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Does Social Mobility Affect Economic Development?

Cross-Country Analysis Using Different Mobility Measures

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Abstract

This paper analyzes the relationship between intergenerational educational mobility and long-term growth across the world using different mobility measures, comparing absolute mobility indicators with relative mobility indicators. The analysis is carried out across a panel of 68 countries over 2000–20. The results indicate that upward mobility in higher education is positively associated with gross domestic product per capita in Europe and Central Asia, but relative mobility indicators are uncorrelated with country income. In Latin America, higher relative mobility is associated with lower income, and higher absolute mobility is associated with higher income. The remaining regions of the world show a mix of these patterns.

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Does Social Mobility Affect Economic Development? Cross-Country Analysis Using Different Mobility Measures

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1. Introduction

Technological progress is the primary driver of economic growth and improvements in living standards. However, higher spending on research and development alone may be insufficient to fuel breakthrough scientific innovations that require an increasing flow of talented, well-trained people (Romer 2000). When all the talents in society are fully realized, the labor markets become more efficient, and productivity grows at a faster rate. But only in socially mobile societies, where family circumstances do not matter in explaining educational outcomes, can talent be better allocated. Thus, it is expected that socially mobile societies may also be more prosperous. The extent to which this expectation is true remains unclear.

Complex interactions between inherited traits, social norms, the environment in which children are raised, labor markets, and public policies determine individuals' opportunities to reach their full potential. Education plays a major role in defining a person's career trajectory and lifetime earnings. The level of investment in a child's education strongly depends on parental income and human capital as well as on parental preferences and risk perceptions (Christoph et al. 2024). Better-educated parents not only earn more, but they are also more effective in producing human capital in their children. The complementarity between parental human capital and investments in children leads wealthier parents to invest more in their children's human capital than poor parents do (Heckman and Mosso 2014; Becker and others 2018). Without government involvement, the intergenerational persistence of education will perpetuate cross-generational income inequality, reducing the chances of talented children from poor families succeeding in life (Corak 2013; van der Weide and others 2023). By drawing such children into science and innovation, policies designed to improve intergenerational mobility could increase the number of inventors and boost economic growth (Bell and others 2019). In fact, as the social returns on discoveries usually greatly exceed the personal returns to innovators, the case for public policy interventions is strong.

A challenge in making policy inferences from the analysis of intergenerational educational mobility is the possibility that the observed immobility is a consequence of other economic failures in society. For example, the primogeniture that strongly suppresses social mobility could be a response to inefficient capital markets and the need to ensure a minimal firm size (Rodríguez 2009). Comparing intergenerational mobility across countries and relying on cross-country variations in educational and welfare policies and regulations could help (partially) disentangle the contributions of different correlates of social mobility.

This paper analyzes the link between changes in intergenerational mobility and long-term development. The paper combines data on intergenerational educational mobility from three rounds of the Life in Transition Survey (2010, 2016, and 2022–23) (EBRD 2024), which covers more than 30 countries in Europe and Central Asia, and data from the Global Database on Intergenerational Mobility (GDIM, Van der Weide and others 2023). Data on mobility is complemented by data on present and past economic outcomes to form a panel of 68 countries over the period 2000-2020. This paper contributes to the literature on intergenerational mobility and development in two ways. Our primary contribution is that, unlike existing studies that focus on subnational districts or specific regions, we carry out a worldwide cross-country analysis of the relationship between intergenerational mobility and country income. This allows us to provide evidence of the nature of this relationship across different development contexts. The second contribution of our paper is to introduce a new measure of intergenerational mobility in education—the mobility gap—and compare its performance with several existing mobility measures. This paper presents the first empirical application of this new measure.

The patterns of intergenerational mobility across countries and generations vary significantly depending on the mobility measure used. In Europe and Central Asia, upward absolute mobility has been declining across birth cohorts, while relative mobility has not changed significantly, suggesting that an absolute reduction in intergenerational mobility in education may be common across the entire education distribution. South Asia has seen increases in absolute and relative mobility, while Latin America has experienced little change in absolute mobility but increases in relative mobility.

The empirical analysis of the association between intergenerational mobility and country income levels shows a significant context-specific relationship. Indicators of relative mobility in Europe and Central Asia are not correlated with country income levels over time. Only a specific dimension of absolute mobility—upward mobility in higher education (the probability that an individual whose parents did not achieve higher education does so)—shows a positive and statistically significant association with country income. In Latin America and the Caribbean, higher relative mobility is associated with lower income, while higher absolute mobility is associated with higher income. This finding suggests that some aspects of mobility may be more relevant for development in some contexts than others.

