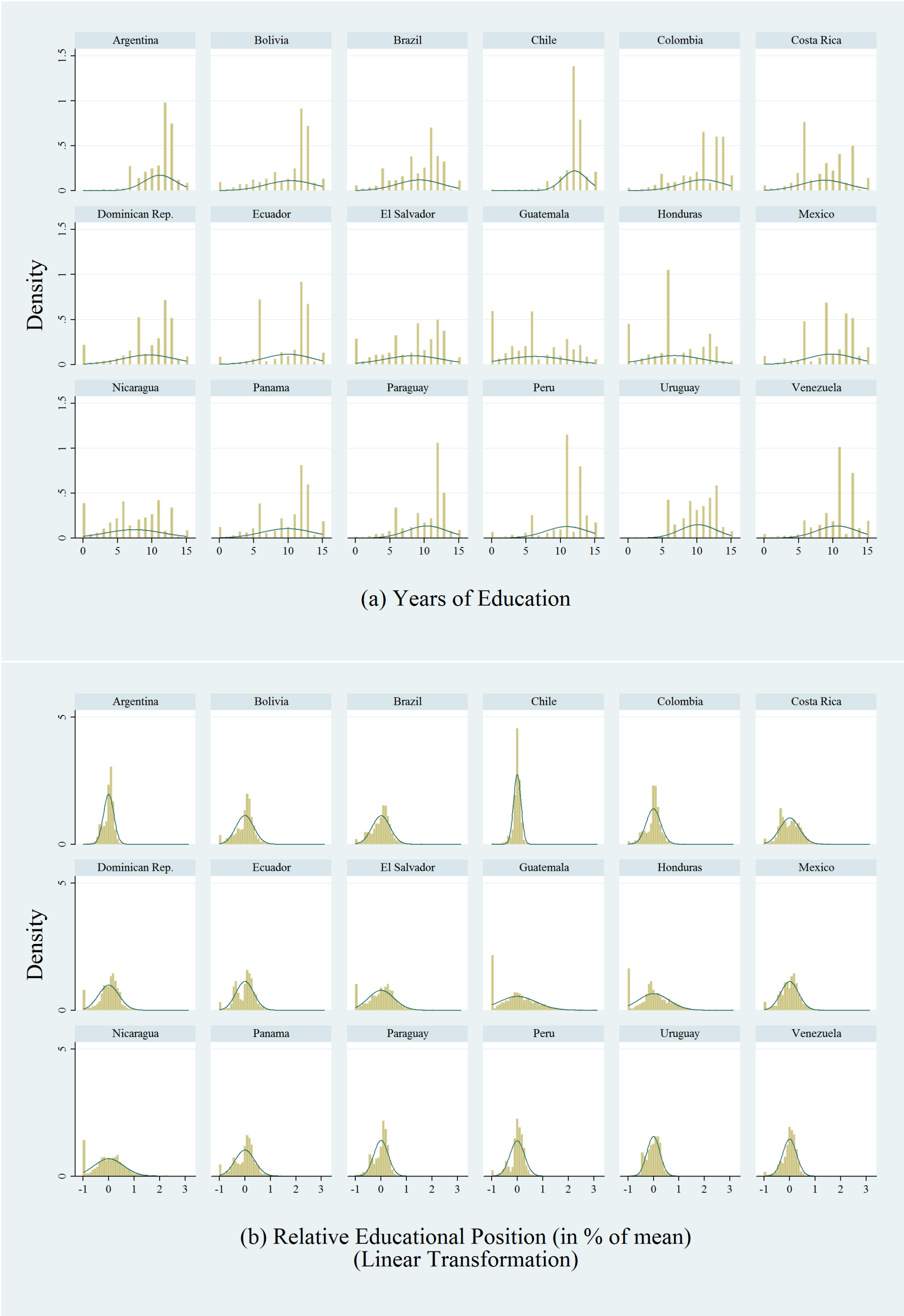
Source: Own estimations, *Latinobarometro* (18 countries).

Figure 3.8.: Mean Education

Table 3.10.: Codification of Educational Attainment

		Latinobarometro		*Household Surveys (Alternative)*	
Completed Years of Education		Freq.	Perc.	Freq.	Perc.
0	No schooling	5,976	4.97	14,059	3.60
1		761	0.63		
2		1,502	1.25		
3	Incomplete primary	2,604	2.17	59,136	15.15
4		3,086	2.57		
5	Complete primary	4,254	3.54	55,115	14.12
6		14,612	12.16		
7		4,078	3.39		
8		5,950	4.95		
9	Incomplete secundary	8,991	7.48	71,838	18.40
10		5,668	4.72		
11		13,632	11.34		
12	Complete secundary	18,383	15.30	109,757	28.12
13	Incomplete university or technical training	18,369	15.29		
14	Complete technical training	5,179	4.31	35,137	9.00
15	Complete university	7,121	5.93	45,304	11.61

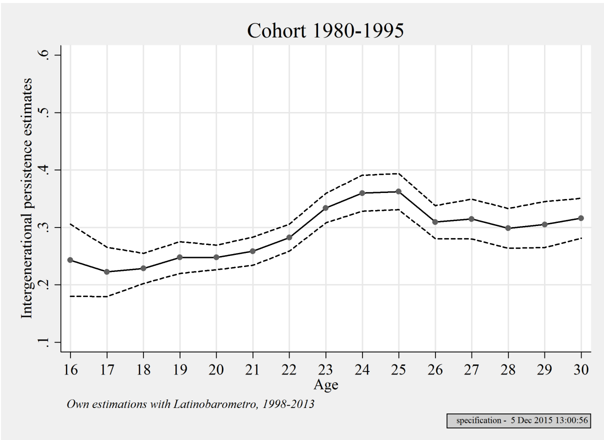
Note: Main specification in the Household Surveys Sample contains the actually measured years of completed education.



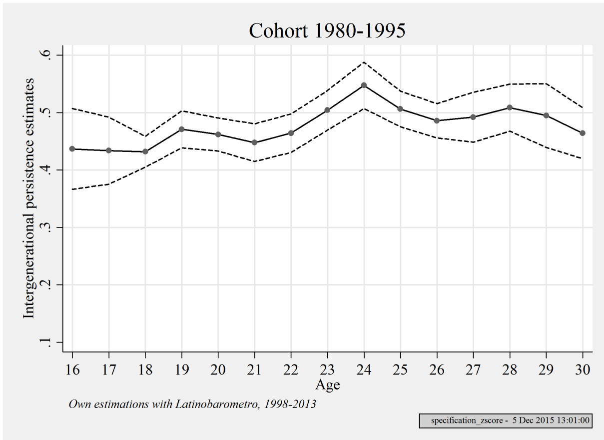
(a) Years of Education

(b) Relative Educational Position (in % of mean)
(Linear Transformation)

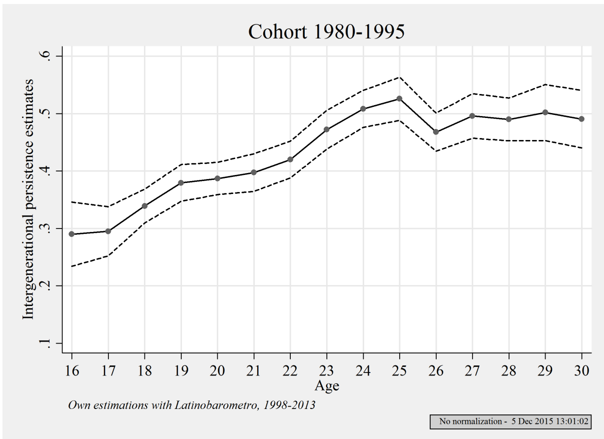
Figure 3.9.: Histograms by Country, Cohort 1980 - 1995 (Data: Latinobarometro, own estimates)



(a) Measurement with linear transformation - correcting for differences in the mean



(b) Measurement with standardization (z-score) - correcting for differences in the variance



(c) Measurement without any normalization

Figure 3.10.: Intergenerational persistence estimates by age of child

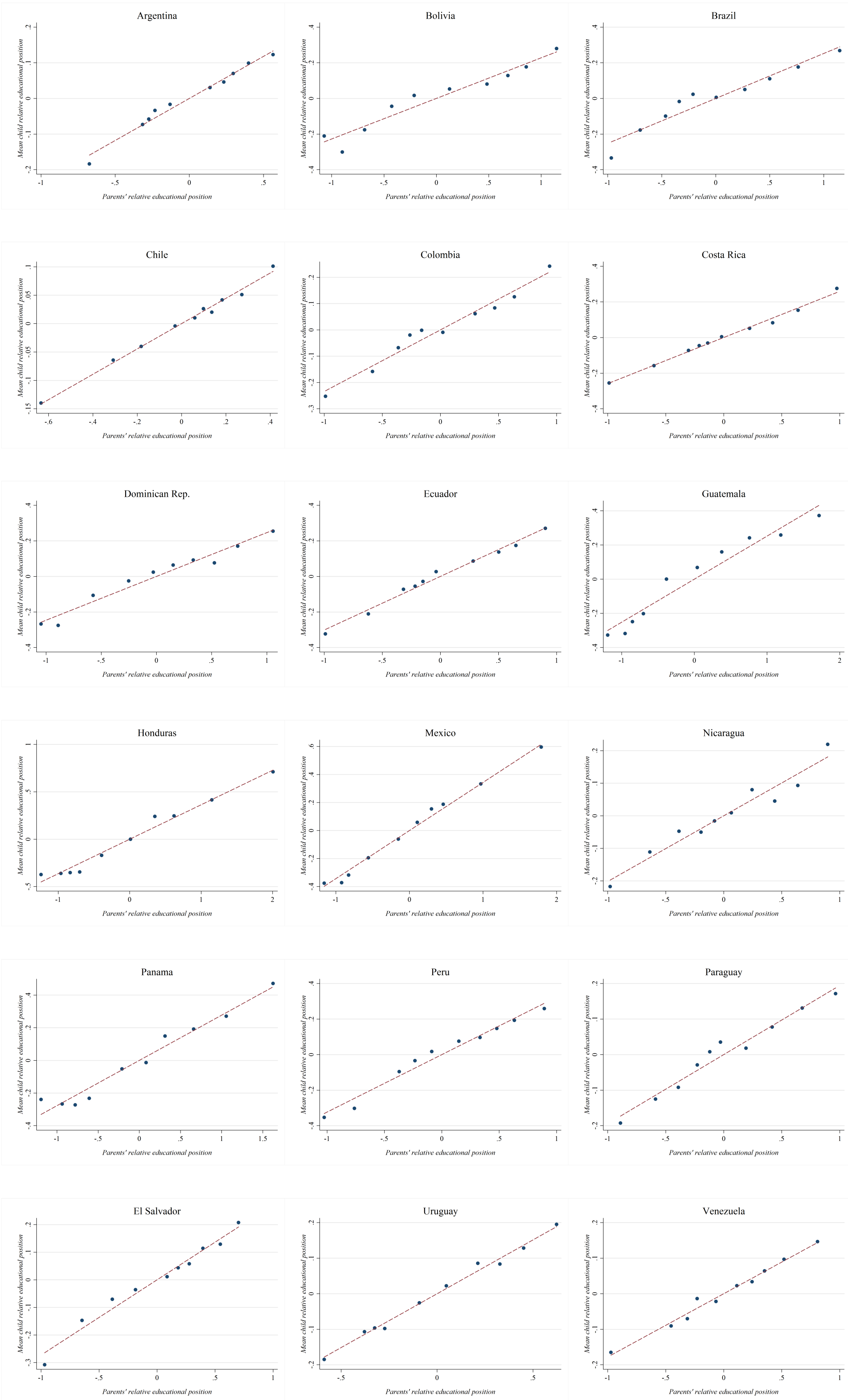


Figure 3.11.: Binned scatter plots for each country: Mean child relative educational position vs. parents' position. Cohort 1980-1995. (Source: Own estimations, *Latinobarometro*)

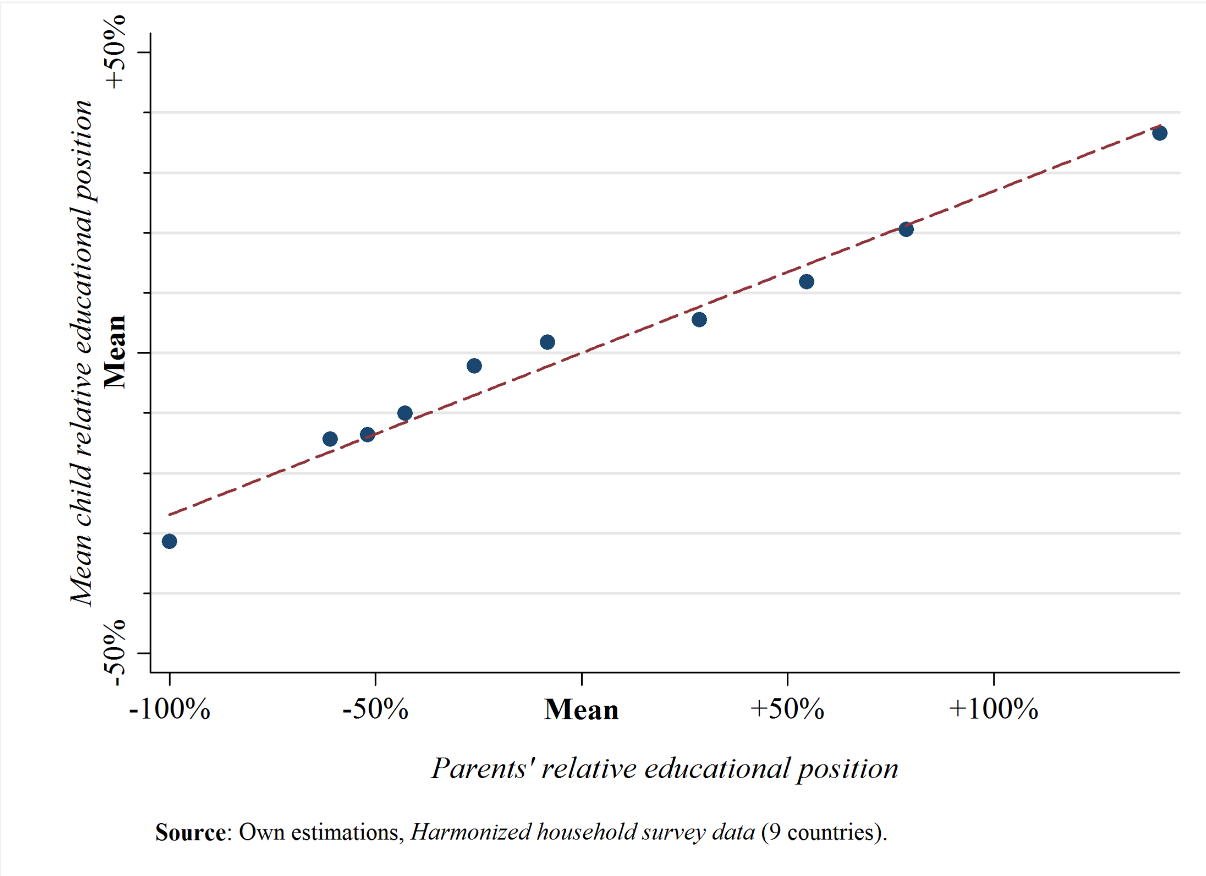


Figure 3.12.: Binned scatter plot: Mean child relative educational position vs. parents' position - Harmonized household survey data

Table 3.11.: Microeconometric Analysis - Latinobarometro

	A-(1)	A-(2)	A-(3)	A-(4)	B-(1)	B-(2)	B-(3)	B-(4)	C-(1)	C-(2)	C-(3)	C-(4)
Parental Education	0.256***	0.256***	0.257***	0.243***	0.254***	0.254***	0.252***	0.250***	0.257***	0.257***	0.253***	0.248***
	(0.0073)	(0.0073)	(0.0069)	(0.0099)	(0.0044)	(0.0044)	(0.0039)	(0.0048)	(0.0040)	(0.0040)	(0.0036)	(0.0033)
Parental Education*$\overline{Gini}(0 \le age \le 6)$	0.192***	0.192***	0.142**	0.363**								
	(0.0667)	(0.0667)	(0.0719)	(0.1639)								
Parental Education*$\overline{GDPp.c.}(0 \le age \le 6)$			-0.014***	-0.013*								
			(0.0039)	(0.0072)								
Parental Education*$\overline{Startingage}(0 \le age \le 6)$				-0.000								
				(0.0113)								
Parental Education*$\overline{Gini}(6 \le age \le 12)$					0.130**	0.130**	0.048	0.107				
					(0.0651)	(0.0651)	(0.0609)	(0.0745)				
Parental Education*$\overline{GDPp.c.}(6 \le age \le 12)$							-0.010***	-0.010***				
							(0.0022)	(0.0026)				
Parental Education*$\overline{Pub.Educ}(6 \le age \le 12)$								-0.009**				
								(0.0039)				
Parental Education*$\overline{Gini}(12 \le age \le 18)$									0.221***	0.221***	0.101	0.109
									(0.0701)	(0.0701)	(0.0637)	(0.0673)
Parental Education*$\overline{GDPp.c.}(12 \le age \le 18)$											-0.009***	-0.006***
											(0.0017)	(0.0018)
Parental Education*$\overline{Pub.Educ}(12 \le age \le 18)$												-0.014***
												(0.0030)
$\overline{Gini}(0 \le age \le 6)$	0.002	-0.021	0.006	0.006								
	(0.0046)	(0.0265)	(0.0220)	(0.0264)								
$\overline{GDPp.c.}(0 \le age \le 6)$			0.002	0.001								
			(0.0015)	(0.0013)								
$\overline{Startingage}(0 \le age \le 6)$				°								
$\overline{Gini}(6 \le age \le 12)$					-0.000	0.009	-0.003	0.054*				
					(0.0061)	(0.0179)	(0.0196)	(0.0278)				
$\overline{GDPp.c.}(6 \le age \le 12)$							-0.002*	0.000				
							(0.0009)	(0.0009)				
$\overline{Pub.Educ}(6 \le age \le 12)$								-0.001***				
								(0.0005)				
$\overline{Gini}(12 \le age \le 18)$									0.010	0.020	0.033	0.025
									(0.0078)	(0.0199)	(0.0206)	(0.0201)
$\overline{GDPp.c.}(12 \le age \le 18)$											0.004***	0.003***
											(0.0009)	(0.0008)
$\overline{Pub.Educ}(12 \le age \le 18)$												0.002***
												(0.0005)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	33007	33007	33007	15777	62911	62911	62911	53912	87937	87937	87907	78845
R^2	0.193	0.193	0.194	0.192	0.185	0.185	0.185	0.179	0.189	0.189	0.189	0.181
N_clust	193	193	193	138	290	290	290	255	365	365	364	329

Data: Latinobarometro 1998-2013. °) dropped because of multicollinearity.

Cluster adjusted s.e. by country and birthyear. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Table 3.12.: Microeconometric Analysis - Harmonized Household Surveys

	A-(1)	A-(2)	A-(3)	A-(4)	B-(1)	B-(2)	B-(3)	B-(4)	C-(1)	C-(2)	C-(3)	C-(4)
Parental Education	0.240***	0.241***	0.274***	0.204***	0.253***	0.253***	0.259***	0.259***	0.271***	0.271***	0.271***	0.272***
	(0.0063)	(0.0064)	(0.0108)	(0.0223)	(0.0059)	(0.0059)	(0.0070)	(0.0080)	(0.0061)	(0.0061)	(0.0056)	(0.0042)
Parental Education*$\overline{Gini}(0 \le age \le 6)$	1.217***	1.251***	0.246	-1.189								
	(0.2699)	(0.2725)	(0.4435)	(1.6530)								
Parental Education*$\overline{GDPp.c.}(0 \le age \le 6)$			-0.027***	-0.016*								
			(0.0072)	(0.0082)								
Parental Education*$\overline{Startingage}(0 \le age \le 6)$				0.027								
				(0.0255)								
Parental Education*$\overline{Gini}(6 \le age \le 12)$					0.826***	0.877***	0.734***	0.833**				
					(0.2157)	(0.2124)	(0.2140)	(0.4030)				
Parental Education*$\overline{GDPp.c.}(6 \le age \le 12)$							-0.010***	-0.010***				
							(0.0033)	(0.0035)				
Parental Education*$\overline{Pub.Educ}(6 \le age \le 12)$								-0.016*				
								(0.0090)				
Parental Education*$\overline{Gini}(12 \le age \le 18)$									0.832***	0.873***	0.797***	1.681***
									(0.2708)	(0.2619)	(0.2215)	(0.2491)
Parental Education*$\overline{GDPp.c.}(12 \le age \le 18)$											-0.014***	-0.008***
											(0.0028)	(0.0018)
Parental Education*$\overline{Pub.Educ}(12 \le age \le 18)$												-0.030***
												(0.0064)
$\overline{Gini}(0 \le age \le 6)$	0.269***	0.938**	-1.005	0.046								
	(0.0886)	(0.4147)	(0.6189)	(0.1298)								
$\overline{GDPp.c.}(0 \le age \le 6)$			-0.037**	0.004								
			(0.0148)	(0.0022)								
$\overline{Startingage}(0 \le age \le 6)$				°								
$\overline{Gini}(6 \le age \le 12)$					0.138	0.600***	0.350**	-0.064				
					(0.1045)	(0.2204)	(0.1747)	(0.0834)				
$\overline{GDPp.c.}(6 \le age \le 12)$							-0.007**	0.002				
							(0.0030)	(0.0023)				
$\overline{Pub.Educ}(6 \le age \le 12)$								-0.004***				
								(0.0016)				
$\overline{Gini}(12 \le age \le 18)$									0.040	-0.095	-0.089	0.016
									(0.0862)	(0.0675)	(0.0668)	(0.0747)
$\overline{GDPp.c.}(12 \le age \le 18)$											0.001	0.007***
											(0.0029)	(0.0024)
$\overline{Pub.Educ}(12 \le age \le 18)$												-0.005**
												(0.0019)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	63843	63843	63843	22362	139610	139610	139610	130915	203787	203787	203787	195320
R^2	0.207	0.208	0.209	0.150	0.225	0.225	0.226	0.225	0.240	0.241	0.242	0.241
N_clust	54	54	54	28	97	97	97	85	134	134	134	128

Data: Harmonized household surveys. °) dropped because of multicollinearity.
Cluster adjusted s.e. by country and birthyear. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Table 3.14.: Intergenerational Mobility in Latin America - Linear Transformation by Z-Score

	(1) LB 1980-1987		(2) LB 1988-1995		(3) HS 1980-1987		(4) HS 1988-1995	
Argentina	0.426***	(0.0134)	0.438***	(0.0289)				
Bolivia	0.517***	(0.0211)	0.476***	(0.0209)				
Brazil	0.453***	(0.0145)	0.440***	(0.0312)	0.414***	(0.0307)	0.296*	(0.1634)
Chile	0.646***	(0.0283)	0.563***	(0.0322)	0.410***	(0.0086)	0.349***	(0.0111)
Colombia	0.559***	(0.0193)	0.607***	(0.0422)	0.430***	(0.0071)	0.373***	(0.0074)
Costa Rica	0.403***	(0.0186)	0.292***	(0.0152)				
Dominican Rep.	0.422***	(0.0214)	0.381***	(0.0289)				
Ecuador	0.508***	(0.0155)	0.494***	(0.0135)	0.493***	(0.0130)	0.478***	(0.0000)
El Salvador	0.508***	(0.0179)	0.452***	(0.0282)				
Guatemala	0.547***	(0.0230)	0.440***	(0.0250)	0.556***	(0.0063)	0.488***	(0.0245)
Honduras	0.516***	(0.0247)	0.549***	(0.0176)				
Mexico	0.348***	(0.0176)	0.442***	(0.0154)	0.456***	(0.0262)	0.385***	(0.0543)
Nicaragua	0.436***	(0.0147)	0.515***	(0.0335)	0.384***	(0.0000)		
Panama	0.501***	(0.0095)	0.444***	(0.0365)	0.512***	(0.0107)	0.460***	(0.0195)
Paraguay	0.529***	(0.0262)	0.336***	(0.0639)				
Peru	0.500***	(0.0117)	0.478***	(0.0204)	0.436***	(0.0069)	0.373***	(0.0070)
Uruguay	0.480***	(0.0088)	0.455***	(0.0308)				
Venezuela	0.373***	(0.0127)	0.282***	(0.0328)				
Demographic controls	Yes		Yes		Yes		Yes	
Country fixed effects	Yes		Yes		Yes		Yes	
Observations	46838		15880		114850		42201	
R^2	0.251		0.231		0.226		0.167	

Outcome variables measured as z-score by age, sex, country and cohort.
Data: LB) Latinobarometro 1998-2013. HS) Household surveys.
Statistical significance level * 0.1 ** 0.05 *** 0.01.

Table 3.15.: Intergenerational Mobility in Latin America - Completed Years of Education without Normalization

	(1)		(2)		(3)		(4)	
Argentina	0.299***	(0.0079)	0.273***	(0.0160)				
Bolivia	0.377***	(0.0215)	0.317***	(0.0154)				
Brazil	0.373***	(0.0110)	0.328***	(0.0249)	0.414***	(0.0338)	0.296*	(0.1486)
Chile	0.458***	(0.0255)	0.394***	(0.0495)	0.323***	(0.0114)	0.250***	(0.0065)
Colombia	0.402***	(0.0186)	0.383***	(0.0223)	0.416***	(0.0121)	0.310***	(0.0113)
Costa Rica	0.333***	(0.0166)	0.249***	(0.0131)				
Dominican Rep.	0.338***	(0.0177)	0.276***	(0.0254)				
Ecuador	0.424***	(0.0141)	0.376***	(0.0239)	0.533***	(0.0208)	0.492***	(0.0000)
El Salvador	0.444***	(0.0181)	0.365***	(0.0196)				
Guatemala	0.521***	(0.0286)	0.414***	(0.0270)	0.684***	(0.0137)	0.549***	(0.0367)
Honduras	0.478***	(0.0322)	0.571***	(0.0177)				
Mexico	0.263***	(0.0157)	0.262***	(0.0208)	0.361***	(0.0219)	0.279***	(0.0396)
Nicaragua	0.356***	(0.0091)	0.427***	(0.0294)	0.368***	(0.0000)		
Panama	0.422***	(0.0111)	0.387***	(0.0356)	0.430***	(0.0131)	0.344***	(0.0226)
Paraguay	0.430***	(0.0202)	0.240***	(0.0492)				
Peru	0.350***	(0.0080)	0.344***	(0.0218)	0.364***	(0.0111)	0.276***	(0.0095)
Uruguay	0.404***	(0.0075)	0.350***	(0.0214)				
Venezuela	0.288***	(0.0124)	0.191***	(0.0220)				
Demographic controls	Yes		Yes		Yes		Yes	
Country fixed effects	Yes		Yes		Yes		Yes	
Observations	46849		15880		114850		42201	
R^2	0.382		0.408		0.294		0.245	

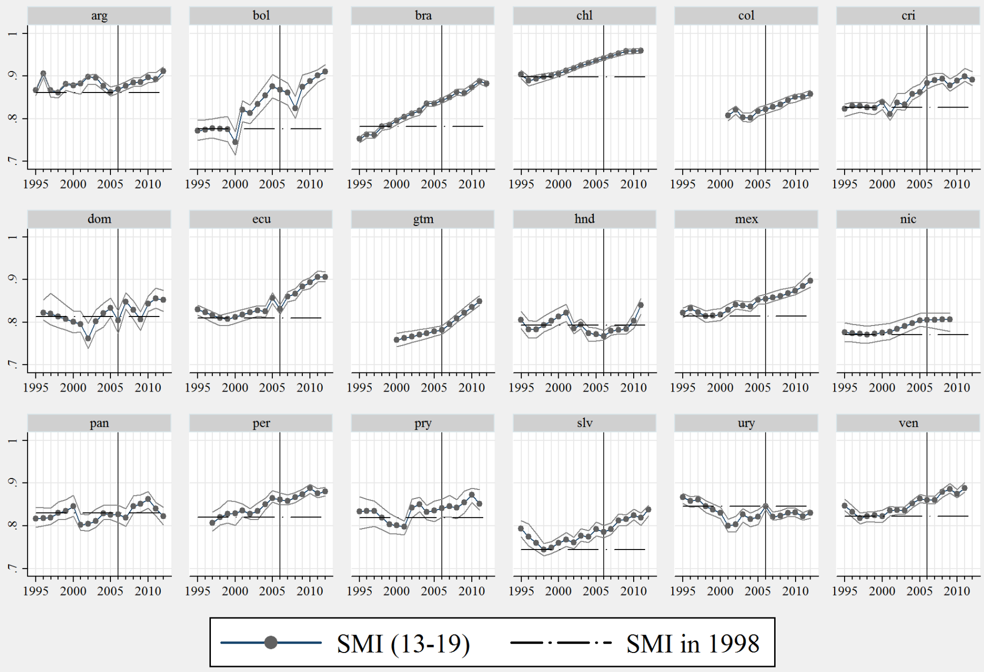
Outcome variables are completed years of schooling.
Statistical significance level * 0.1 ** 0.05 *** 0.01.

3.6.2. Social Mobility Index

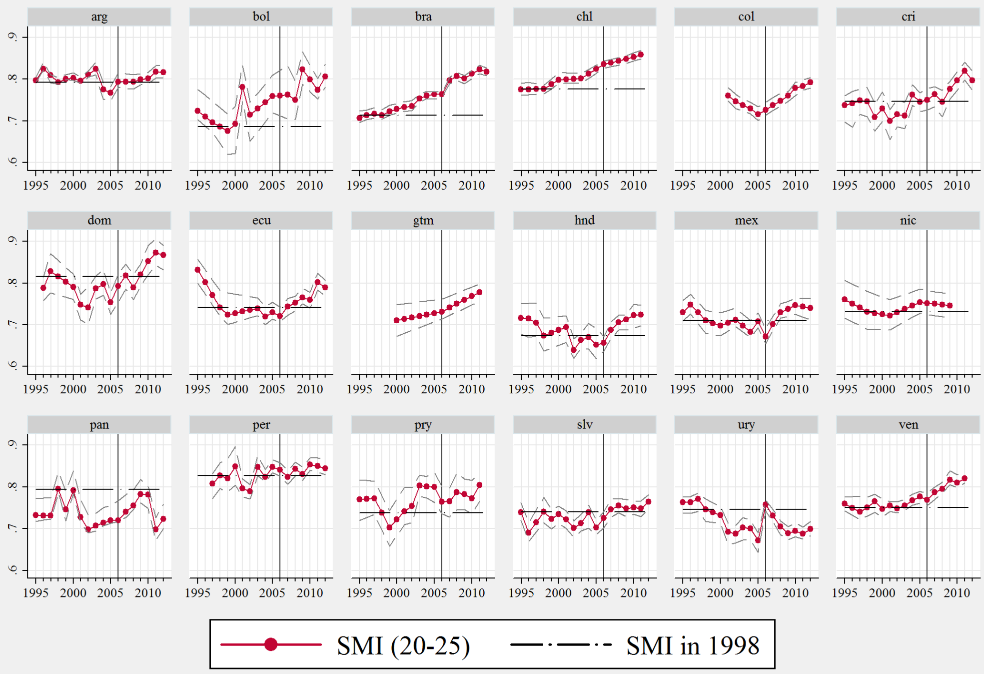
A brief note should be spend on an alternative measurement of intergenerational mobility, called Social Mobility Index (SMI) and proposed by Andersen (2004), which is included in the SEDLAC data for each year and country in which survey data is available. The SMI is based on the schooling gap experienced by teenagers and adolescents - i.e. the difference between the maximal possible and the actual years of schooling of the child - and relates it to parental background as well as individual control variables. The weight of the parental background characteristics obtained trough a decomposition proposed by Fields (2003)[46]

[46]Fields, Gary S, "ACCOUNTING FOR INCOME INEQUALITY AND ITS CHANGE: A NEW METHOD, WITH APPLICATION TO THE DISTRIBUTION OF EARNINGS IN THE UNITED STATES", in Polachek, Solomon W., ed., Worker Well-Being and Public Policy (Research in Labor Economics, Volume 22) (Emerald Group Publishing Limited, 2003), pp. 1–38.

defines then the SMI. The higher is the SMI and the higher is the estimated degree of social intergenerational mobility. Two versions of the index are displayed in SEDLAC, SMI-1 for the age interval 13 to 19 and SMI-2 for 20 to 25. The SMI has some advantages: It makes full use of the available individual data, it is comparable across countries and over time, and it includes nearly all children and young adults in data. However, it faces also two strong limitations which probably limits its usefulness for an analysis of intergenerational mobility. First, it is not representative, since it takes into account only individuals still living with their parents. The higher the age, the higher the restrictiveness of this assumption; thus especially the SMI-2 should suffer from serious bias deriving from it. Second, the schooling gap might not be a good outcome variable proxying future socioeconomic status; a limitation which should affect especially the SMI-1. As such, the SMI is probably rather a measurement of equality of opportunity for children or young adults. Since the limitations for an analysis of intergenerational mobility probably outweigh the advantages, in the present study own measurements of intergenerational mobility are estimated based on completed years of education and retrospective questions about parental education following the main literature as explained above. In the Online Appendix, the SMI-1 and SMI-2 are reported for the sake of completeness, and generally confirm the pattern of rising social intergenerational mobility in most Latin American countries.



Social Mobility Index age 13-19 (Andersen, 2004)



Social Mobility Indexes age 20-25 (Andersen, 2004)

Figure 3.13.: Mobility trends - Social Mobility Index (Andersen, 2004)

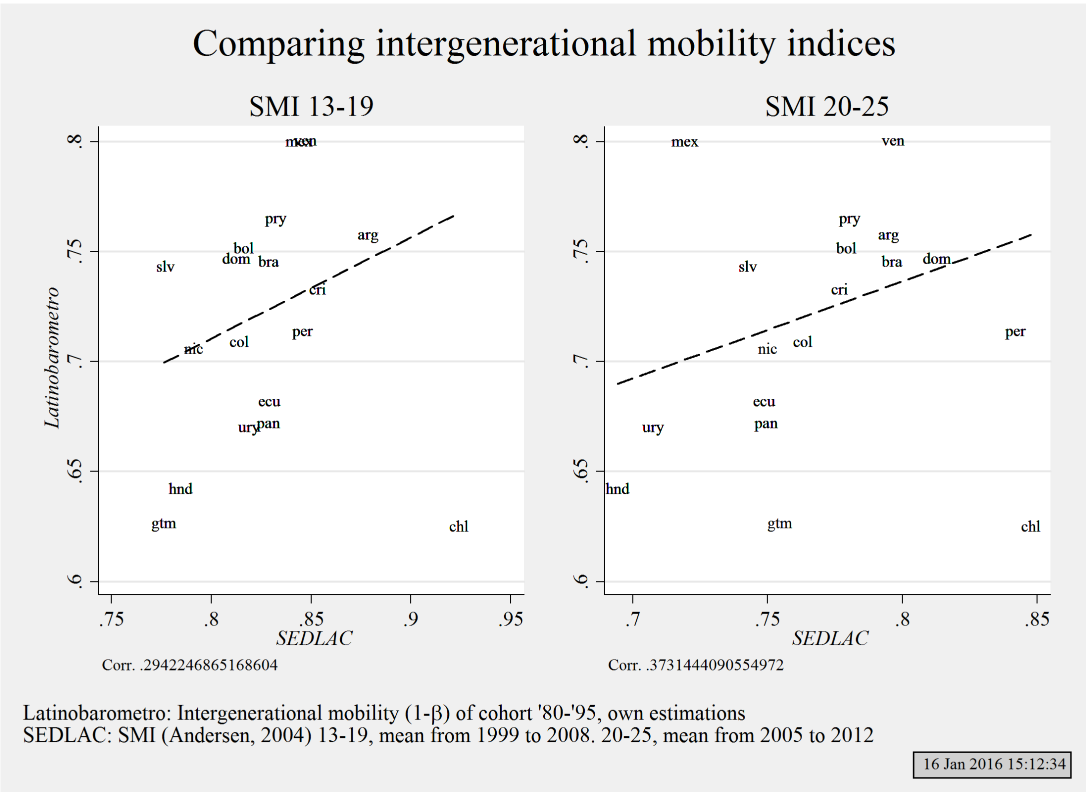


Figure 3.14.: Comparison of intergenerational mobility indices

4. Educational Inequality, Intergenerational Mobility and Economic Development

4.1. Introduction

Among the oldest and most argued topics in economics are the causes and consequences of economic inequality. On the one hand, the high levels of inequality experienced in most developed and developing countries during the last century have attracted special attention by researchers and policy makers. On the other hand, there are differing views on the beneficial, detrimental or neutral impact of economic inequality and it remains difficult to generate clear causal statements regarding the way inequality affects economic performance and vice versa. For instance, influential theoretical models and empirical analyses on the relationship between inequality and growth have thus far yielded opposite results (Banerjee and Duflo, 2003).[1] Hence, scholars have argued that answers to questions related to inequality require taking into account that the observed level of income inequality displays both the rewards obtained by individuals for their efforts as well as the returns to given circumstances that they cannot control, like the socioeconomic status of their parents (Roemer, 2000).[2] Extending distributional analysis to the degree of intergenerational mobility in a society has arisen as a possible solution (Corak, 2013a).

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? 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

[1] See Furman and Stiglitz (1998) for an overview of the consequences of inequality for growth. Neves et al. (2016) recently reviewed the empirical literature on the inequality-growth nexus and performed a Meta-Analysis. Their results point at non-significant results on average with a high amount of heterogeneity in effect sizes across countries.

[2] For instance, Marrero and Rodríguez (2013) show that across U.S. states, inequality of opportunity has a negative impact on growth, while the impact of income inequality based on merit and effort is positive.

necessary to study the subject in a harmonized framework.

Furthermore, while large data sets with multiple and comparable measures of economic inequality and even historical time series are available for a multitude of countries, this is not the case for intergenerational mobility. The subject has been extensively analyzed within countries, for instance, for the United States (Chetty et al., 2014c,b) and India (Azam and Bhatt, 2015), but 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.

We provide a panel of comparable summary indicators for intergenerational education mobility in 18 countries over more than 50 years that we make available for future research. The present study aims to introduce this new data set and provide a comprehensive analysis of the 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 recently reviewed by Torche (2014). First, we examine more countries over a longer time span and in a harmonized framework. Second, we provide more precise estimates that rely on several survey waves and a greater number of observations. Third, we obtain 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. Finally, we provide resulting panel data for use in future research.

The paper is structured as follows: Section 4.2 describes the data sources and harmonization procedure used to obtain our estimates. Section 4.3 explains the applied methodologies. Section 4.4 presents and summarizes our results: First, it describes the uncovered cross-country patterns, trends, heterogeneity by gender, and degrees of assortative mating. Then, it examines the association between our intergenerational mobility estimates and economic performance and institutional characteristics. Section 4.5 concludes.

4.2. Data

4.2.1. Description of Data Sources

The sources of information used to obtain our estimates are derived from two sets of 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 in the questionnaire. To avoid a so-called *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.[3]

The first harmonized survey data set is derived from the annual opinion survey *Latinobarómetro*. Latinobarómetro records individual and household characteristics of a nationally representative sample of adult respondents in 18 Latin American countries since 1995, including questions about own and parental education since 1998.[4] The annual survey uses a sample of 1000 to 1200 individuals per country, representing more than 600 million inhabitants. It is carried out by local firms under technical supervision of the Latinobarómetro Corporation, a private non-profit organization based in Santiago (Chile).[5] For the present study, we use the survey waves that include retrospective questions on parental education (1998 to 2015). The second data set is retrieved through an ex-post harmonization of selected national household surveys that are mainly conducted by national statistical offices. All estimates based on both data sets (henceforth Latinobarómetro and National Household Surveys) are obtained by weighting each observation by the inverse probability of selection, normalizing the weights over the different survey waves. All the surveys used in our analysis are listed and described in Appendix A (Additional Material).

One advantage of Latinobarómetro is that it is harmonized ex-ante and is specifically developed to be used in cross-country studies. The other household surveys are not uniform across Latin American countries. Therefore, we made all possible efforts to make statistics comparable across countries and over time by using similar definitions of variables in each country and survey year, and by applying consistent methods of processing the data. In particular, the inclusion of retrospective questions is not a universal characteristic found in all household surveys. Thus, while with the sample retrieved from Latinobarómetro we estimated the indexes for 18 countries, with the National Household Surveys estimates for 9 countries could be obtained. The advantage of many of the National Household Surveys is that they offer a substantially higher 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.

4.2.2. Restriction criteria

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 en-

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

[4]The Dominican Republic was included for the first time in 2004. The representativeness of the survey has varied over time reaching 100% of the total population in all countries around the year 2000.

[5]The study receives financing from Latin American and non-Latin American governments, the private sector, and international organizations. 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.

sures 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 the individual and her parents reside together in the same household is not relevant for inclusion in our sample. The main restriction criteria is therefore the availability of information on own and parental education. Our final samples, including all countries and cohorts, is comprised of 198,949 individuals from the Latinobarómetro survey and 1,179,217 individuals from the National Household Surveys.

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. In order to prove if selectivity issues bias our intergenerational mobility estimates, we compare the average years of education of all individuals in the household survey with a sample of individuals for whom we have information regarding parental educational background. Differences are negligible in both data sets, counting at most 0.4 years of schooling, and in most countries not statistically significant. Furthermore, no clear pattern hints at a specific direction of a possible selectivity bias (e.g. for Peru, the average of the sample used to compute our estimates is 0.2 years lower than the unrestricted sample, while for Brazil the mean of our sample is 0.4 years higher).

4.2.3. Measurement of educational attainment

In Latinobarómetro the information recorded regarding parental education refers only to the parent with highest education among the two. 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 most commonly done in the literature (Black and Devereux, 2011b), to obtain our baseline estimates.

In order to improve the comparability of the completed years of education, which is our main result variable, we use the same coding used by Latinobarómetro to process the National Household Survey. That is, we truncate the years of education at the university level because the degree of heterogeneity is greater at that level. Thus, completed years of education range from 0 to 15. Furthermore, Latinobarómetro uses the same variable to measure the education of individuals and their parents. Most other surveys record years of formal education for individuals who are interviewed, but are not as precise for data regarding 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.[6]

Figure 4.1 shows the mean and coefficient of variation of completed years of education in our samples, comparing the statistics obtained from Latinobarómetro and the National

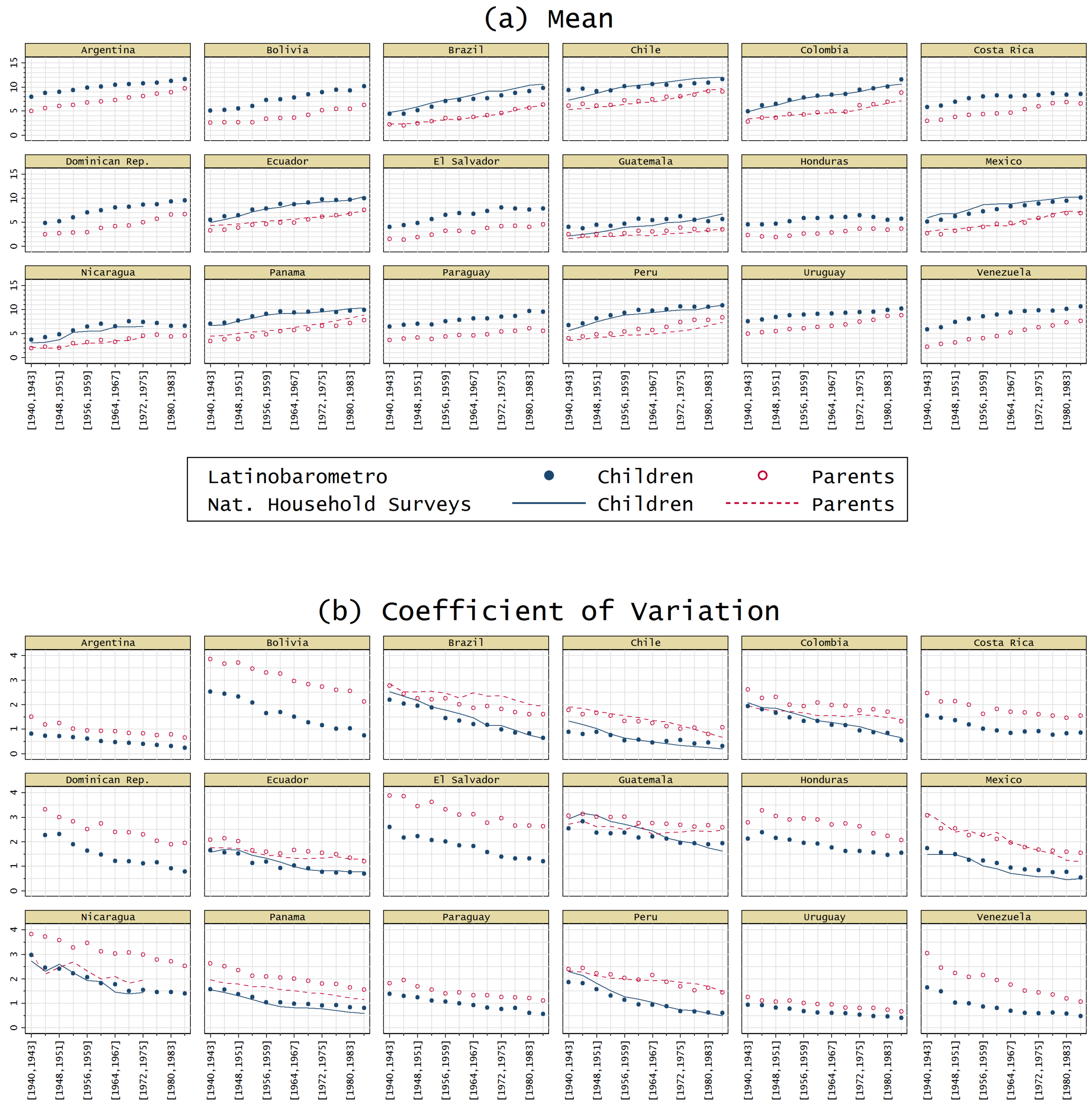
[6]Detailed information on the codification of educational attainment for parents and children in each country is available in the Additional Material.

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; on the other end of the spectrum we find Argentina, Chile, and Colombia, with around 12 years.

In order to give an idea of how educational attainment is related to economic well-being, Figure 4.2 shows the mean income levels for six broad educational categories and the returns to education – measured by the ratio of incomes achieved by high and low educated people – for two different cohorts in each Latin American country. This analysis helps to read our intergenerational education mobility estimates and put the results in the right context.[7] We see that, although substantial differences between countries exist, higher educational degrees are clearly associated with higher level of income. Furthermore, despite the educational expansions experienced in all countries, returns to education are rather similar for people of different ages. Thus, apart from the intrinsic value of educational mobility as one of the drivers of human development, our measures are also meaningful indicators for intergenerational mobility of (material) well-being.

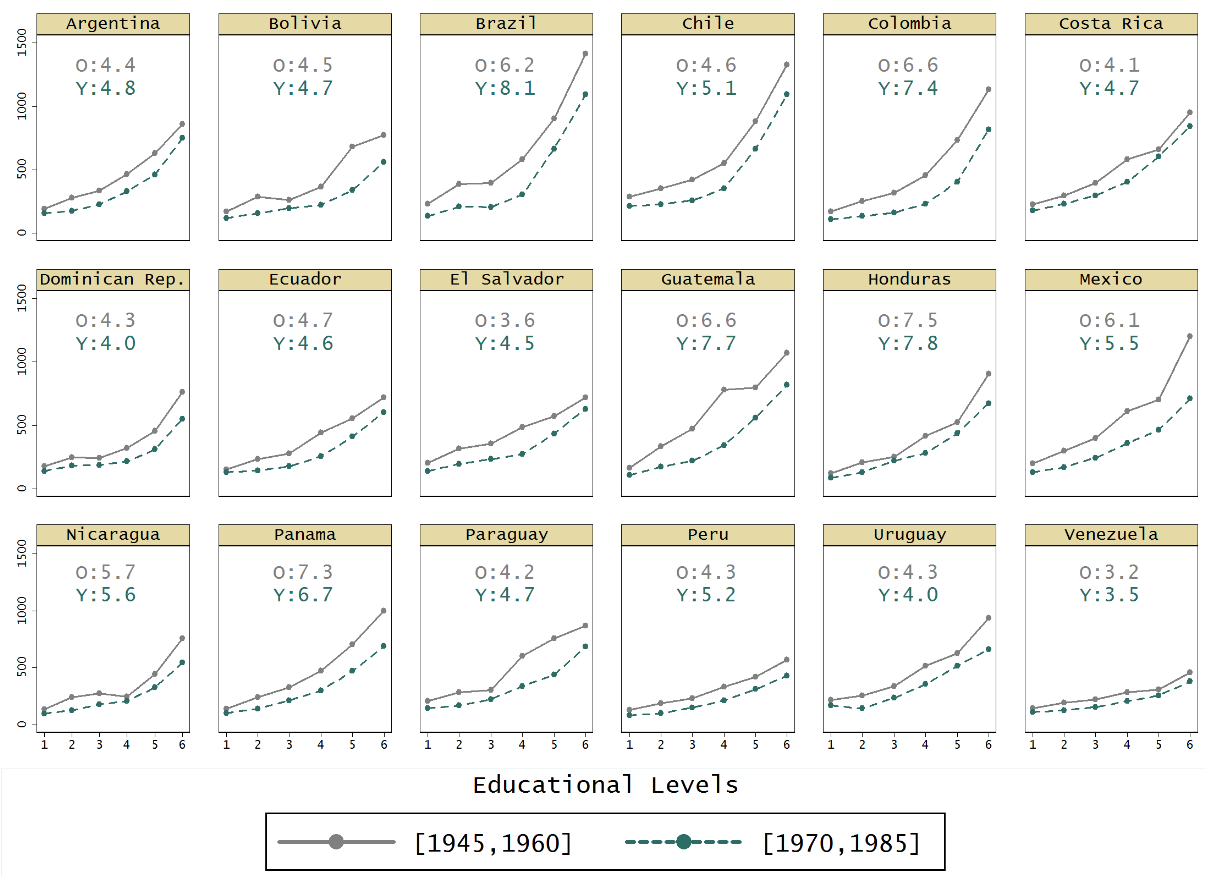
[7]As shown by Blanden (2013), there is a meaningful correlation between estimates of intergenerational income mobility and educational mobility across countries.