The following section reviews relevant studies of intergenerational educational mobility. Section 3 examines measures of mobility. Section 4 describes the study's empirical methodology. Section 5 describes the data. Section 6 presents the main patterns of intergenerational educational mobility. Section 7 presents the main results of the empirical analysis and associated robustness tests. Section 8 concludes.

2. Literature review

Multiple studies carried out a descriptive exploration of the patterns of intergenerational educational mobility. Hertz et al. (2007) use data from 42 countries between 1992 and 2005 to measure the persistence of educational attainment across generations by birth cohort. They find significant variation in the cross-country levels of intergenerational educational mobility, with high persistence of educational attainment in Latin America and much higher educational mobility in countries of Northern Europe. Chevalier, Denny, and McMahon (2009) study the patterns of intergenerational educational mobility in 20 developed countries, including the United States, Canada, New Zealand, and 17 European countries, and find that expanding access to higher education is not always associated with increased mobility. Causa and Johanson (2010) find a positive and significant correlation between parental human capital and their children's educational and wage outcomes in countries of the Organisation for Economic Co-operation and Development (OECD).

Financial constraints may hold back high-ability individuals from disadvantaged backgrounds. Razzu and Wambile (2022) study intergenerational educational mobility in 34 countries of Sub-Saharan Africa for cohorts born in the 1960s–1990s. They find that children's educational outcomes depend strongly on their parents' educational status but that the strength of this association is weaker for younger generations. The authors point to high heterogeneity in educational mobility across African countries. Van der Weide and others (2023) compile a global database of intergenerational educational mobility in 153 countries and demonstrate that such mobility is estimated to be lower in the average developing country than in the average high-income country.

Among the few papers that study the link between social mobility and economic development, Aydemir and Yazici (2019) discover that regions of Türkiye with better school availability, greater social capital, higher home resources, and lower educational inequalities tend to have higher intergenerational mobility. Güell and others (2018) find similar results in Italy, where provinces with higher levels of economic activity, lower inequality, and higher social capital and educational attainment have greater intergenerational social mobility. Lee and Lee (2022) analyze the persistence of intergenerational education attainments by age cohorts in 30 developed economies and find that higher per capita GDP positively correlates with social mobility. Neidhofer and others (2023) estimate the relationship between changes in educational intergenerational mobility and regional economic indicators in a sample of 52 regions in six countries in Latin America. They report that increasing social mobility correlates with rising income per capita, income growth, and other development indicators.

A few studies reach different conclusions. Clark and others (2014) conduct a multi-country historical analysis of social mobility based on surnames. They argue that economic development, progressive income redistribution, and development of public education matter less than other studies suggest, claiming that mobility varies little across societies and is, therefore, uncorrelated with economic outcomes.

3. Measures of educational mobility

We use four measures to capture trends in intergenerational educational mobility across countries and generations.

Oriented mobility measures

The new approach to measuring intergenerational mobility proposed by Foster and Rothbaum (2023, unpublished) addresses the shortcomings of many measures of intergenerational mobility and proposes new axiomatically sound, practical, simple-to-implement, and easy-to-communicate measures. This paper offers the first empirical application of this method.

The two most common approaches to measuring intergenerational mobility are to estimate correlations between and the elasticity (as a regression coefficient) of children's education with respect to their parents' education (see, for example, Aydemir and Yazici (2019)). Despite their popularity, both methods have shortcomings.

First, they may fail to register dynamic changes in educational structure. For example, increases in educational attainment by children of better-educated parents and stagnation or decline in the attainment of children from less-educated households could lead to an increase, a decrease, or no change in intergenerational mobility measured by the elasticity (Corak 2013).

Second, the approaches produce misleading subgroup comparisons because they measure regression to the subgroup mean rather than the population mean. As a result, two age cohorts could have the same intergenerational mobility even if the later cohort had much higher mean educational attainment.

Third, the correlation and elasticity measures are not decomposable by group, making it challenging to use them for targeting (e.g., Blyth 1972).[2]

Transition matrices are another popular class of intergenerational mobility measures (Shorrocks 1978). The transition matrices define groups (such as primary, secondary, and higher education) and estimate the probability of transitioning from one group to another. The transition matrixes capture the distribution of movements across groups; they can separate outcomes for children from, for instance, households with low and high levels of education.