Figure 4.1.: 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 1982-2015.

Figure 4.2.: Education as indicator for well-being: average income by educational level.



Notes: Average household per capita income (constant 2005 PPP international USD). 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.

4.3. Estimated Mobility Indexes

Pioneering works by Becker and Tomes (1979) and Solon (1992a) conceptualize the mechanisms and transmission channels that explain the observed degree of persistence between the economic outcomes of parents and children. However, especially in cross country comparisons, different indexes measuring intergenerational mobility may yield very different pictures. Researchers should therefore adopt the measurement which fulfill the needs of the dimension they aim to analyze and the questions they seek to answer.[8]

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 mobility). In this study, and with the creation of the associated database, we try to offer an exhaustive panorama of absolute and relative indexes and show the overall picture of intergenerational mobility in Latin America from different angles.

Future research using our estimates should use the indexes which fit the requirements of the research question regarding two key aspects: i) what is the intuition behind the phenomena that has 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 certain educational degree. The indexes are estimated for each cohort j and country k separately.[9]

4.3.1. 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 on parents' outcomes.[10] 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 parent with the highest educational attainment among the two:

$$y^c_{ijk} = \alpha_{jk} + \beta_{jk} \cdot y^p_{ijk} + \gamma_{jk} X_{ijk} + \epsilon_{ijk}. \tag{4.3.1}$$

In this equation, α is a constant, X is a vector of control variables for age and sex and ϵ is the error term. The slope coefficient can also be standardized to take differences in the

[8]For conceptual and methodological reviews on intergenerational mobility, see Black and Devereux (2011b); Jäntti and Jenkins (2013); Piketty (2000).

[9]Neidhöfer (2016) develops a method to transform the educational outcomes of parents and children in a way that makes them more appropriate as a proxy measure for socioeconomic status and more comparable across time (see also Neidhöfer and Stockhausen, 2016). Here, this correction is not necessary since the analysis is performed for each cohort separately. Proper methods are applied to standardize the estimated coefficients ex-post, as explained below.

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

distributions of children's and parents' outcomes into account:

$$r_{jk} = \beta_{jk} \frac{\sigma^p_{jk}}{\sigma^c_{jk}}. \tag{4.3.2}$$

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

β and r are measures for positional mobility that capture both dimensions, structural mobility as well as exchange mobility, and reflect the degree of regression to the population mean between two generations. Its wider use in the literature has the advantage of comparability between these and other estimates for the same or other countries. Hereby, r "corrects" β by the changes in inequality in the marginal distributions of the outcome of interest. Scholars still argue about which of the two is more suitable for cross-country (and cross-cohort) comparisons (see Jäntti and Jenkins, 2013). Therefore, it seems important to report both.

An index which fully controls for the marginal distributions – and not only for the changes in inequality – and captures the pure positional change aspect of mobility, is Spearman's rank correlation coefficient:

$$\rho_{jk} = \frac{cov(rank^c_{jk}, rank^p_{jk})}{\sigma^c_{jk,rank}\sigma^p_{jk,rank}}. \tag{4.3.3}$$

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 get lost if one measures mobility by (2) and (3). However, if exchange mobility is the only important aspect to be accounted for, (1) might not be the suitable index to rely on.

The outcome that is most often available for two subsequent generations and is also comparable across countries is educational attainment measured in completed years of education. The indexes thus 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.[11]

[11] 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 has been questioned since the slope might vary with rising parental education. So far, linear and non-linear measures has been 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 Additional 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.

4.3.2. Transition probabilities

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

The *probability of bottom upward mobility*

$$BUM_{jk} = Prob(y^{c}_{ijk} \geq s | \, y^{p}_{ijk} < s), \tag{4.3.4}$$

and the *probability of upper class persistence*

$$UCP_{jk} = Prob(y^{c}_{ijk} \geq s | \, y^{p}_{ijk} \geq s). \tag{4.3.5}$$

The indicators yield the probabilities of children to achieve at least a secondary educational degree (s) conditional on their parents' education. Parent's education is hereby measured by two different types: i) low parental education, i.e. less than completed secondary education. ii) high parental education, i.e. at least a secondary school degree. 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.

4.3.3. Absolute and directional mobility

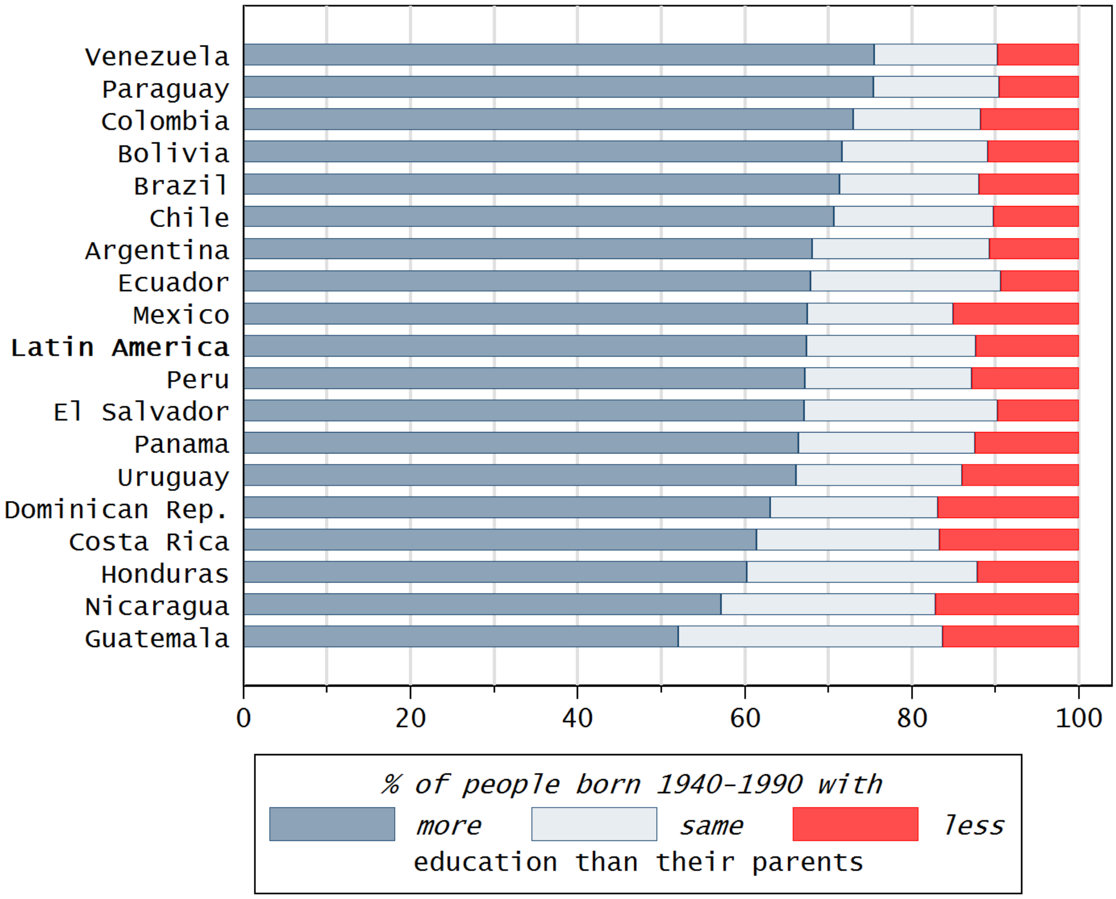
The measures described above cover the relative and absolute dimensions of intergenerational mobility, understood as the movement of families within the distribution over time. However, they do not give comparable information about the size of those movements. Two more indexes – initially developed by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

$$M1_{jk} = \frac{1}{N_{jk}} \sum_{i=1}^{N_{jk}} |y^{c}_{ijk} - y^{p}_{ijk}|. \tag{4.3.6}$$

$$M2_{jk} = \frac{1}{N_{jk}} \sum_{i=1}^{N_{jk}} (y^{c}_{ijk} - y^{p}_{ijk}), \tag{4.3.7}$$

$M1$ 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.

Figure 4.3.: Absolute educational mobility in Latin America.



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

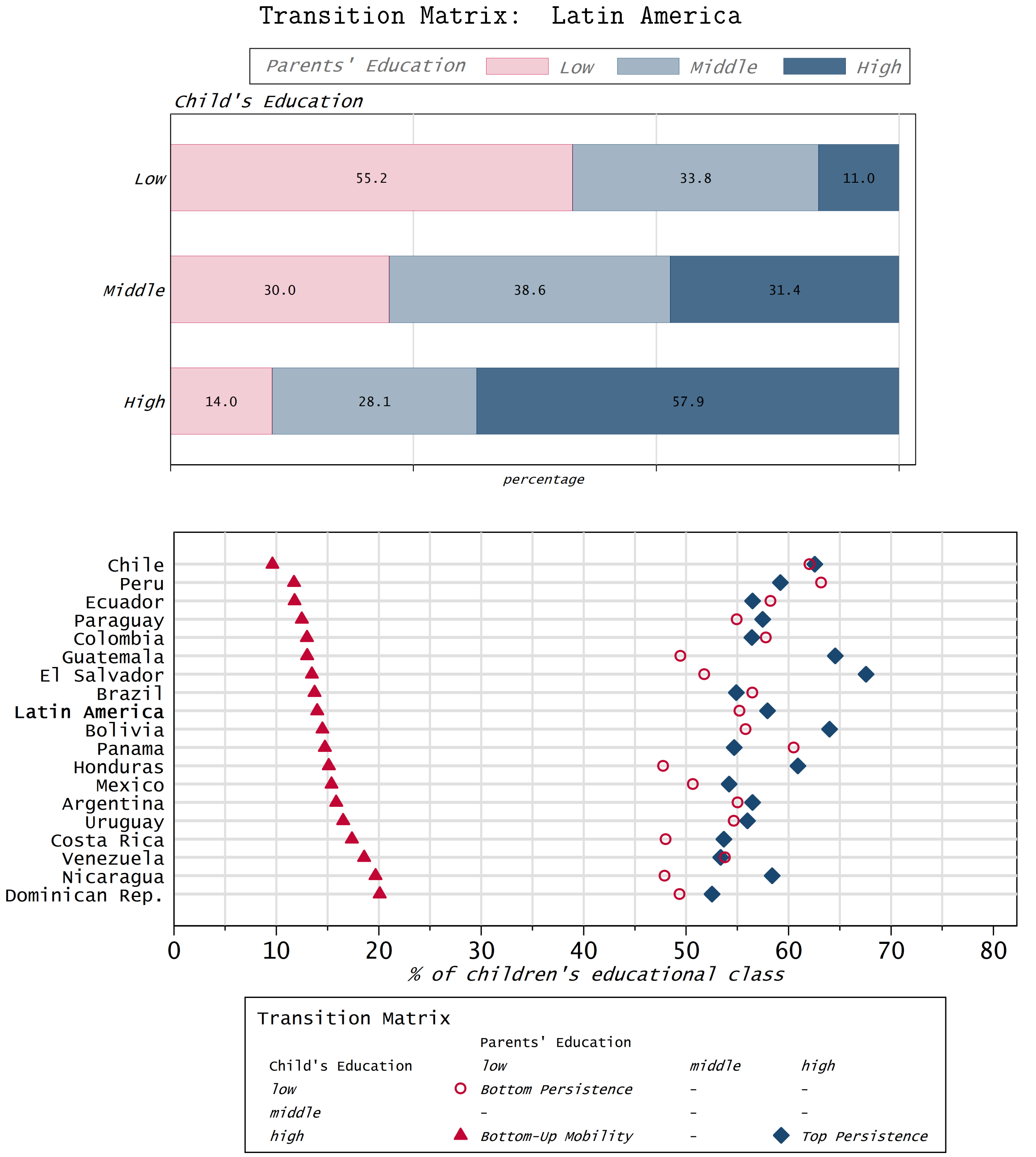
4.4. Results: Intergenerational Mobility in Latin America

4.4.1. Cross-Country Patterns

Before reporting the intergenerational mobility trends through the summary measures described in Section 4.3, we describe the cross-country differences in mobility patterns for the entire sample. First, Figure 4.3 illustrates absolute (or structural) mobility patterns, and, then, Figure 4.4 illustrates relative (or exchange) mobility; both using Latinobarómetro as data source. Tables 4.1, 4.2 and 4.3 show descriptive statistics of the summary measures described in Section 4.3 for each country and the Latin American average using both data sources.

Figure 4.3 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

Figure 4.4.: Educational persistence in Latin America: Insights from transition matrices (People born 1940-1990).



Notes: The points show the percentage of individuals in three different cells of the transition 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 %, T*op persistence* 51.2 % / 55.8 %, B*ottom-up mobility* 21.5 % / 17.8 %. *Source*: Latinobarometro 1998-2015, own estimates.

Table 4.1.: 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	0.16	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	0.58	0.08	0.49	0.65	0.51	0.07	0.45	0.56
Honduras	0.54	0.09	0.44	0.63	0.47	0.10	0.40	0.54
Mexico	0.38	0.21	0.29	0.53	0.40	0.12	0.35	0.48
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	0.15	0.39	0.63	0.50	0.08	0.44	0.57

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	0.46	0.20	0.35	0.63	0.53	0.09	0.48	0.66
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	0.75	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 4.2.: 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	0.25	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	0.67	0.11	0.57	0.77	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	0.63	0.20	0.45	0.91	0.36	0.42	0.15	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	0.73	0.12	0.58	0.85	0.27	0.29	0.15	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	0.78	0.11	0.63	0.94	0.24	0.31	0.09	0.35
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 4.3.: 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	0.14	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	0.10	2.6	3.6	2.0	0.16	1.5	2.5
Honduras	3.5	0.09	3.2	3.9	2.7	0.17	2.0	3.3
Mexico	4.3	0.08	3.6	4.8	3.1	0.11	2.5	3.6
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	3.0	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	3.4	5.0	3.6	0.17	2.9	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.

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 4.4 is more informative about the movement of families within the distribution. In the upper part, a transition matrix for Latin America is displayed. 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 transition matrix contain the percentage of individuals in the children's generation associated with the respective parental educational class. Complete intergenerational mobility is displayed by equal entries in each cell of a transition matrix. As has been argued in past, under certain circumstances complete mobility can be understood as equality of opportunity.[12]

We see that the Latin American reality is far from achieving complete mobility. Focusing on the three most meaningful cells of the transition matrix – 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 4.4 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 Dominican Republic. To give a benchmark for these estimates, we compute transition matrices 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.

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)

[12] For an exhaustive discussion of conceptual differences between intergenerational mobility and equality of opportunity, see Roemer (2004).

evaluate intergenerational mobility adopting multiple measures and ii) to measure the mobility of people born in different year spans separately.

4.4.2. Trends

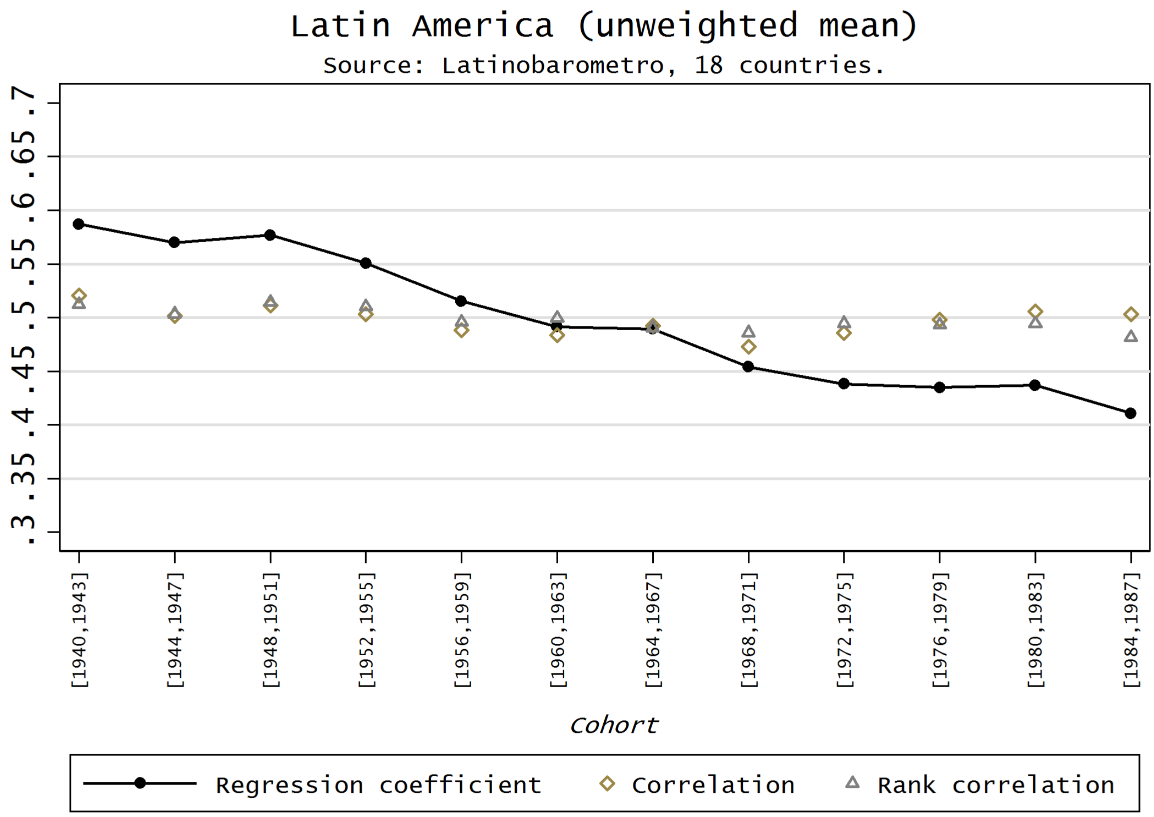
Figures 4.5, 4.7 and 4.9 show the trends and geography of intergenerational mobility in Latin America measured by the seven indexes explained in Section 4.3 with the Latinobarómetro survey. Figures 4.6, 4.8 and 4.10 show the corresponding averages for the nine countries where we have National Household 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 will restrict the descriptive analysis in this section mainly to the results obtained with Latinobarómetro. Furthermore, we exclude point estimates obtained from less than 200 individual observations. Charts for each country with both surveys are included in Appendix C (Additional Material).

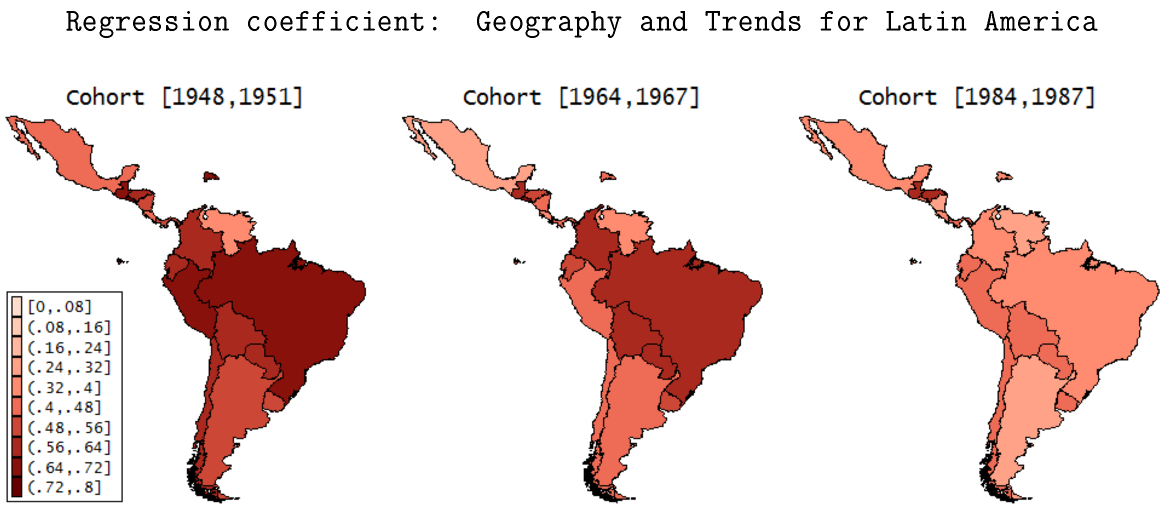
Figure 4.5 and 4.6 show intergenerational mobility measured by the regression coefficient (β), the standardized coefficient (r) and the Spearman's rank correlation coefficient (ρ). Aggregate results for Latin America are constructed as the unweighted average of the 18 or 9 countries analyzed, depending on whether Latinobarómetro or National Household Surveys were 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.[13] Comparing these trends with the ones observed for other countries, we see that, while Latin America has historically been perceived as one of the regions with the least social mobility worldwide, the educational mobility of the youngest cohorts is on similar levels as developed countries like the U.S. and Germany (see Hertz et al., 2007; Neidhöfer and Stockhausen, 2016). The map shows that this increase was recorded for almost all Latin American countries. In contrast, r and ρ are relatively stable around 0.5 over 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, 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.

Figures 4.7 and 4.8 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 individ-

[13] The results for the older cohorts are consistent with past estimates, e.g. by Hertz et al. (2007). Because of surviving bias associated with own and parental education the sample of older individuals that 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.

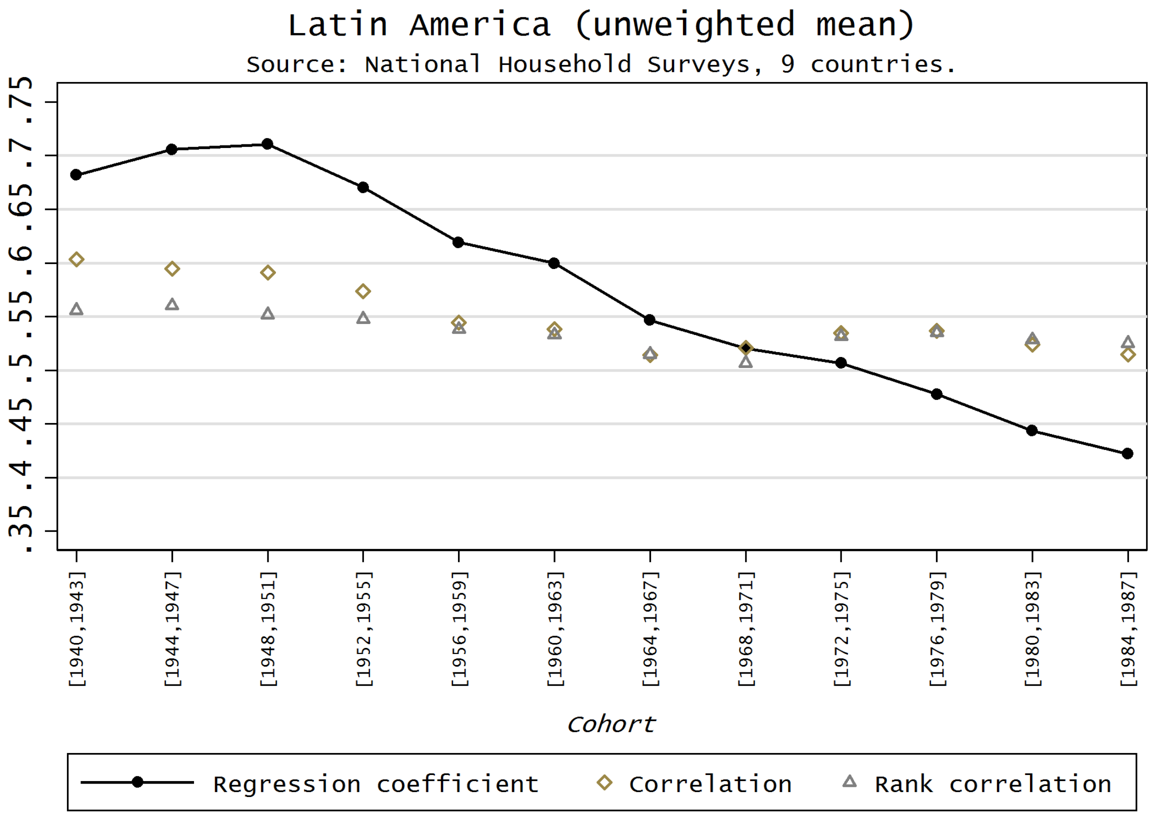
Figure 4.5.: Educational persistence in Latin America: Regression and correlation coefficients.





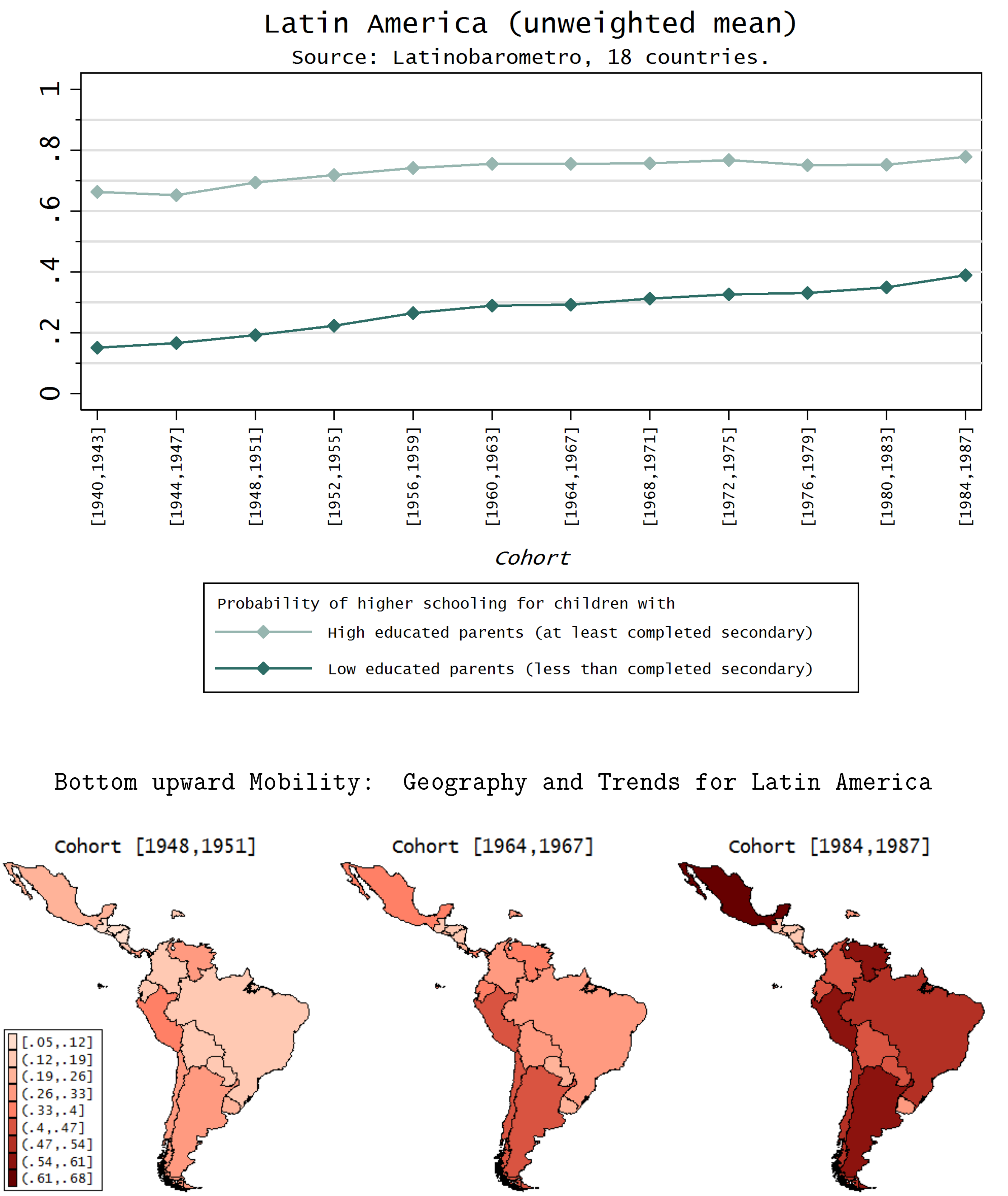
Notes: Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. Bootstrapped confidence interval. *Source*: Latinobarometro 1998-2015, own estimates.

Figure 4.6.: Educational persistence in Latin America: Regression and correlation coefficients.



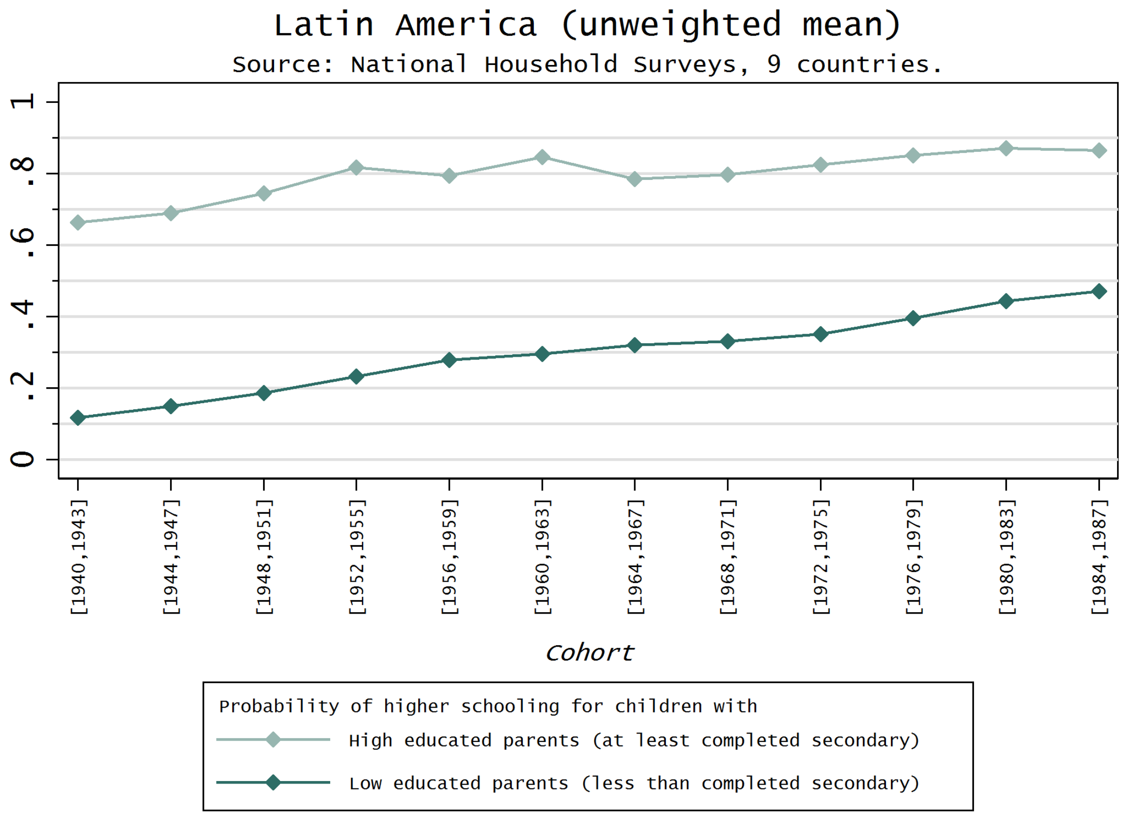
Notes: Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. Bootstrapped confidence interval. *Source*: National Household Surveys 1982-2015, own estimates.

Figure 4.7.: Educational inequality in Latin America: bottom-upward Mobility (BUM) and upper class persistence (UCP).



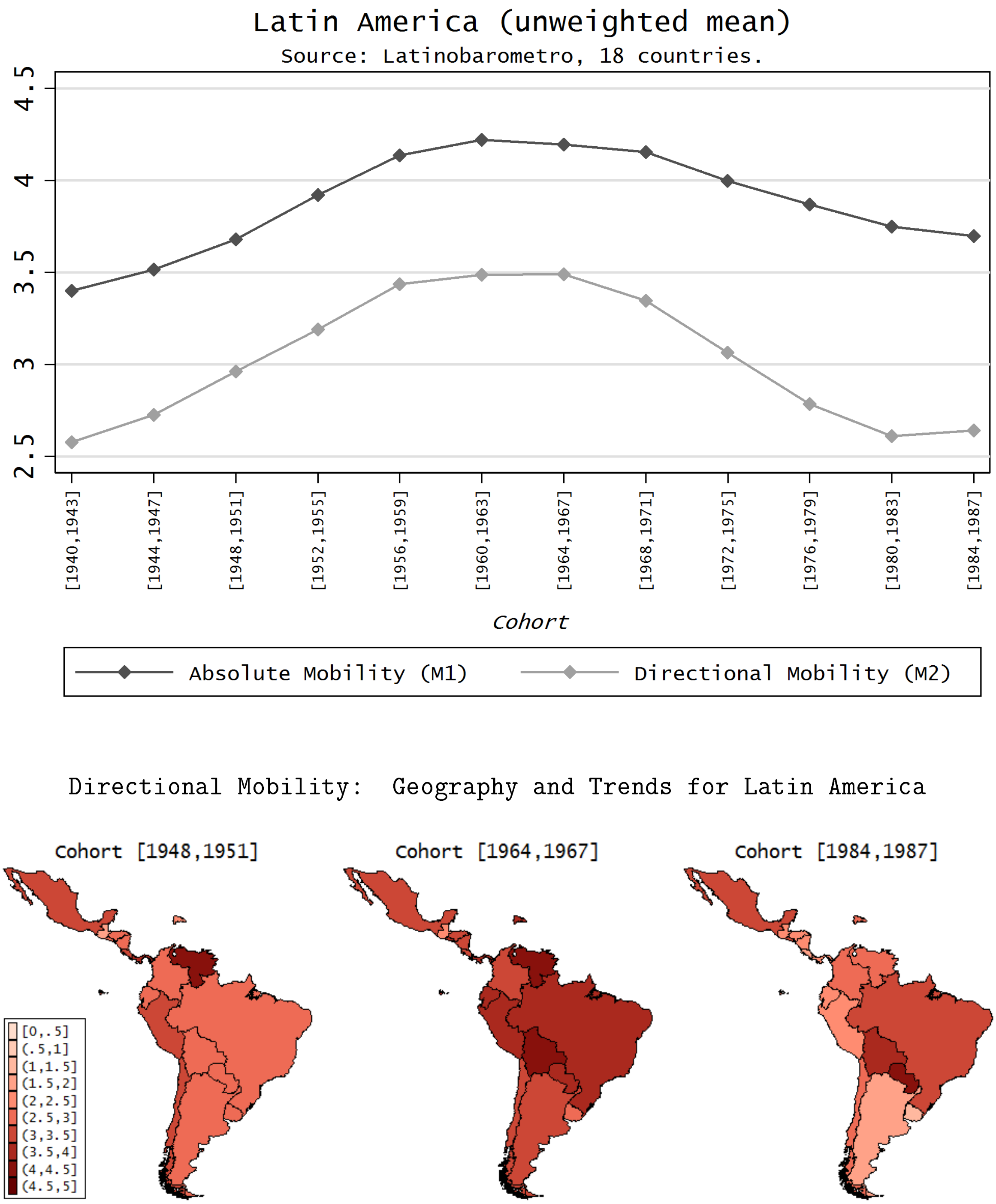
Notes: Estimated probability of higher education (at least completed secondary) of children with different parental educational background. Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22.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

Figure 4.8.: Educational inequality in Latin America: bottom-upward Mobility (BUM) and upper class persistence (UCP).



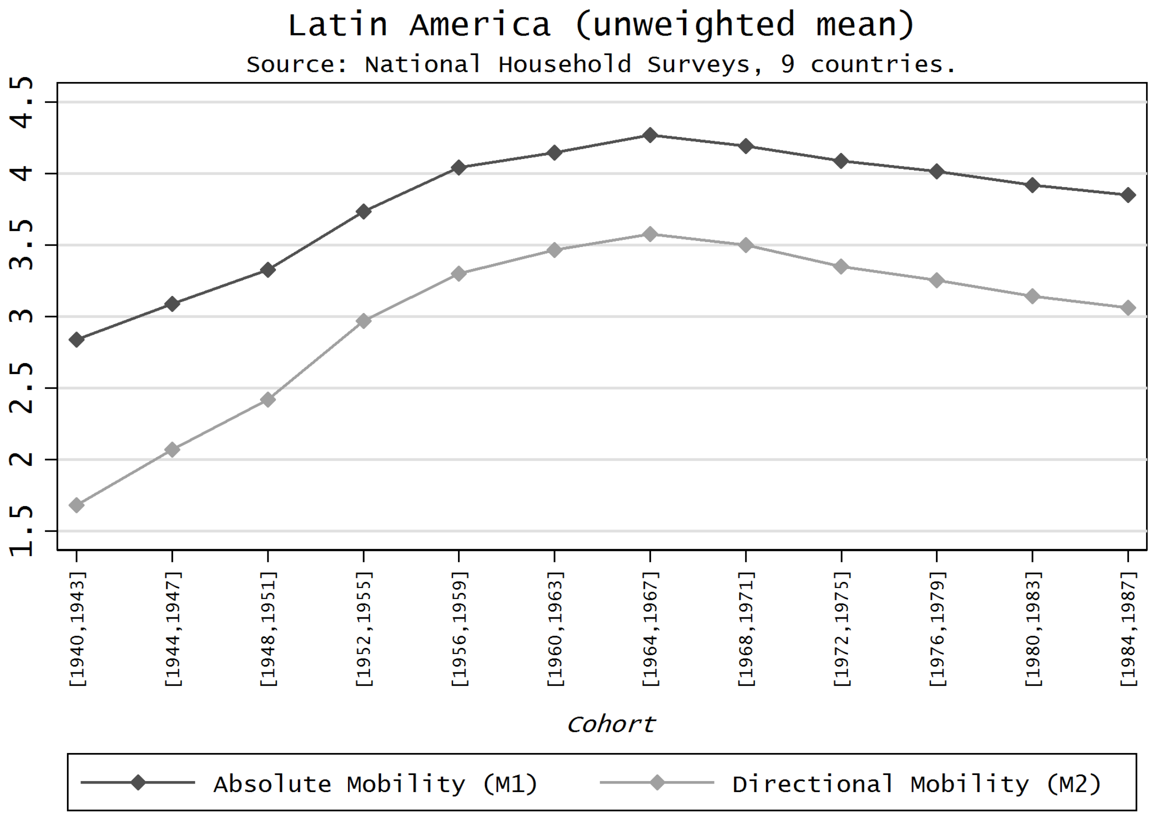
Notes: Estimated probability of higher education (at least completed secondary) of children with different parental educational background. Points show the unweighted mean over all countries of the estimates for each cohort. Samples for each cohort and country restricted to individuals older than 22. Bootstrapped confidence interval. *Source*: National Household Surveys 1982-2015, own estimates.

Figure 4.9.: 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 4.10.: 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 1982-2015, own estimates.

Table 4.4.: Assortative mating and intergenerational mobility – Linear Regressions.

	(1) β	(2) ρ	(3) r	(4) BUM	(5) UCP	(6) $M1$	(7) $M2$
Spouse correlation (parents)	0.921***	0.444***	0.131**	-1.028***	0.178	-0.648	-0.830
	(0.3416)	(0.1479)	(0.0650)	(0.3710)	(0.2549)	(1.7139)	(1.8928)
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 1982-2015, own estimates.

uals 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 in most of the countries bottom-up mobility increased – up to a 300 % increase in Brazil and Mexico – it is on low levels and almost unchanged over time in Central American countries, like Guatemala, Honduras and Nicaragua.[14] 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 in this age interval.

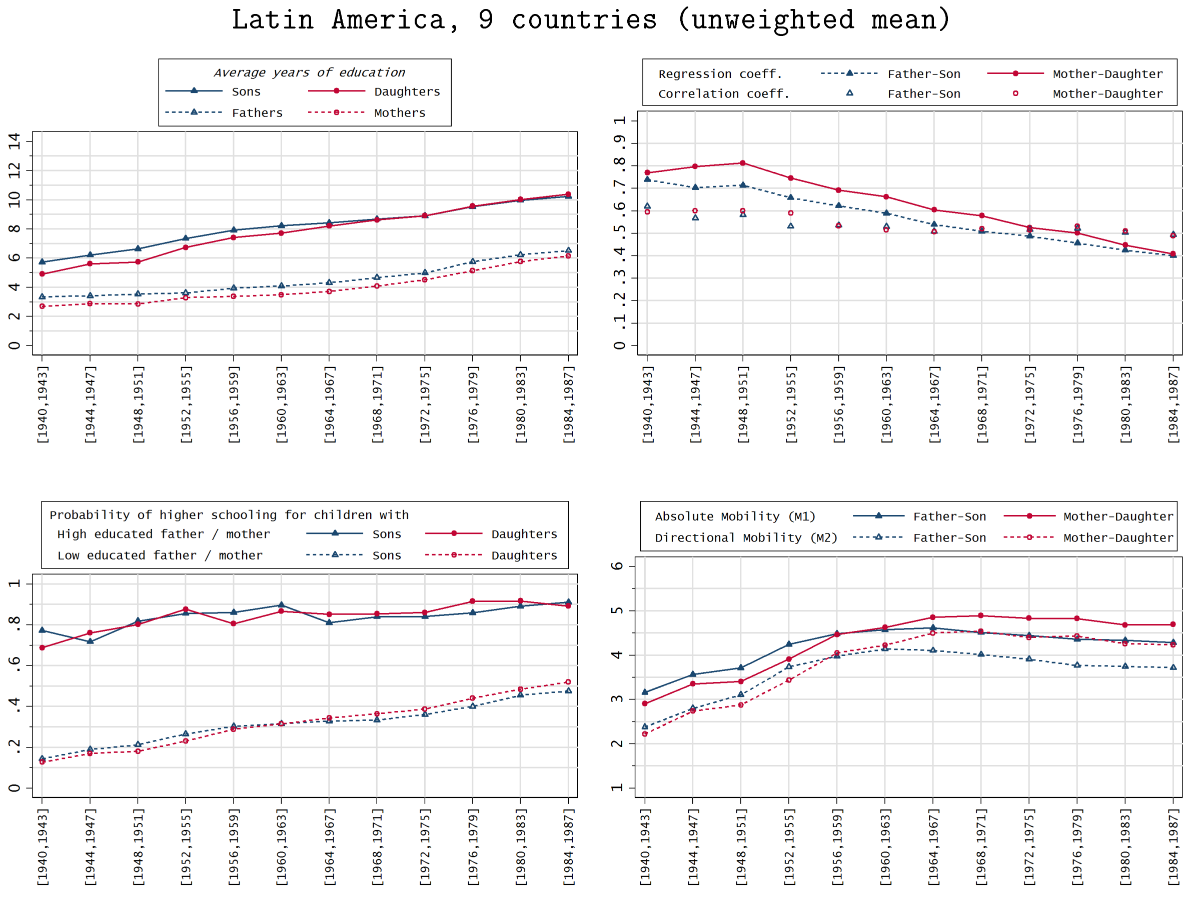
Figures 4.9 and 4.10 show absolute and directional mobility trends. These measures show the magnitude and pattern of the change between the educational attainment of parents and children on average. As is evident, since the outcome measure – completed years of education – is bounded, rising parental 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 parents' and children's education reaches a maximum and later decreases as parents'education rises. Interestingly, the gap between M1 and M2 does not change significantly across cohorts, showing that downward mobility is almost stable around one year of schooling on average.

4.4.3. Heterogeneity by Gender and Assortative Mating

In this part of the analysis, we first 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

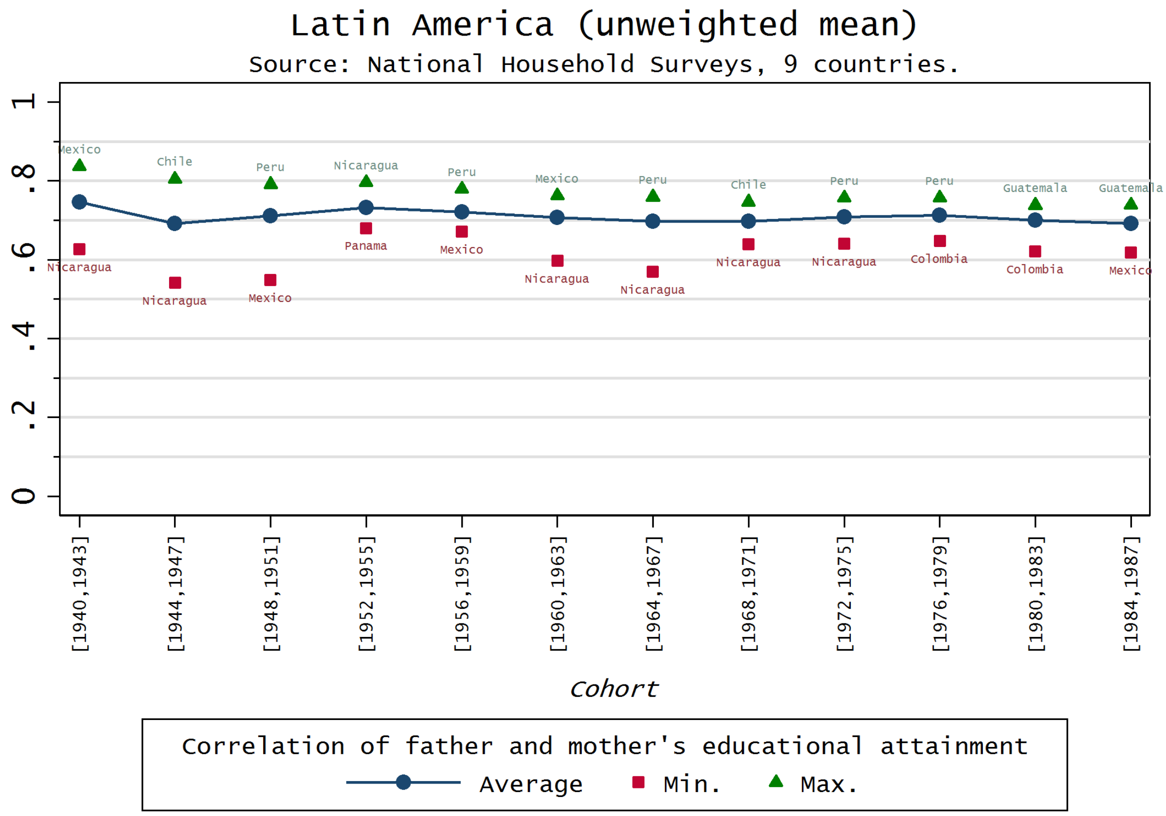
[14]The spatial dimension of this phenomenon is a striking finding that might deserve special attention in future studies.

Figure 4.11.: Average educational attainment by gender and intergenerational mobility for father-son and mother-daughter pairs.



Source: National Household Surveys 1982-2015, own estimates.

Figure 4.12.: 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 1982-2015, own estimates.

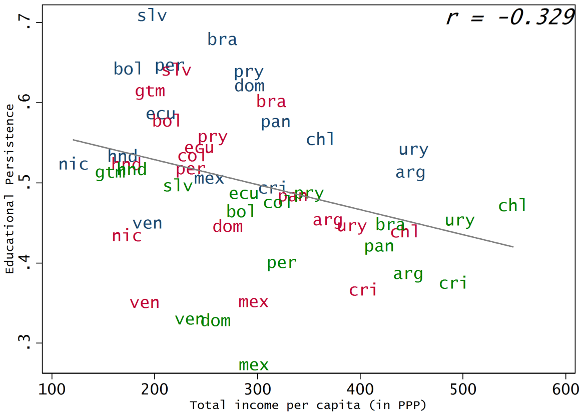
because the returns on sons' education are expected to be higher, or because of traditional gender roles. For this last reason, imitation might cause the educational attainments of children to be related more strongly to the education of the parent with the same sex (see e.g. Schneebaum et al., 2015). 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 have been able to empirically prove this relationship so far (e.g. Chadwick and Solon, 2002; Ermisch et al., 2006; Guell et al., 2015). We can perform this evaluation for nine countries where we have information on both the father's and the mother's educational attainment.

As shown in Figure 4.11, 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.

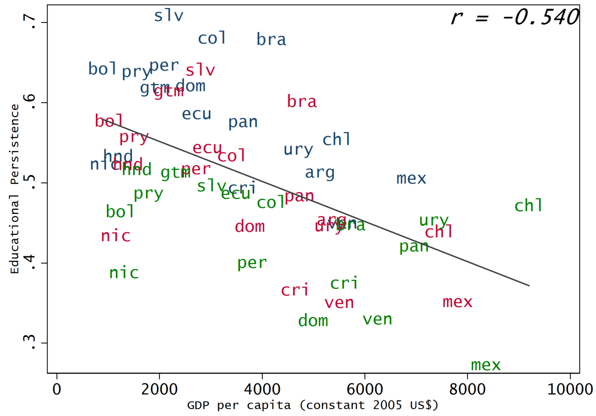
Taking into account the high degree of assortative mating in Latin American countries, these findings are not particularly surprising: when the education of both parents is similar, the education of only one of the two is a valid proxy for the education of the other. Our findings show that assortative mating in Latin America, measured by the correlation of father's and mother's educational attainment, is constantly high (around 0.7, with countries ranging between 0.6 and 0.8; see Figure 4.12). Interestingly, most countries show a slight but decreasing trend. Indeed, past research found 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 4.4, 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 a clear association between assortative mating and intergenerational mobility.

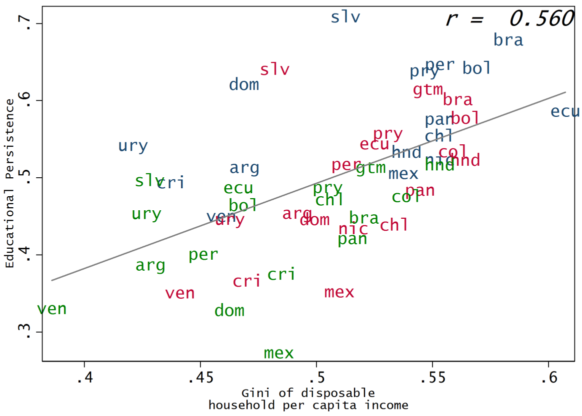
Figure 4.13.: Educational persistence and economic performance.



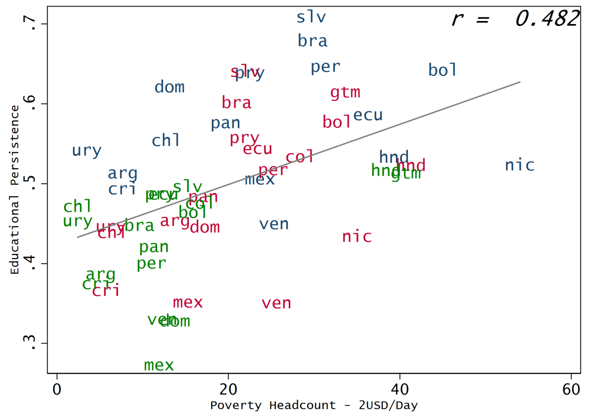
(a) Average income
(Source: SEDLAC)



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



(c) Inequality
(Source: SEDLAC)



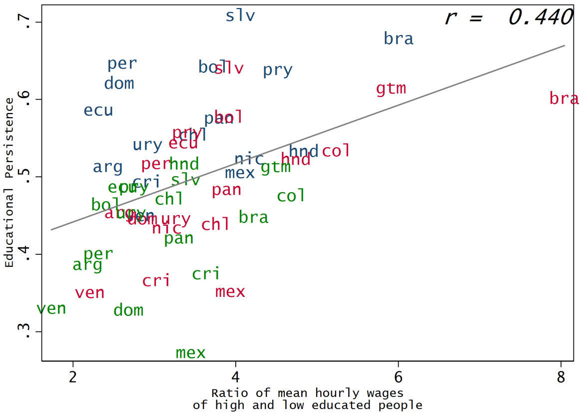
(d) Poverty
(Source: SEDLAC)

Notes: Intergenerational mobility of the cohorts '40-'54 , '55-'69, '70-'84 is associated with the corresponding macroeconomic or institutional characteristic in the years 1990-99, 2000-09, 2010-14. *Source*s: Latinobarometro 1998-2015, own estimates of educational persistence; SEDLAC; World Bank Data.

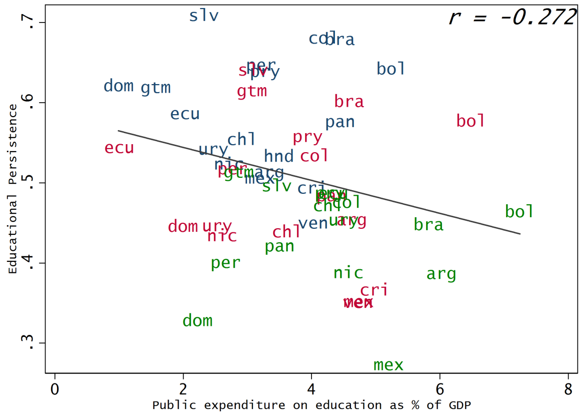
4.4.4. Intergenerational Mobility, Institutions and Economic Performance

The aim of this part of the analysis is to show the association between intergenerational mobility and macroeconomic and institutional characteristics. The first descriptive part of 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. In the second part, all estimated indexes are evaluated separately in models that control for cross-country heterogeneity. In order to make use of all the available data, we take the average of our educational persistence estimates from three broader cohorts (people born 1940-54, 1955-69 and 1970-84) and associate them with data at the country level averaged over three time periods (1990-99, 2000-09 and 2010-14), respectively. The criteria on how to match the

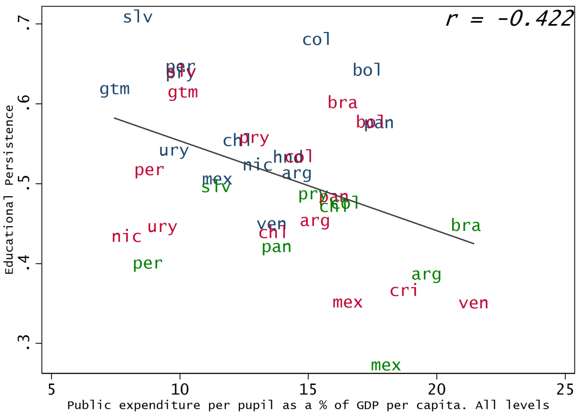
Figure 4.14.: Educational persistence and institutional characteristics of the education system.



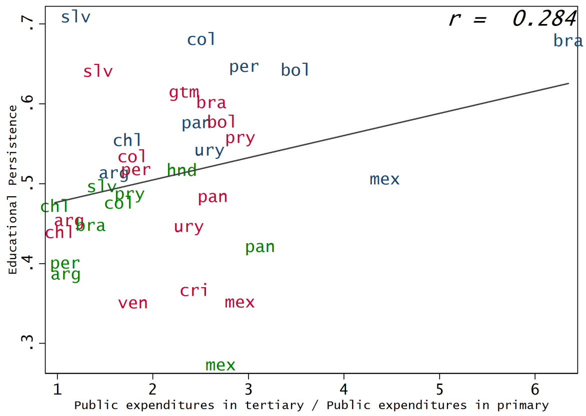
(a) Returns to Education
(Source: SEDLAC)



(b) Public education
(Source: World Bank)



(c) All levels

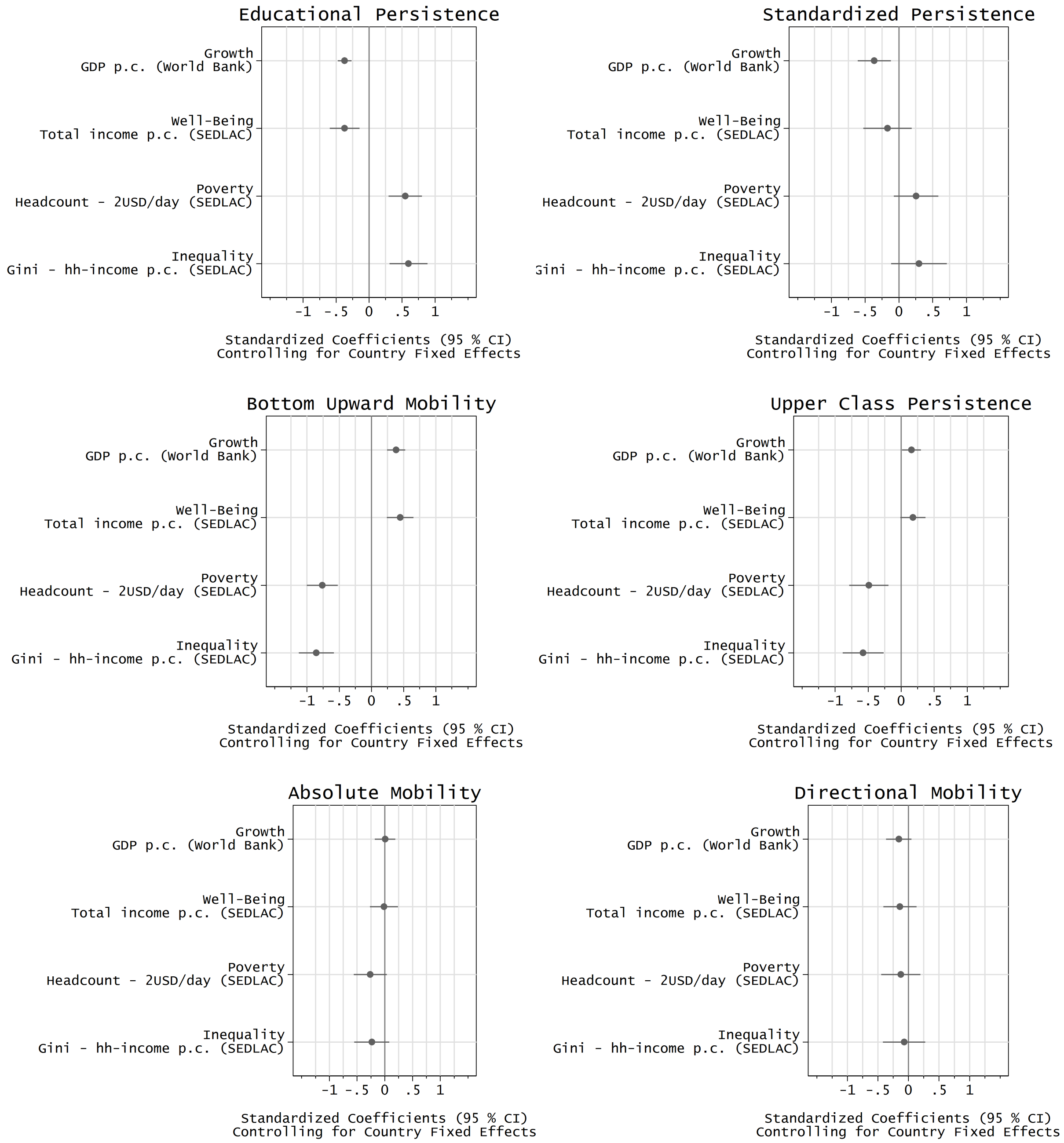


(d) Type of expenditure

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

Notes: Intergenerational mobility of the cohorts '40-'54 , '55-'69, '70-'84 is associated with the corresponding macroeconomic or institutional characteristic in the years 1990-99, 2000-09, 2010-14. *Sources*: Latinobarometro 1998-2015, own estimates of educational persistence; SEDLAC; World Bank Data.

Figure 4.15.: Intergenerational mobility and economic performance. Regression analysis controlling for country fixed effects.



Notes: Intergenerational mobility of the cohorts ’40-’54 , ’55-’69, ’70-’84 is associated with the corresponding macroeconomic or institutional characteristic in the years 1990-99, 2000-09, 2010-14. Points show the standardized linear regression coefficients and their corresponding confidence interval (95 %) of separate regressions for each of the indicated variables. All regressions control for country fixed effects. In cases where the confidence interval line crosses the zero-line, point estimates are not statistically significant at the 0.05 level. *Source*s: Latinobarometro 1998-2015, own estimates of intergenerational mobility; SEDLAC; World Bank Data.

two data sets is thereby completely determined by the time periods for which information is available. Hence, these correlations cannot be interpreted as causal effects. Yet, they might be seen as a first step to understand potential underlying mechanisms.

Figure 4.13 and Figure 4.14 show scatter-plots, linear fits and the related correlation coefficients. We find that higher degrees of intergenerational mobility are associated with: i) High levels of household income per capita and 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. iv) Higher amounts of public expenditure in education and, in particular, the share of expenditure devoted to primary education. These findings confirm the predictions of influential theoretical models (Becker and Tomes, 1979) and the patterns uncovered in empirical findings in the past.[15]

Finally, we regress a series of macroeconomic outcomes separately using our intergenerational mobility estimates controlling for country fixed effects. The association of our estimates and the macroeconomic outcomes is performed as explained above. Figure 4.15 shows the estimated standardized coefficients and their respective confidence interval. We see that the two mobility indicators that capture the structural mobility component, educational mobility (β) and bottom upward mobility (BUM), are positively associated with economic growth and well-being, and negatively with poverty and inequality. The standardized persistence estimates (r) have a qualitatively similar association with the above mentioned macroeconomic outcomes, however they are not statistically significant. 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. Furthermore, since absolute ($M1$) and directional mobility ($M2$) – i.e. the magnitude of the change from one generation to the next – show no meaningful association, the strength of the structural mobility component seems to be less influential than the marginal improvement of human capital in itself. Last, the probability of upper class persistence (UCP) shows the same pattern of conditional correlation with economic performance as the BUM. This is mainly due to the fact that the two measures are highly correlated: changes in the probability of attaining a secondary education degree, like reforms that raise levels of compulsory education, are likely to affect all individuals regardless of their parental background. Including both as independent variables in the regressions, the coefficients of BUM are significantly different from zero, while the coefficients of UCP are not.

[15] For instance, the negative relationship between inequality and intergenerational mobility has been shown to hold within the U.S. (Chetty et al., 2014b) and China (Fan et al., 2015), as well as across and within Latin American countries (Neidhöfer, 2016). Güell et al. (2015) find that intergenerational mobility within Italy is positively correlated with economic performance. It is argued that one of the primary mechanisms that cause this relationship is investment in children's human capital in the presence of credit constraints. Rising private and public investments in the human capital of poor children, driven by economic growth, anti-poverty programs or public educational expenditures, thus leads to higher intergenerational mobility. For a survey of the theoretical explanations of the underlying mechanisms, see (Neidhöfer, 2016).

These preliminary analyses using our database open up interesting avenues for future research. Especially because of the temporal structure of the associations, the potential mechanisms behind the statistical relationships shown here must be understood as either implying a steady-state relationship or as an indication of the effect of intergenerational mobility on economic performance and institutions. For instance, a mechanism driving the latter might operate through preferences for redistribution that have been recently shown to be positively associated with perceptions about social mobility (see Alesina et al., 2017). A more suitable way to analyze the driving forces of social intergenerational mobility would be to relate a cohort's level of mobility with indicators of its initial conditions, as in Neidhöfer (2016). The exact identification of causal channels goes beyond the scope of this work. Nevertheless, the dataset created here makes it possible for these aspects to be analyzed in greater detail in the future.

4.5. Conclusions

In this paper, we introduced a new panel data set of intergenerational mobility estimates for Latin America and provided a comprehensive descriptive analysis of observed trends and patterns. We found that intergenerational mobility of educational attainment has been on the rise in Latin America, driven by the educational expansions of the last decades that have particularly benefited children from the bottom of the distribution. In contrast, the educational persistence at the top of the distribution has remained consistently high and has not changed substantially. Furthermore, we found intergenerational mobility to be positively associated with economic growth and progressive public expenditure in education, and negatively associated with income inequality, poverty, returns to education, and the degree of assortative mating. The positive relationship between intergenerational mobility and economic performance was also found in estimations controlling for cross-country heterogeneity by fixed effects.

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 by Hertz et al. (2007). In the future, these estimates can be used to analyze the characteristics that influence or are influenced by the degree of intergenerational mobility of socioeconomic status. 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, and 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.

4.6. Additional Material

4.6.1. Summary of Data Sources

4.6.1.1. Household Surveys

Our main source of information for all 18 Latin American countries in our analysis is the Latinobarometro survey. Using the survey waves 1998 to 2015 our overall sample comprises 211,401 observations. We complement this with National Household Surveys that include information on parental educational achievements collected through retrospective questions. This second data set comprises 1,078,445 observation in total that derive from different data sources.

Data from Brazil comes from the *Pesquisa Nacional por Amostra de Domicilios* (PNAD), which is carried out by the *Instituto Brasilero de Geografía y Estadísticas* (IBGE) on a yearly basis. 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 the most recent one 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 accounted for 2.3% of Brazil's population in the 2000 Census.

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.[16] The survey has been regularly implemented every two years since 1985 during November and in some cases, up to mid-December. We use surveys for 2006 to 2015, since previous surveys don't provide information about parents.

The same is true for Peru, using the *Encuesta Nacional de Hogares* (ENAHO), which is carried out in four waves since 1997, and continues until today. The fourth wave of the survey is nationally representative, and it is officially used to estimate poverty rates. After year 2000 the survey was enlarged and a new sample frame was used, including questions about parents. We use surveys for 2001 to 2015. However, from 2002 on the survey asked only the household head about the education of parents. 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 Na-*

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

cional 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) have 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 population at the national, urban, rural and regional level. The MxFLS has been 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 rounds: 2002, 2005-2006 and 2009-2012.

Finally, for Nicaragua the only useful source 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 4.5.: *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 4.5.: *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, 2000-2011, 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, 2000-2011, 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
	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

4.6.1.2. 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

4.6.2. Description of the Database

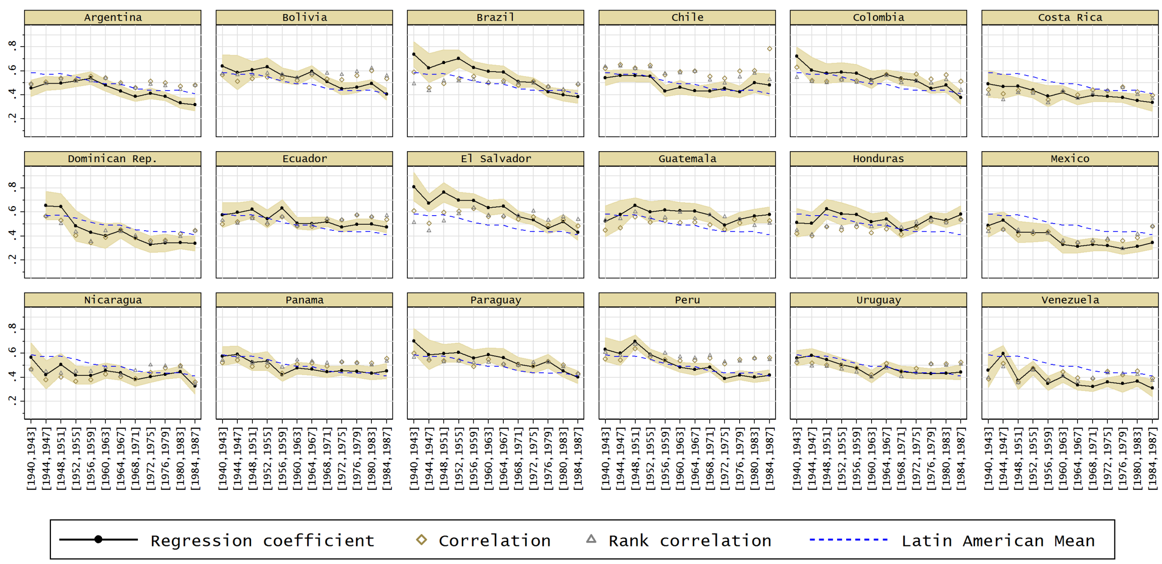
We provide databases containing all mobility indicators described in this project. The variables contained in each database are described in Table 4.6. The data is divided in four different sets of different periodization of the birth cohorts, separated at intervals of one to four years, respectively. 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.

Table 4.6.: 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	3421.34	7508.60	19	45046
b	Intergenerational persistence parameter	Conditional correlation between years of education of children and parents (beta)	0.49	0.14	0.02	0.91
bstd	Intergenerational correlation (b standarized)	Parameter b weighted by the ratio of standard deviations of years of schooling of childen and parents	0.50	0.09	0.06	0.79
corr_spearman	Spearman's correlation	Spearman's rank correlation coefficient (rho)	0.49	0.08	-0.05	0.67
blog	Intergenerational elasticity	Parameter b estimated using the logarithm of the outcome of interest (years of schooling)	0.34	0.12	0.00	0.70
prob_high	Prob(high education) | High parental education	Predicted probability of upper class persistence (UCP)	0.75	0.13	0.16	0.97
prob_low	Prob(high education) | Low parental education	Predicted probability of bottom upward mobility (BUM)	0.27	0.15	0.03	0.81
M1	Absolute mobility	Absolute mobility (M1)	3.79	0.68	1.60	5.23
M2	Directional mobility	Directional mobility (M2)	2.90	0.83	0.50	4.78
educ	Years of schooling	Average of own years of schooling	8.14	2.19	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)	5.25	2.12	1.39	12.58
var	Variance of years of schooling	Variance of own years of schooling	16.66	5.43	0.84	33.08
var_parents	Variance of parental years of schooling	Variance of parents' years of schooling	17.56	4.31	6.79	32.96
age	Age	Average age of individuals in sample	40.93	13.59	23.00	72.54
male	Share of males	Share of males in sample	0.49	0.06	0.33	0.81

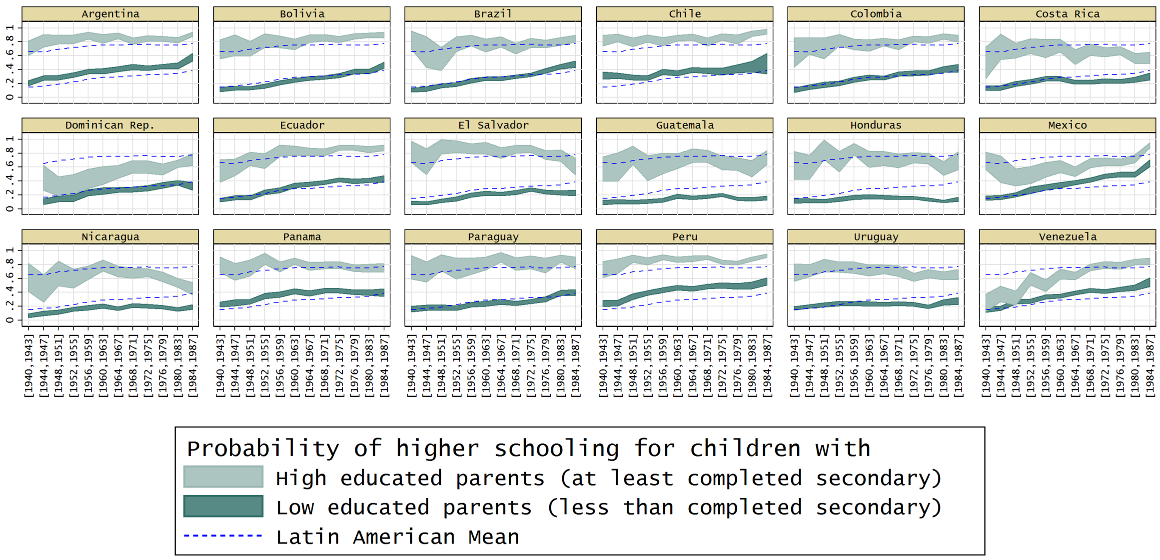
4.6.3. Country-Wise Estimates

Figure 4.16.: Educational persistence in Latin America: Regression and correlation coefficients by country. *Source*: Latinobarometro 1998-2015, own estimates.



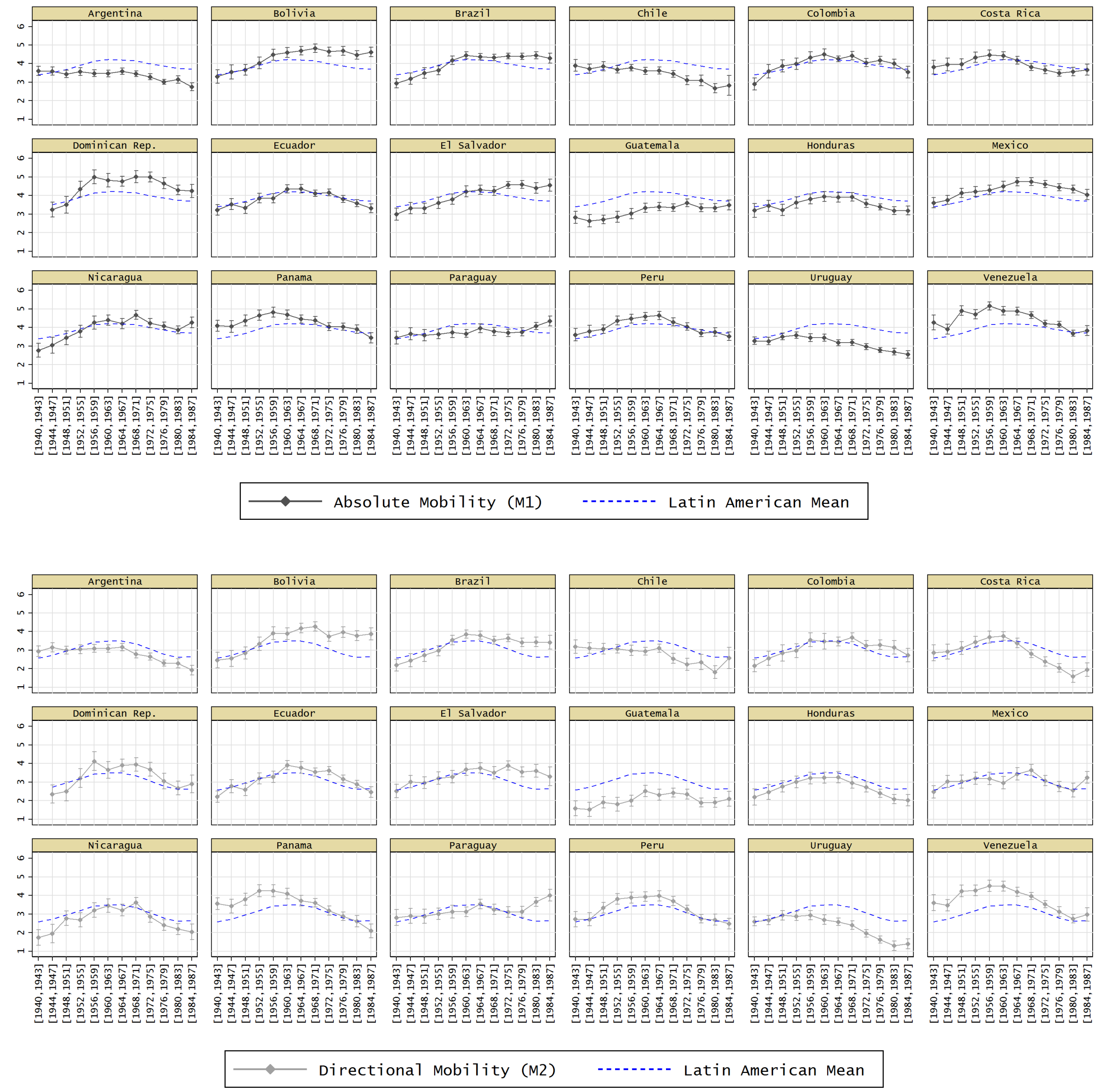
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure 4.17.: Educational inequality in Latin America: bottom-upward Mobility (BUM) and upper class persistence (UCP). *Source*: Latinobarometro 1998-2015, own estimates.



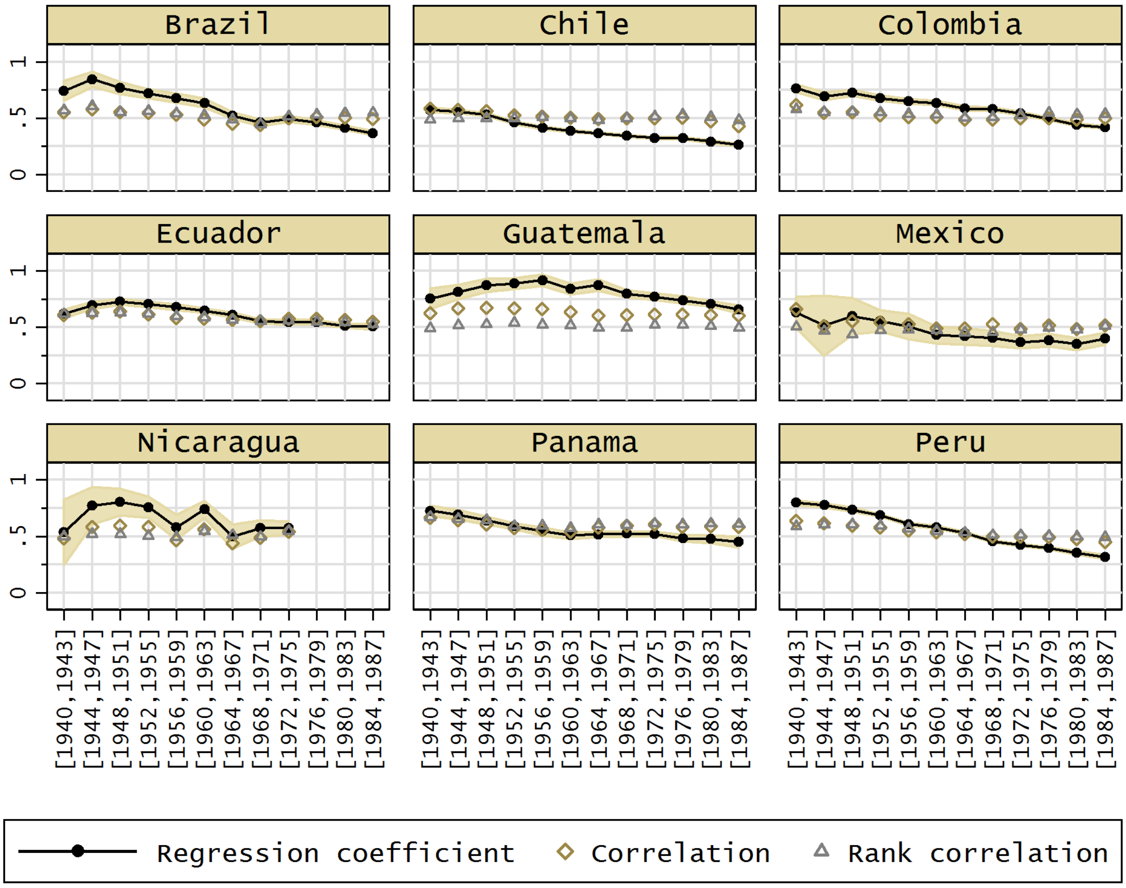
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure 4.18.: Educational mobility in Latin America: absolute ($M1$) and directional ($M2$) mobility in years of education. *Source*: Latinobarometro 1998-2015, own estimates.



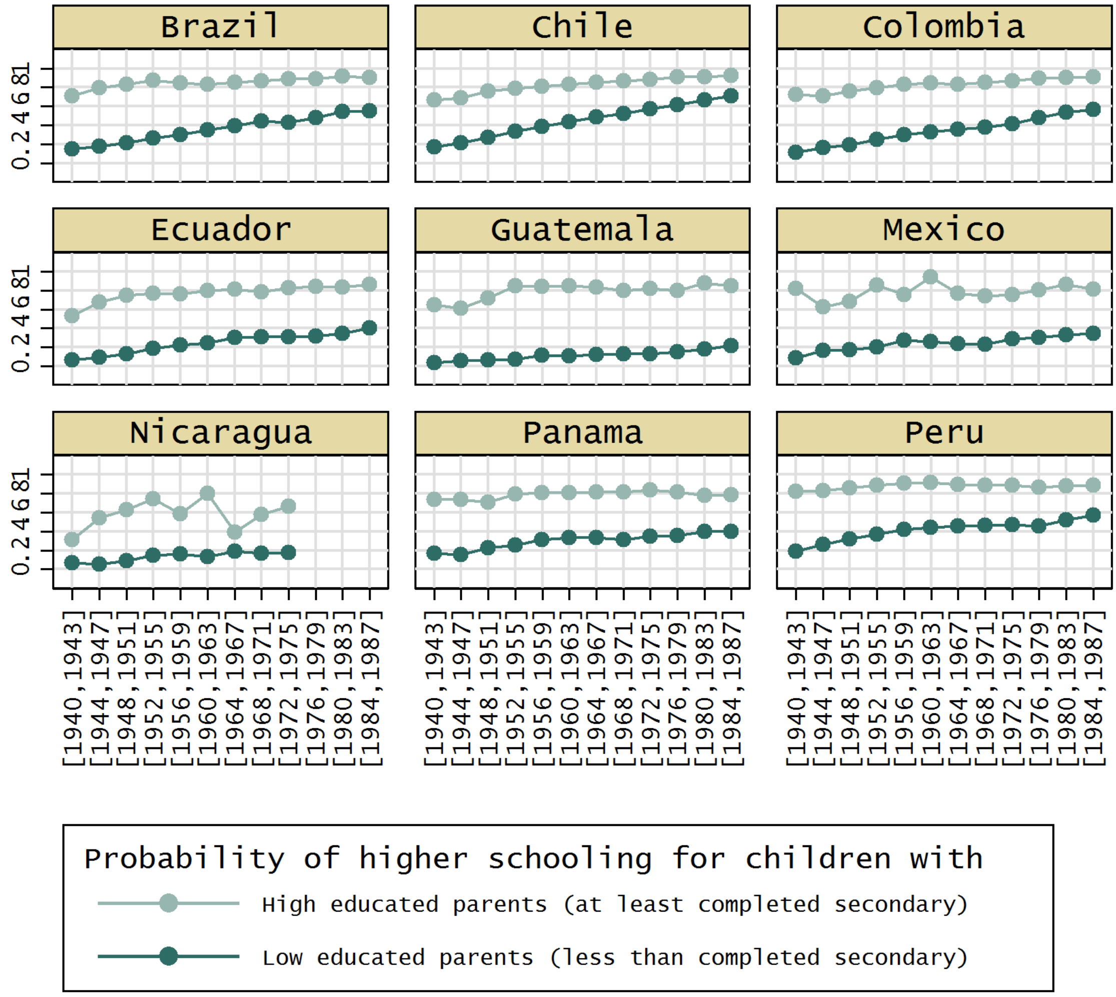
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure 4.19.: Educational persistence in Latin America: Regression and correlation coefficients by country. *Source*: National Household Surveys 1982-2015, own estimates.



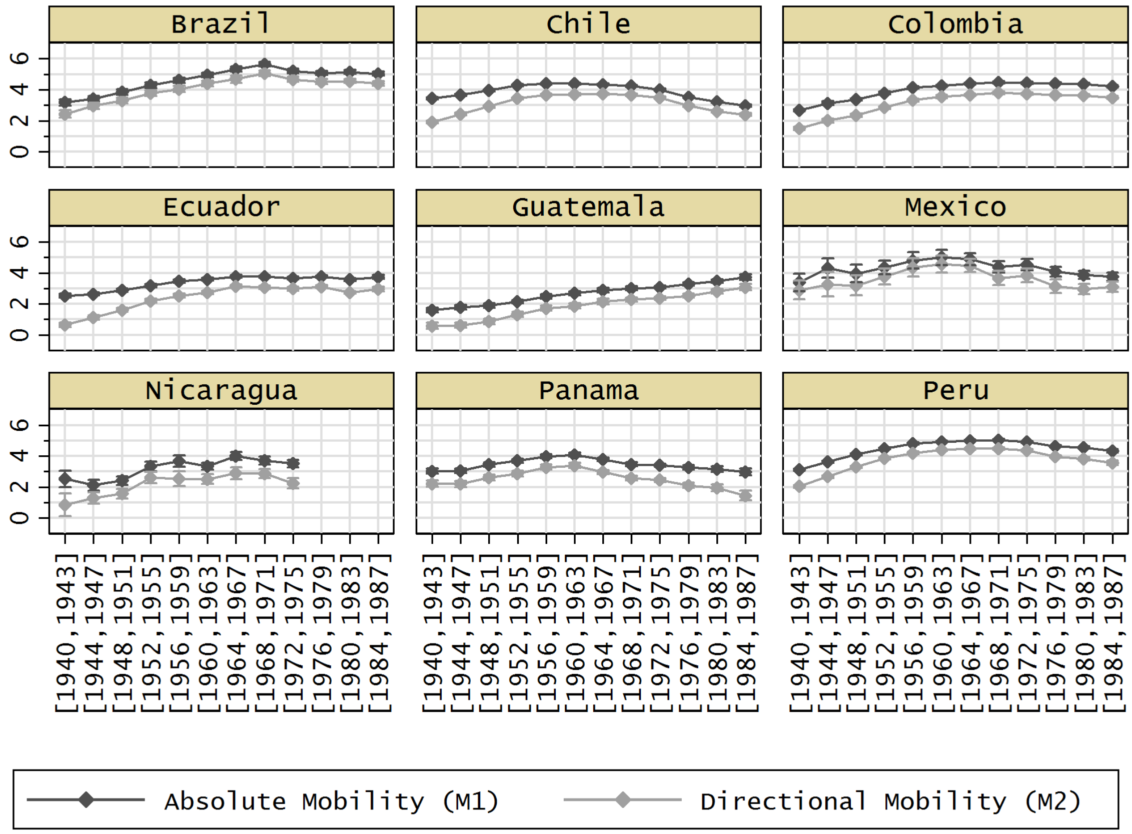
Notes: Samples for each cohort and country restricted to individuals older than 22. Only point estimates displayed relying on at least 200 observations. Bootstrapped confidence interval.

Figure 4.20.: Educational inequality in Latin America: bottom-upward Mobility (*BUM*) and upper class persistence (*UCP*). *Source*: National Household Surveys 1982-2015, 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 4.21.: Educational mobility in Latin America: absolute ($M1$) and directional ($M2$) mobility in years of education. *Source*: National Household Surveys 1982-2015, 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 4.22.: Educational persistence in Latin America for father-son and mother-daughter pairs. *Source*: National Household Surveys 1982-2015, own estimates.

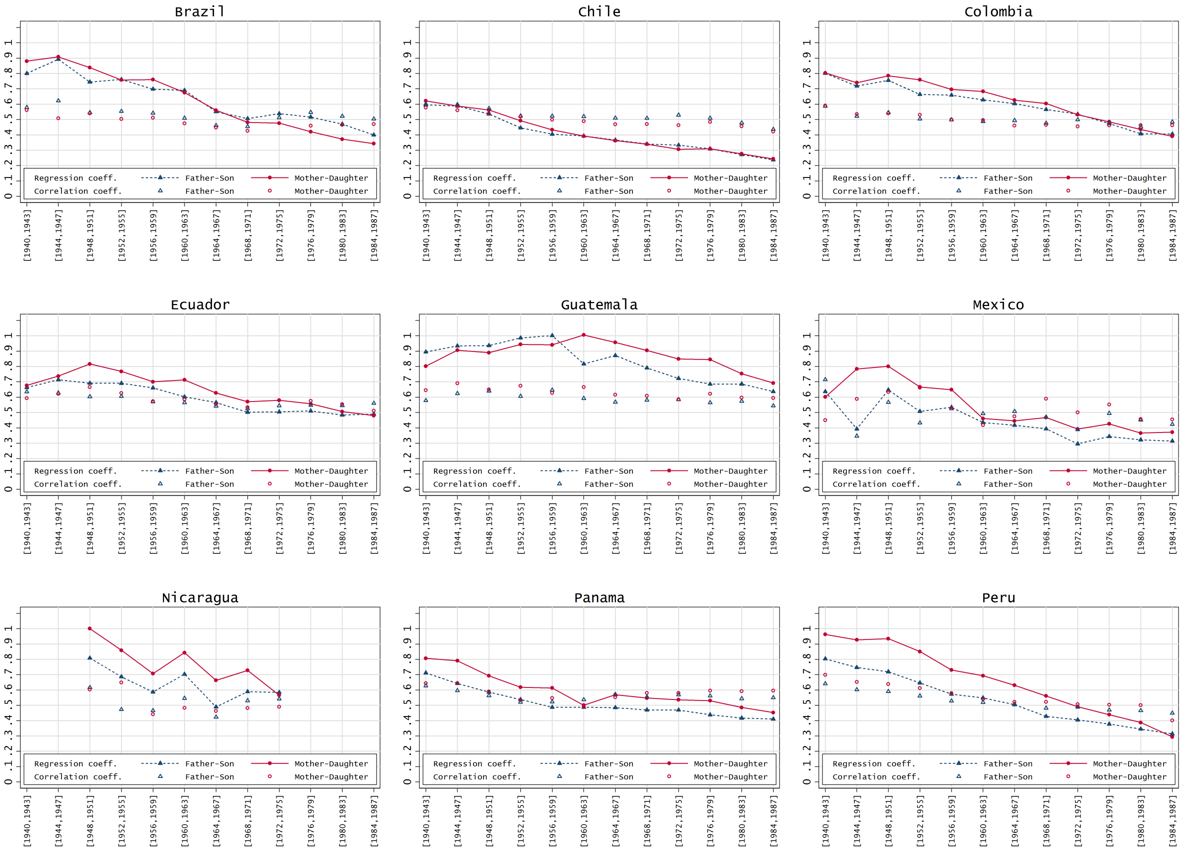


Figure 4.23.: Average educational attainment, intergenerational mobility for father-son and mother-daughter pairs, and assortative mating. *Source*: National Household Surveys 1982-2015, own estimates.

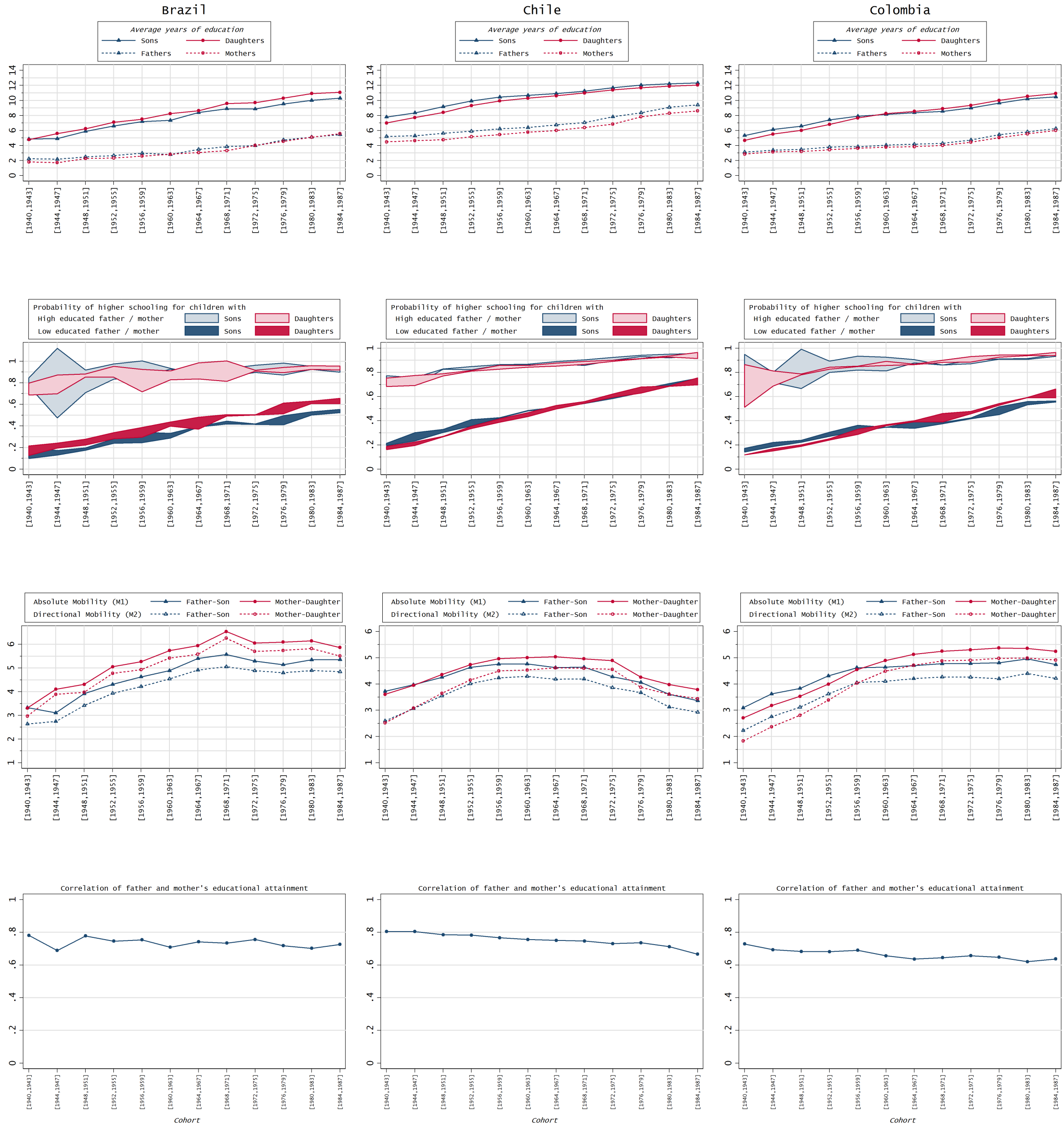


Figure 4.24.: Average educational attainment, intergenerational mobility for father-son and mother-daughter pairs, and assortative mating. *Source*: National Household Surveys 1982-2015, own estimates.

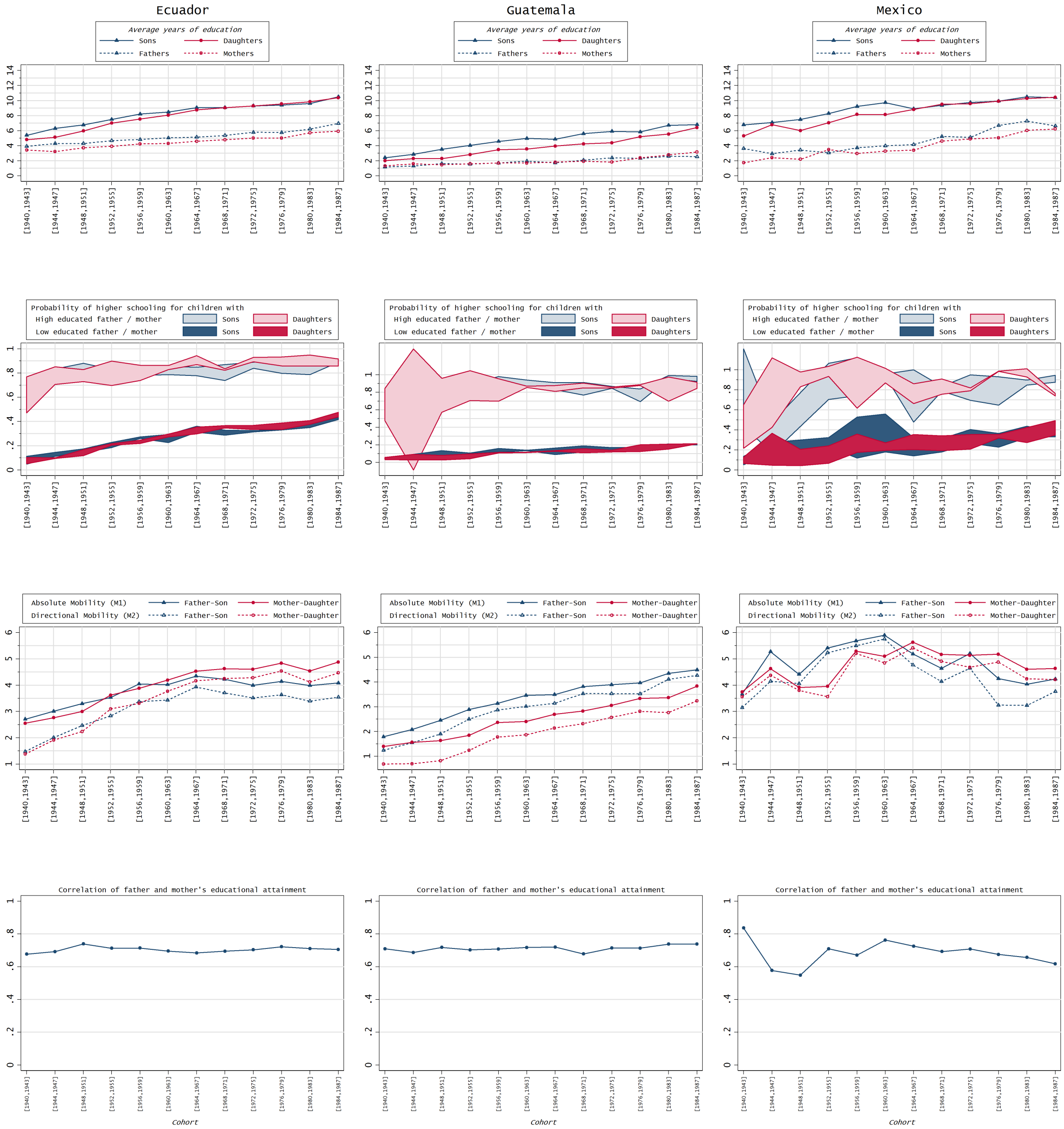


Figure 4.25.: Average educational attainment, intergenerational mobility for father-son and mother-daughter pairs, and assortative mating. *Source*: National Household Surveys 1982-2015, own estimates.

4.6.4. 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 has been questioned by recent analyses showing that the slope coefficients might vary for families in different parts of the distribution Bratberg et al. (2017). Especially 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 has been questioned. However, cross country studies show a high correlation between linear and non-linear measures of relative intergenerational mobility (see Blanden, 2013). Figure 4.26 shows an evaluation of non-linear patterns in the correlation of parents' and children's years of education. Generally, the issue certainly requires particular attention that would go 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 has been used e.g. by Magee et al. (2000) to estimate assortative mating patterns in educational levels.[17] The outcome variables in our application both have six categories: illiterate, incomplete primary, complete primary, incomplete secondary, complete secondary, incomplete higher education, complete higher education.

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

$$y^*_{pi} = X'_{pi}\delta_p + \varepsilon_{pi} \tag{4.6.1}$$

$$y^*_{ci} = X'_{ci}\delta_c + \varepsilon_{ci} \tag{4.6.2}$$

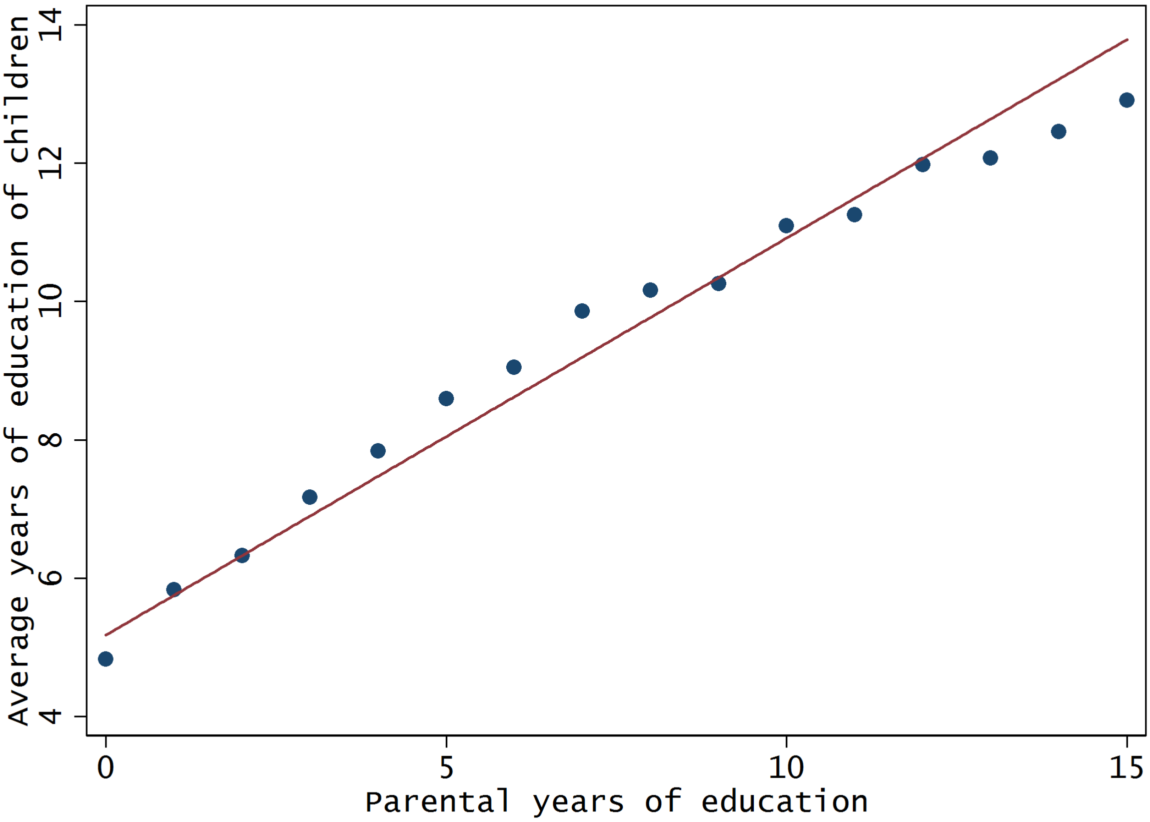
where i denotes the family. δ_p and δ_c are vectors of parameters for X_p and X_c that include age and sex and satisfy the exogeneity conditions $E[X_{pi}\varepsilon_{pi}] = E[X_{ci}\varepsilon_{ci}] = 0$. ε_p and ε_c are the error terms, distributed as a bivariate standard normal. Denote the cutoffs of the observed categorical variables indicating parents' educational level $j\epsilon(1,2,3,4,5,6,7)$ 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

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

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 4.27 and 4.28 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.

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

Figure 4.26.: 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.

References

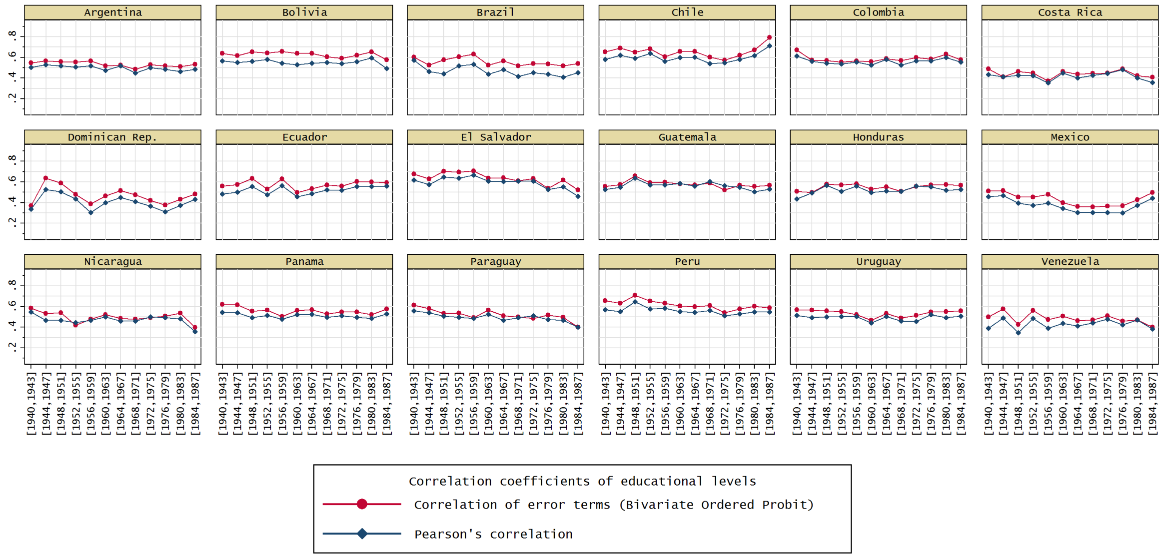
Blanden, J. (2013), Cross-country Rankings In Intergenerational Mobility: A Comparison Of Approaches From Economics And Sociology. Journal of Economic Surveys, 27: 38–73.

Bratberg, E., Davis, J., Mazumder, B., Nybom, M., Schnitzlein, D. D. and Vaage, K. (2017), A Comparison of Intergenerational Mobility Curves in Germany, Norway, Sweden, and the US. Scandinavian Journal of Economics, 119: 72–101.

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

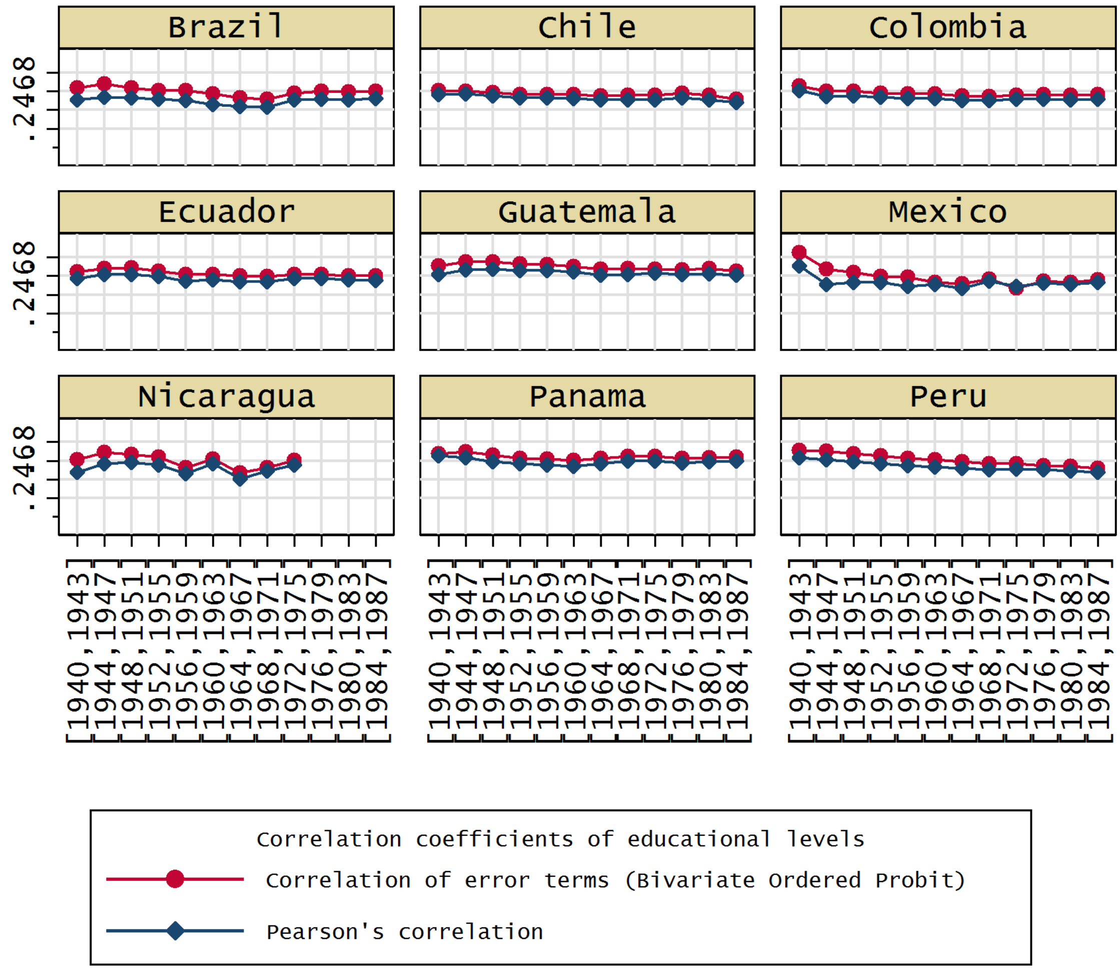
Sajaia, Z. (2008), Maximum likelihood estimation of a bivariate ordered probit model: implementation and Monte Carlo simulations. The Stata Journal, 4(2): 1-8.

Figure 4.27.: 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 4.28.: 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 1988-2015, own estimates.

Bibliography

ACEMOGLU, D. AND J. A. ROBINSON, *Why Nations Fail: The Origins of Power, Prosperity and Poverty* (New York: Crown, 2012).

ADERMON, A., M. LINDAHL AND D. WALDENSTRÖM, "Intergenerational Wealth Mobility and the Role of Inheritance: Evidence from Multiple Generations," (2015).

AIZER, A., "Rising Inequality and Intergenerational Mobility: The Role of Public Investments in Human Capital," *CESifo Economic Studies* 60 (2014), 280–311.

ALESINA, A. AND D. RODRIK, "Distributive Politics and Economic Growth," *The Quarterly Journal of Economics* 109 (1994), 465–490.

ALESINA, A., S. STANTCHEVA AND E. TESO, "Intergenerational Mobility and Preferences for Redistribution," , 2017.

ALVAREDO, F. AND L. GASPARINI, "Recent Trends in Inequality and Poverty in Developing Countries," in *Handbook of Income Distribution*volume 2, chapter 9 (2015), 697–805.

ANDERSEN, L. E., "Social Mobility in Latin America," in S. Duryea, M. Ureta and A. C. Edwards, eds., *Critical Decisions at a Critical Age - Adolescents and Young Adults in Latin America*03, chapter 6 (Washington DC: Inter-American Development Bank, 2003), 219 – 257.

ANDREWS, D. AND A. LEIGH, "More inequality, less social mobility," *Applied Economics Letters* 16 (oct 2009), 1489–1492.

ATKINSON, A., "Bringing income distribution in from the cold," *The Economic Journal* 107 (1997), 297–321.

AZAM, M. AND V. BHATT, "Like Father, Like Son? Intergenerational Educational Mobility in India," *Demography* 52 (2015), 1929–1959.

AZEVEDO, V. AND C. BOUILLON, "Intergenerational social mobility in Latín América: a review of existing evidence," *Revista de análisis económico* 25 (2010).

BANERJEE, A. V. AND E. DUFLO, "Inequality and Growth: What Can the Data Say?," *Journal of Economic Growth* 8 (2003), 267–299.

BARONE, G. AND S. MOCETTI, “Intergenerational Mobility in the Very Long Run: Florence 1427-2011,” (2015), 1–25.

BARRO, R. J. AND J. W. LEE, “A new data set of educational attainment in the world, 1950-2010,” *Journal of Development Economics* 104 (2013), 184–198.

BECKER, G. S. AND N. TOMES, “An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility,” *The Journal of Political Economy* 87 (1979), 1153–1189.

———, “Human Capital and the Rise and Fall of Families,” *Journal of Labor economics* 4 (1986), 1–47.

BEHRMAN, J. AND P. TAUBMAN, “Intergenerational Earnings Mobility in the United States: Some Estimates and a Test of Becker’s Intergenerational Endowments Model,” *The Review of Economics and Statistics* 67 (1985), 144–151.

BENABOU, R., “Equity and Efficiency in Human Capital Investment: The Local Connection,” *The Review of Economic Studies* 63 (1996), 237–264.

BÉNABOU, R., “Inequality and growth,” in *NBER Macroeconomics Annual*volume 11 (1996), 11–92.

BINDER, M. AND C. WOODRUFF, “Inequality and Intergenerational Mobility in Schooling: The Case of Mexico*,” *Economic Development and Cultural Change* 50 (2002), 249–267.

BJÖRKLUND, A. AND M. JÄNTTI, “Intergenerational Income Mobility in Sweden compared to the United States,” *The American Economic Review* 87 (1997), 1009–1018.

———, “Intergenerational Income Mobility and the Role of Family Background,” in *The Oxford Handbook of Economic Inequality*August (2012), 1–66.

BLACK, S. E. AND P. J. DEVEREUX, “Recent Developments in Intergenerational Mobility,” in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*1 edition (Elsevier, 2011a).

BLACK, S. E., P. J. DEVEREUX, P. LUNDBORG AND K. MAJLESI, “Poor Little Rich Kids? The Determinants of the Intergenerational Transmission of Wealth,” *NBER Working Papers* July (2015).

BLACK, S. E. S. AND P. J. P. DEVEREUX, “Recent developments in intergenerational mobility,” in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*volume 4 of *Handbook of Labor Economics*, chapter 12 (Elsevier B.V., 2011b), 1487–1541.

BLANDEN, J., “Cross-Country Rankings in Intergenerational Mobility: A Comparison of Approaches from Economics and Sociology,” *Journal of Economic Surveys* 27 (2013), 38–73.

BÖNKE, T. AND G. NEIDHÖFER, "Parental Background Matters: Intergenerational Mobility and Assimilation of Italian Immigrants in Germany," *German Economic Review* (2016), 1–31.

BORGERHOFF MULDER, M., S. BOWLES, T. HERTZ, A. BELL, J. BEISE, G. CLARK, I. FAZZIO, M. GURVEN, K. HILL, P. L. HOOPER, W. IRONS, H. KAPLAN, D. LEONETTI, B. LOW, F. MARLOWE, R. MCELREATH, S. NAIDU, D. NOLIN, P. PIRAINO, R. QUINLAN, E. SCHNITER, R. SEAR, M. SHENK, E. A. SMITH, C. VON RUEDEN AND P. WIESSNER, "Intergenerational wealth transmission and the dynamics of inequality in small-scale societies.," *Science (New York, N.Y.)* 326 (2009), 682–8.

BORJAS, G. J., "Ethnic Capital and Intergenerational Mobility," *The Quarterly Journal of Economics* 107 (1992), 123–150.

———, "The Intergenerational Mobility of Immigrants," *Journal of Labor Economics* 11 (1993), 113–135.

BOURGUIGNON, F., "Appraising income inequality data bases in Latin America," *Journal of Economic Inequality* (2015), 557–578.

BRATBERG, E., J. DAVIS, B. MAZUMDER, M. NYBOM, D. SCHNITZLEIN AND K. VAAGE, "A Comparison of Intergenerational Mobility Curves in Germany, Norway, Sweden, and the United States," *Scandinavian Journal of Economics* (2016).

BRAUN, S. T. AND J. STUHLER, "The Transmission of Inequality Across Multiple Generations: Testing Recent Theories with Evidence from Germany," *The Economic Journal* (dec 2016a).

———, "The Transmission of Inequality across Multiple Generations: Testing Recent Theories with Evidence from Germany," *Economic Journal* (2016b).

BRUNORI, P., F. H. FERREIRA AND V. PERAGINE, "Inequality of opportunity, income inequality and economic mobility: some international comparisons," in *Getting Development Right: Structural Transformation, Inclusion, and Sustainability in the Post-Crisis Era*January (Palgrave Macmillan, 2013), 85.

CASTELLANI, F. AND E. LORA, "Is Entrepreneurship a Channel of Social Mobility in Latin America?," *Latin American Journal of Economics* 51 (2014), 179–194.

CEDLAS AND THE WORLD BANK, "A guide to the SEDLAC: Socioeconomic Database for Latin America and the Caribbean.," Technical Report, Centro de Estudios Distributivos, Laborales y Socials, Universidad Nacional de La Plata, and the World Bank., 2012.

CELHAY, P. AND S. GALLEGOS, "Persistence in the Transmission of Education: Evidence across Three Generations for Chile," *Journal of Human Development and Capabilities* 16 (2015), 420–451.

CHADWICK, L. AND G. SOLON, "Intergenerational Income Mobility among Daughters," *American Economic Review* 92 (2002), 335–344.

CHAN, T. W. AND V. BOLIVER, "The Grandparents Effect in Social Mobility: Evidence from British Birth Cohort Studies," *American Sociological Review* 78 (2013), 662–678.

CHAN, T. W. AND B. HALPIN, "Who Marries whom in Great Britain?," in H.-P. Blossfeld and A. Timm, eds., *Who Marries Whom? Educational Systems as Marriage Markets in Modern Societies* (Dordrecht: Springer Netherlands, 2003), 171–194.

CHECCHI, D., A. ICHINO AND A. RUSTICHINI, "More Equal but Less Mobile? Education Financing and Intergenerational Mobility in Italy and in the US," *Journal of Public Economics* 74(3) (1999), 351–393.

CHETTY, R., N. HENDREN, P. KLINE AND E. SAEZ, "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States," *The Quarterly Journal of Economics* (2014a), 0–22.

———, "Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States," *The Quarterly Journal of Economics* 129 (nov 2014b), 1553–1623.

CHETTY, R., N. HENDREN, P. KLINE, E. SAEZ AND N. TURNER, "Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility," *American Economic Review Papers and Proceedings* 104 (2014c), 141–147.

CHEVALIER, A., K. DENNY AND D. MCMAHON, "A Multi-country Study of Intergenerational Educational Mobility," in P. Dolton, R. Asplund and E. Barth, eds., *Education and Inequality Across Europe*chapter 12 (Edward Elgar Pub, 2009).

CINGANO, F., "Trends in Income Inequality and its Impact on Economic Growth," OECD, 2014.

CLARK, G., *The Son also Rises: Surnames and the History of Social Mobility* (Princeton University Press, 2014).

CLARK, G. AND N. CUMMINS, "Intergenerational Wealth Mobility in England, 1858-2012: Surnames and Social Mobility," *Economic Journal* 125 (2015), 61–85.

COLLADO, M. D., I. ORTUÑO-ORTÍN AND A. ROMEU, "Long Run Intergenerational Social Mobility and the Distribution of Surnames," (2013).

CORAK, M., "Income Inequality, Equality of Opportunity, and Intergenerational Mobility," *Journal of Economic Perspectives* 27 (2013a), 79–102.

———, "Inequality from Generation to Generation: The United States in Comparison," in Robert Rycroft, ed., *The Economics of Inequality, Poverty, and Discrimination in the 21st Century* (ABC-CLIO, 2013b), 107–126.

CORAK, M., M. J. LINDQUIST AND B. MAZUMDER, "A comparison of upward and downward intergenerational mobility in Canada, Sweden and the United States," *Labour Economics* 30 (2014), 185–200.

CORD, L. J. ., L. LUCCHETTI AND C. RODRIGUEZ-CASTELAN, "Shifting gears to accelerate shared prosperity in Latin America and Caribbean. Latin America and the Caribbean poverty and labor brief.," Technical Report June, World Bank, Washington DC, 2013.

CORNEO, G. AND O. JEANNE, "Status, the distribution of wealth, and growth," *The Scandinavian Journal of Economics* 103 (2001), 283–293.

CORNEO, G. AND F. NEHER, "Income inequality and self-reported values," *The Journal of Economic Inequality* 12 (apr 2013), 49–71.

COUCH, K. A. AND T. A. DUNN, "Intergenerational Correlations in Labor Market Status: A Comparison of the United States and Germany," *The Journal of Human Resources* 32 (1997), 210–232.

CRUCES, G., C. GARCÍA DOMENCH AND L. GASPARINI, "Inequality in Education: Evidence for Latin America *," in *Falling Inequality in Latin America* (Oxford University Press, 2014), 318–339.

CUARESMA, J. C., K. SAMIR AND P. SAUER, "Age-Specific Education Inequality, Education Mobility and Income Growth," WWW for Europe, 2013.

DAHAN, M. AND A. GAVIRIA, "Sibling Correlations and Intergenerational Mobility in Latin America," *Economic Development and Cultural Changes* 49 (2001), 537–554.

DANIELSBACKA, M., A. O. TANSKANEN AND A. ROTKIRCH, "Impact of Genetic Relatedness and Emotional Closeness on Intergenerational Relations," *Journal of Marriage and Family* 77 (2015).

DAUDE, C. AND V. ROBANO, "On intergenerational (im)mobility in Latin America," *Latin American Economic Review* 24 (2015), 9.

DAVIES, J. B., J. ZHANG AND J. ZENG, "Intergenerational Mobility under Private vs. Public Education*," *Scandinavian Journal of Economics* 107 (sep 2005), 399–417.

DEARDEN, L., S. MACHIN AND H. REED, "Intergenerational Mobility in Britain," *Economic Journal* 107 (1997), 47–66.

DEATON, A., *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy* (Published for the World Bank [by] Johns Hopkins University Press, 1997).

DURLAUF, S. N., "A theory of persistent income inequality," *Journal of Economic Growth* 1 (1996), 75–93.

DUSTMANN, C. AND A. GLITZ, "Migration and Education," volume 4 of *Handbook of the Economics of Education* (Elsevier, 2011).

DWORKIN, R., "What is equality? Part 2: Equality of resources," *Philosophy & Public Affairs* 10 (1981a), 283–345.

———, "What is Equality? Part I: Equality of Welfare," *Philosophy & Public Affairs* 10 (1981b), 185–246.

EMRAN, M., W. GREENE AND F. SHILPI, "When Measure Matters: Coresidency, Truncation Bias, and Intergenerational Mobility in Developing Countries," *Journal of Human Resources* (2017).

ERMISCH, J., M. FRANCESCONI AND T. SIEDLER, "Intergenerational Mobility and Marital Sorting," *Economic Journal* 116 (jul 2006), 659–679.

ERMISCH, J., M. JANTTI AND T. M. SMEEDING, *From Parents to Children: The Intergenerational Transmission of Advantage: The Intergenerational Transmission of Advantage.* (Russell Sage Foundation, 2012).

FAN, Y., J. YI AND J. ZHANG, "The Great Gatsby Curve in China : Cross-Sectional Inequality and Intergenerational Mobility," , 2015.

FERREIRA, F. H., J. MESSINA, J. RIGOLINI, L.-F. LÓPEZ-CALVA, M. A. LUGO AND R. VAKIS, *Economic Mobility and the Rise of the Latin American Middle Class* (Washington, DC: World Bank, 2013).

FIELDS, G. AND E. OK, "The meaning and measurement of income mobility," *Journal of Economic Theory* 377 (1996), 349–377.

FIELDS, G. S., "Does Income Mobility Equalize Longer-term Incomes? New Measures of an Old Concept," *Journal of Economic Inequality* 8 (2010), 409–427.

FRICK, J. R., S. P. JENKINS, D. R. LILLARD, O. LIPPS AND M. WOODEN, "The Cross-National Equivalent File (CNEF) and its Member Country Household Panel Studies," *Journal of Applied Social Science Studies* 127 (2007), 627–654.

FURMAN, J. AND J. E. STIGLITZ, "Economic consequences of income inequality," *Income Inequality: Issues and Policy Options, Jackson Hole, Wyoming, Federal Reserve Bank of Kansas City* (1998).

GALOR, O., *Inequality and Economic Development: The Modern Perspective* (Edward Elgar Publishing Ltd, 2009).

GALOR, O. AND O. MOAV, "From physical to human capital accumulation: Inequality and the process of development," *Review of Economic Studies* 71 (2004), 1001–1026.

GALOR, O. AND D. TSIDDON, "Technological Progress and Economic Growth," *The American Economic Review* 87 (1997), 363–382.

GALOR, O. AND J. ZEIRA, "Income Distribution and Macroeconomics," *Review of Economic Studies* 60 (1993), 35.

GASPARINI, L., G. CRUCES AND L. TORNAROLLI, "Recent Trends in Income Inequality in Latin America," *Economía* 11 (2011), 147–190.

GASPARINI, L. AND N. LUSTIG, "The Rise and Fall of Income Inequality in Latin America," in *The Oxford Handbook of Latin American Economics*February (Oxford University Press, 2011).

GAVIRIA, A., C. GRAHAM AND L. BRAIDO, "Social Mobility and Preferences for Redistribution in Latin America," *Economía* 8 (2007), 55–96.

GRAVE, B. S. AND C. M. SCHMIDT, "The Dynamics of Assortative Mating in Germany," *Ruhr Economic Papers* 346 (2012).

GÜELL, M., M. PELLIZZARI, G. PICA AND J. V. RODRIGUEZ MORA, "Correlating Social Mobility and Economic Outcomes," Centre for Economic Policy Research, 2015.

GUELL, M., J. V. RODRIGUEZ MORA AND C. I. TELMER, "The Informational Content of Surnames, the Evolution of Intergenerational Mobility, and Assortative Mating," *The Review of Economic Studies* 82 (apr 2015), 693–735.

HÄLLSTEN, M., "Inequality across Three and Four Generations in Egalitarian Sweden: 1st and 2nd Cousin Correlations in Socio-economic Outcomes," *Research in Social Stratification and Mobility* 35 (2014), 19–33.

HASSLER, J. AND J. MORA, "Intelligence, social mobility, and growth," *American Economic Review* 90 (2000), 888–908.

HASSLER, J., J. MORA AND J. ZEIRA, "Inequality and mobility," *Journal of Economic Growth* 12 (2007), 235–259.

HECKMAN, J. J. AND S. MOSSO, "The Economics of Human Development and Social Mobility.," *Annual review of economics* 6 (aug 2014), 689–733.

HERRINGTON, C. M., "Public education financing, earnings inequality, and intergenerational mobility," *Review of Economic Dynamics* 18 (2015), 822–842.

HERTEL, F. R. AND O. GROH-SAMBERG, "Class Mobility across Three Generations in the U.S. and Germany," *Research in Social Stratification and Mobility* 35 (2014), 35–52.

HERTZ, T., T. JAYASUNDERA, P. PIRAINO, S. SELCUK, N. SMITH AND A. VERASHCHAGINA, "The Inheritance of Educational Inequality: International Comparisons and Fifty-year Trends," *The BE Journal of Economic Analysis & Policy* 7 (2007).

———, "The Inheritance of Educational Inequality: International Comparisons and Fifty-Year Trends," (2008).

HODGE, R. W., "Occupational Mobility as a Probability Process," *Demography* 3 (1966), 19–34.

HOLTER, H. A., "Accounting for cross-country differences in intergenerational earnings persistence: The impact of taxation and public education expenditure," *Quantitative Economics* 6 (2015), 385–428.

HUFE, P., A. PEICHL, J. ROEMER AND M. UNGERER, "Inequality of income acquisition: the role of childhood circumstances," *Social Choice and Welfare* (2017), 1–46.

ICHINO, A., L. KARABARBOUNIS AND E. MORETTI, "The political economy of intergenerational income mobility," *Economic Inquiry* 49 (jan 2011), 47–69.

JÄNTTI, M. AND S. P. JENKINS, "Income Mobility," *SOEPpapers on Multidisciplinary Panel Data Research 607* (2013).

———, "Income Mobility," in A. B. Atkinson and F. Bourguignon, eds., *Handbook of Income Disribution*volume 2B, 2 edition, chapter 10 (Elsevier, 2015), 807–935.

JERRIM, J. AND L. MACMILLAN, "Income Inequality, Intergenerational Mobility, and the Great Gatsby Curve: Is Education the Key?," *Social Forces* 00 (2015), 1–29.

JOHNSTON, D. W., S. SCHURER AND M. A. SHIELDS, "Exploring the Intergenerational Persistence of Mental Health: Evidence from Three Generations," *Journal of Health Economics* 32 (2013), 1077–1089.

KERNEY, M. S. AND P. B. LEVINE, "Income Inequality, Social Mobility, and the Decision To Drop Out of High School," in *Brookings Papers on Economic Activity* (2016).

KEYNES, J. M., *The economic consequences of the peace* (Macmillan and Co. Limited, 1920).

KNIGGE, A., "Beyond the Parental Generation: The Influence of Grandfathers and Great-grandfathers on Status Attainment," *Demography* (2016).

KROEGER, S. AND O. THOMPSON, "Educational Mobility across Three Generations of American Women," *Economics of Education Review* 53 (aug 2016), 72–86.

KUZNETS, S., "Economic Growth and Income Inequality," *American Economic Review* 45(1) (1955), 1–28.

LaFave, D. and T. Duncan, “Extended Families and Child Well-being,” (2014).

Lee, C.-I. and G. Solon, “Trends in Intergenerational Income Mobility,” *Review of Economics and Statistics* 91 (2009), 766–772.

Levy, S. and N. Schady, “Latin America’s social policy challenge: Education, Social Insurance, Redistribution,” *Journal of Economic Perspectives* 27 (2013), 193 – 218.

Lindahl, M., M. Palme, S. S. Massih and A. Sjögren, “Long-term Intergenerational Persistence of Human Capital: An Empirical Analysis of Four Generations,” *Journal of Human Resources* 50 (2015), 1–33.

Loury, G. C., “Intergenerational Transfers and the Distribution of Earnings,” *Econometrica* 49 (1981), 843–867.

Lucas, R. E. B. and S. P. Kerr, “Intergenerational Income Immobility in Finland: Contrasting Roles for Parental Earnings and Family Income,” *Journal of Population Economics* 26 (2013), 1057–1094.

Lustig, N., L. F. Lopez-Calva and E. Ortiz-Juarez, “Declining Inequality in Latin America in the 2000s: The Cases of Argentina, Brazil, and Mexico,” *World Development* 44 (apr 2013), 129–141.

Maoz, Y. D. and O. Moav, “Intergenerational Mobility and the Process of Development,” *The Economic Journal* 109 (1999), 677–697.

Mare, R. D., “A Multigenerational View of Inequality,” *Demography* 48 (2011), 1–23.

Marrero, G. a. and J. G. Rodríguez, “Inequality of opportunity and growth,” *Journal of Development Economics* 104 (sep 2013), 107–122.

Mayer, S. E. and L. M. Lopoo, “Government spending and intergenerational mobility,” *Journal of Public Economics* 92 (feb 2008), 139–158.

Moav, O., “Cheap children and the persistence of poverty,” *Economic Journal* 115 (2005), 88–110.

Neidhöfer, G., “Intergenerational Mobility and the Rise and Fall of Inequality: Lessons from Latin America,” CEDLAS, 2016.

Neidhöfer, G., J. Serrano and L. Gasparini, “Educational Inequality and Intergenerational Mobility in Latin America: A New Database,” (2017).

Neidhöfer, G. and M. Stockhausen, “Dynastic Inequality Compared Multigenerational Mobility in the US , the UK , and Germany,” Freie Universität Berlin, 2016.

NEVES, P. C., Ó. AFONSO AND S. T. SILVA, "A Meta-Analytic Reassessment of the Effects of Inequality on Growth," *World Development* 78 (2016), 386–400.

NYBOM, M. AND J. STUHLER, "Biases in standard measures of intergenerational income dependence," Uppsala : Inst. for Evaluation of Labour Market and Education Policy, 2015.

———, "Heterogeneous Income Profiles and Lifecycle Bias in Intergenerational Mobility Estimation," *Journal of Human Resources* 51 (2016), 239–268.

NYBOM, M. AND K. VOSTERS, "Intergenerational Persistence in Latent Socioeconomic Status: Evidence from Sweden," *Journal of Labor Economics* (2016).

OECD, *Education at a Glance 2015: OECD Indicators* (2015a).

———, *In It Together: Why Less Inequality Benefits All* (Paris: OECD Publishing, 2015b).

OLIVETTI, C., D. M. PASERMAN AND L. SALISBURY, "Three-generation Mobility in the United States, 1850-1940: The Role of Maternal and Paternal Grandparents," (2016).

OWEN, A. L. AND D. N. WEIL, "Intergenerational earnings mobility, inequality and growth," *Journal of Monetary Economics* 41 (feb 1998), 71–104.

PERSSON, T. AND G. TABELLINI, "Is inequality harmful for growth?," *American Economic Review* 84 (1994), 600–621.

PETERS, H. E., "Patterns of Intergenerational Mobility in Income and Earnings," *Review of Economics & Statistics* 74 (1992), 456.

PFEFFER, F. T., "Multigenerational Approaches to Social Mobility. A Multifaceted Research Agenda.," *Research in Social Stratification and Mobility* 35 (2014), 1–12.

PIKETTY, T., "Chapter 8 Theories of persistent inequality and intergenerational mobility," in *Handbook of Income Distribution*volume 1 (2000), 429–476.

———, *Capital in the Twenty-first Century* (Belknap Press, 2014).

PIKETTY, T. AND E. SAEZ, "Income Inequality in the United States," *Quarterly Journal of Economics* 118 (2003), 1–39.

PIRAINO, P., S. MULLER, J. CILLIERS AND J. FOURIE, "The Transmission of Longevity across Generations: The Case of the Settler Cape Colony," *Research in Social Stratification and Mobility* 35 (2014), 105–119.

RAWLS, J., *A Theory Of Justice* (Harvard University Press (Cambridge MA), 1971).

RIDGE, J., *Mobility in Britain Reconsidered* (Oxford University Press, 1974).

ROEMER, J. E., *Equality of Opportunity* (Harvard University Press, 2000).

———, "Equal opportunity and intergenerational mobility: going beyond intergenerational income transition matrices," in M. Corak, ed., *Generational Income Mobility in North America and Europe* (Cambridge University Press, 2004).

———, "What is the Justification of Studying Intergenerational Mobility of Socioeconomic Status?," in John Ermisch, Markus Jäntti and T. M. Smeeding, eds., *From Parents to Children: The Intergenerational Transmission of Advantage* (New York: Russell Sage Foundation, 2012).

ROEMER, J. E. AND A. TRANNOY, "Equality of Opportunity," in *Handbook of Income Distribution*volume 2, 1 edition (Elsevier B.V., 2015), 217–300.

SACERDOTE, B., "Nature and nurture effects on children's outcomes: What have we learned from studies of twins and adoptees," *Handbook of social economics* (2010), 1–48.

———, "Nature and Nurture Effects On Children's Outcomes: What Have We Learned From Studies of Twins And Adoptees?," volume 1 of *Handbook of Social Economics* (Elsevier B.V., 2011), 1–30.

SAUER, P. AND M. ZAGLER, "(In)equality in Education and Economic Development," *Review of Income and Wealth* 12142 (oct 2014), n/a–n/a.

SCHNEEBAUM, A., B. RUMPLMAIER AND W. ALTZINGER, "Gender and migration background in intergenerational educational mobility," *Education Economics* (2015), 1–23.

SCHNITZLEIN, D. D., "A New Look at Intergenerational Mobility in Germany Compared to the US," *Review of Income and Wealth* (2015), online first.

SCHÜTZ, G., H. URSPRUNG AND L. WÖSSMANN, "Education Policy and Equality of Opportunity," *Kyklos* 61 (2008), 279–308.

SCHWARTZ, C. R. AND R. D. MARE, "Trends in Educational Assortative Marriage From 1940 to 2003," *Demography* 42 (2005), 621–646.

SEN, A., "Equality of What?," in S. McMurrin, ed., *Tanner Lectures on Human Values* (1980), 197–220.

SHORROCKS, A., "Income Inequality and Income Mobility," *Journal of Economic Theory* 19 (1978a), 376–393.

SHORROCKS, A. F., "The Measurement of Mobility," *Econometrica* 46 (1978b), 1013–1024.

SOLON, G., "Intergenerational Income Mobility in the United States," *The American Economic Review* 82 (1992a), 393–408.

———, "Intergenerational income mobility in the United States," *The American Economic Review* 82 (1992b), 393–408.

———, "Intergenerational mobility in the labor market," in *Handbook of labor economicsvolume* 3 (Elsevier, 1999), 1761—-1800.

———, "Cross-country differences in intergenerational earnings mobility," *The Journal of Economic Perspectives* 16 (2002), 59–66.

———, "A model of intergenerational mobility variation over time and place," in *Generational Income Mobility in North America and Europe*1979 (2004), 38–47.

———, "Theoretical Models of Inequality Transmission across Multiple Generations," *Research in Social Stratification and Mobility* 35 (2014a), 13–18.

———, "Theoretical models of inequality transmission across multiple generations," *Research in Social Stratification and Mobility* 35 (mar 2014b), 13–18.

SOLON, G., S. J. HAIDER AND J. M. WOOLDRIDGE, "What Are We Weighting For?," *Journal of Human Resources* 50 (apr 2015), 301–316.

STUHLER, J., "Mobility across Multiple Generations: The Iterated Regression Fallacy," (2014).

TORCHE, F., "Intergenerational Mobility and Inequality: The Latin American Case," *Annual Review of Sociology* 40 (2014), 619–642.

WARREN, J. R. AND R. M. HAUSER, "Social Stratification across Three Generations: New Evidence from the Wisconsin Longitudinal Study," *American Sociological Review* 62 (1997), 561.

WILKINSON, R. AND K. E. PICKETT, *The Spirit Level: Why Greater Equality Makes Societies Stronger* (New York, Berlin, London: Bloomsbury Press, 2009).

ZENG, Z. AND Y. XIE, "The Effects of Grandparents on Children's Schooling: Evidence from Rural China.," *Demography* 51 (2014), 599–617.

ZYLBERBERG, Y., "Dynastic Income Mobility," (2016).

Acknowledgements

Firstly, I would like to express my sincere gratitude to my advisor Prof. Giacomo Corneo for his guidance, continuous support, motivation, and innumerable helpful suggestions. I could not have imagined having a better advisor and mentor than him and I am looking forward to our future collaborations.

Besides, I would like to thank my second supervisor Prof. Viktor Steiner for his insightful comments and his thorough questions which helped me to widen my research from various perspectives. Special thanks go also to Prof. Ronnnie Schöb for having permitted me to present my works at his brown-bag seminar and for the many fruitful remarks and comments received by him and the other seminar participants in this occasions, to Prof. Timm Bönke for his participation as co-author in my first research project and the useful suggestions provided at the very beginning of my research career, and to Prof. Hans-Jürgen Burchardt for his evaluations of my research as external adviser for my funding institution.

My sincere thanks goes also to the whole team of the Center for Distributive Labor and Social Studies at the University of La Plata for their hospitality in my several research stays at their institute. I am particularly indebted to Prof. Leonardo Gasparini for his precious support, kindness, and reliability during my visits, as well as working on our joint projects. Many thanks also to my co-author Joaquin Serrano for our wonderful collaboration.

I thank my fellow colleagues of the PhD Program in Public Economics and Inequality and, generally, at the Department of Economics at Freie Universität Berlin, for stimulating discussions and for all the fun we had in the last years. A special mention for my co-author Maximilian Stockhausen, it has been a real pleasure to collaborate with him and I am looking forward to working on more joint research projects in future.

A particular acknowledgement goes to the Hans Böckler Foundation for their generous financial support of my PhD and to all the colleagues there for their kind help and assistance, in particular to Jens Becker, Beate Kaps, Iris Henkel, and Werner Simons. Without the granted support it would not have been possible to conduct this research.

Last but not least I would like to thank my family: My wife, for her love, trust, immense patience, and continuous encouragements. My children, for showing me the real essence of living. My parents and my brother, for unconditionally supporting me in every step of my life and for being always there when I need them. Verily, my greatest thanks go to The One and Almighty, for his mercy in filling my life with his love and for surrounding me with so lovely and supporting people!

English Summary (Abstracts)

Chapter 1 - Intergenerational Mobility and the Assimilation of Immigrants

We investigate the hypothesis of failed integration and low social mobility of immigrants. An intergenerational assimilation model is tested empirically on household survey data and validated against registry data provided by the Italian Embassy in Germany. Although we confirm substantial disparities between educational achievements of immigrants and natives, we find that the children of Italian immigrants exhibit high intergenerational mobility and no less opportunity than natives to achieve high schooling degrees. These findings suggest a rejection of the failed assimilation hypothesis. Additionally, we evaluate different patterns by time of arrival, Italian region of origin and language spoken at home.

Chapter 2 - Intergenerational Mobility and the Long-Run Persistence of Human Capital

Using harmonized household survey data, we analyse long run social mobility in the US, the UK, and Germany and test recent theories of multigenerational persistence of socio-economic status. In this country comparison setting we find evidence against a universal law of social mobility. Our results show that the long run persistence of socio-economic status and the validity of a first-order Markov chain in the intergenerational transmission of human capital is country-specific. Furthermore, we find that the direct and independent effect of grandparents' social status on grandchildren's status tends to vary by gender and institutional context.

Chapter 3 - Intergenerational Mobility and the Rise and Fall of Income Inequality

Countries with high income inequality also show a strong association between parents' and children's economic well-being; i.e. low intergenerational mobility. This study is the first to test this relationship in a between-country *and* within-country setup, using harmonized micro data from 18 Latin American countries spanning multiple cohorts. It is shown that experiencing higher income inequality in childhood is associated with lower intergenerational mobility measured in adulthood. Following the same methodology, the influence of economic growth and public education is evaluated: both are positively, significantly, and substantially associated with intergenerational mobility.

Chapter 4 - Educational Inequality, Intergenerational Mobility and Economic Development

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 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 has been rising in Latin America, on average. 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.

German Summary

Diese Dissertation beinhaltet vier empirische Analysen zum Thema soziale intergenerative Mobilität in Industrienationen und Entwicklungsländern. Hierbei werden vorrangig vier verschiedene Dimensionen durchleuchtet, für deren Untersuchung das Thema soziale Mobilität von unabdingbarer Bedeutung ist: 1) Die ökonomische langfristige Integration von Migranten in ihrem Gastland. 2) Die langfristige und generationsübergreifende Persistenz von Humankapital. 3) Die negative Auswirkung von hoher Einkommensungleichheit in der Elterngeneration auf die Chancengleichheit der Kinder. 4) Wachstum und nachhaltige Entwicklung.

Im ersten Kapitel wird die intergenerative Assimilierung von italienischen Einwanderern und deren Kindern in die deutsche Gesellschaft analysiert. Zu diesem Zweck wird ein Modell gezeigt welches den generationsübergreifenden Prozess ökonomischer Assimilierung von Migranten im Gastland darstellt und auf die Gruppe der als Gastarbeiter eingewanderten Italiener angewendet und geschätzt. Die Datenbasis hierfür bildet das Sozioökonomische Panel, sowie administrative Daten der italienischen Botschaft in Deutschland. Die Ergebnisse zeigen, dass die Kinder der italienischen Gastarbeiter ein hohes Maß an intergenerativer Mobilität aufweisen und keine geringeren Chancen haben, höhere Schulabschlüsse zu erreichen wie Einheimische aus Familien mit vergleichbarem Bildungshintergrund. Diese Befunde deuten darauf hin, dass niedrigere Bildungsergebnisse von Kindern italienischen Ursprungs kein Zeichen für eine fehlgeschlagene Integration von Italienern in die deutsche Gesellschaft seien, sondern einen noch nicht abgeschlossenen jedoch fortlaufenden Assimilationsprozess widerspiegeln. Wir sind der Auffassung, dass diese Erkenntnisse über die Gruppe der italienischen Migranten in Deutschland hinaus auch allgemein für die intergenerative Assimilierung von großen, homogenen Gruppen von Migranten gelten.

Im zweiten Kapitel wird mithilfe von harmonisierten Haushaltsumfrage-Daten die langfristige soziale Mobilität in Deutschland, dem Vereinigten Königreich und den USA vergleichend analysiert. Außerdem wird das Thema behandelt, ob und in welchem Maß der sozioökonomische Status von Großeltern in direkter Verbindung mit den Bildungsergebnissen der Enkelkinder steht. Es zeigt sich, dass deutliche Unterschiede unter den Ländern bestehen, wobei Deutschland das niedrigste und das Vereinigte Königreich das höchste Niveau an langfristiger sozialer Mobilität aufweist. Daher findet die kontroverse These von Gregory Clark, die besagt, dass die intergenerative Transmission von sozialem Status und Humankapital in der langen Frist einem "universellen Gesetz" folgen würde, keinen Rückhalt in unseren empirischen Ergebnissen.

Das dritte Kapitel analysiert den Zusammenhang zwischen Einkommensungleichheit und intergenerationaler Mobilität. Mithilfe von harmonisierten Haushaltsumfrage-Daten aus 18 lateinamerikanischen Ländern wird dieser Zusammenhang getestet. Die Ergebnisse zeigen, dass Menschen aus bildungsfernen Familien, die in ihrer Kindheit einem hohen Maß an ökonomischer Ungleichheit ausgesetzt waren, deutlich geringere Chancen haben, ihren sozia-

len Status im Vergleich zu dem ihrer Eltern zu verbessern. Für Menschen aus bildungsnahen Familien gilt hingegen der umgekehrte Fall: Wachsen diese in Zeiten von hoher Einkommensungleichheit auf, so halten oder verbessern sie ihre soziale Position mit höherer Wahrscheinlichkeit. Außerdem zeigt die Studie, dass der Staat durch Investitionen in die Bildung diesem Prozess entgegensteuern kann, um Chancengleichheit zu fördern.

Das letzte Kapitel konstruiert auf einer ähnlichen Datenbasis wie das vorherige Kapitel einen neuen Panel-Datensatz mit Indizes für Bildungsungleichheit und intergenerativer Bildungsmobilität für Lateinamerika über einen Zeitraum von 50 Jahren. Die Erstellung dieses Datensatzes stellt einen wichtigen Beitrag dar, der eine tiefgehende Erforschung von den Ursachen und Folgen von Chancengleichheit von einer makroökonomischen Perspektive ermöglicht, wie es bislang noch nicht möglich gewesen ist. Ziel dieser Studie ist es, sowohl einen Einblick in den Datensatz zu gewähren und als Leitfaden dafür zu dienen, als auch die deskriptiven Ergebnisse zur Entwicklung von sozialer Mobilität in Lateinamerika im Zeitverlauf zu beschreiben.

Eidesstattliche Erklärung

Berlin, August 2017

Erklärung gem. § 4 Abs. 2

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe, und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

Erklärung gem. § 10 Abs. 3

Hiermit erkläre ich, dass ich für die Dissertation folgende Hilfsmittel und Hilfen verwendet habe: Stata (statistische Software), sowie alle angegebenen Literaturreferenzen.

Auf dieser Grundlage habe ich die Arbeit selbstständig verfasst.

Guido Neidhöfer
Berlin, 2017