Although they yield richer policy implications than the elasticity and correlation-based measures, transition matrices have their own problems. Among them are data censoring and arbitrary thresholds, when only movements across these thresholds "count" as mobility and thus are amplified in the analysis, while movements not observed due to censoring are not counted.[3] As a result, it might be challenging to separate the effects on intergenerational mobility of the underlying fundamental changes in the educational structure from the effects of censoring and the choice of cutoffs. Transition matrices also produce no headline measures, which is crucial for the ability of policy makers to communicate their intentions to the public and, thus, for successful policy implementation.

Distance-based mobility measures, often used to analyze income mobility (see Cowell 1985; Field and Ok 1996; Batana and Duclos 2010; Corak, Lindquist, and Mazumder 2014; Bárcena-Martín and Cantó 2024), are seldom used to analyze educational intergenerational mobility. Unlike

[2] Spearman correlations or rank-rank coefficients are also used in the analysis of intergenerational mobility.
[3] Because years of education are rarely available and often derived from educational levels, the problem of arbitrary thresholds might not be very relevant for studies of educational mobility.

transition matrixes, distance-based measures require no arbitrary thresholds, and they capture the churning or flux of educational attainments across groups well. These measures can also be used to generate policy-relevant headline metrics. Distance-based mobility measures ignore the direction of change or the "quality" of mobility, however, and are not helpful for policy targeting or identifying groups that benefited most from mobility or suffered the most from lack of it.

The new oriented distance-based approach to measuring intergenerational mobility aims to assess whether children have greater educational attainment than their parents and, if so, by how much. Foster and Rothbaum (2023) discuss the axiomatics and theoretical considerations for the class of oriented mobility measures $M(p)$. We summarize the theoretical results relevant to our empirical analysis.[4]

Define the set of upward movers such that

$$Q^U = Q^U(\boldsymbol{p}) = \{i : s_i^p < s_i^c\},\ p_i = \begin{pmatrix} s_i^p \\ s_i^c \end{pmatrix}, i = 1, \dots n \tag{1}$$

and a set of downward movers such that:

$$Q^D = Q^D(\boldsymbol{p}) = \{i : s_i^p > s_i^c\}, \tag{2}$$

where $\boldsymbol{p}$ is a vector of parent–child dyads p_i, s_i^p is the parent's years of education, s_i^c is the child's years of education, and n is the number of dyads. Once dyads are categorized according to equations (1) and (2), they can be aggregated to obtain oriented measures of intergenerational mobility. The most straightforward metric is the oriented headcount ratio:

$$H^o = \frac{q^o}{n}\ for\ O = U, D, \tag{3}$$

where $q^o = |Q^o|$ is the number of movers.

The oriented headcount ratio conveys meaningful information about mobility. Like the headcount ratios in poverty analysis, however, it is a crude way of assessing the extent of mobility. This shortcoming could be remedied by incorporating the average educational gap between a parent and a child by defining the oriented educational gap I^oas follows:

[4] Foster and Rothbaum (2023) show that distance-based oriented mobility measures satisfy the dominance, invariance, and subgroup standard for the mobility measures axioms and the expansion axiom. Neidhofer and others (2023) also propose an oriented measure of upward mobility, but they provide no axiomatic foundation for their measure.

$$I^o = \frac{1}{q^o}\sum_{i \in Q^o}\left|s_i^c - s_i^p\right| \text{ and } G^o = H^o I^o \text{ to be the Oriented mobility gap.}^{5} \tag{4}$$

Absolute mobility measures

The oriented mobility gap captures broad movements of the education distribution across generations. Alternative absolute mobility measures focus on the movement of certain parts of the education distribution. A measure proposed by Alesina and others (2021) estimates the probability of completing primary education by children whose parents did not. Neidhofer and others (2023) used a similar measure, the probability of upward mobility, focusing on completing secondary school. These measures may not have adequate empirical support in higher-income countries, where primary education completion is almost universal and secondary education is increasingly so, as Van der Weide and others (2023) point out. Because our sample represents mostly a mix of high- and middle-income countries, we redefine this measure, which we denoted as upward mobility in higher education (UMHE), as the probability of completing higher education by children whose parents did not:

$$UMHE = Prob\,(s_i^c \geq tertiary \mid s_i^p < tertiary) \tag{5}$$

Relative mobility measures

One of the common measures of relative mobility is intergenerational persistence (IP) in education, defined as the additional years of schooling of a child associated with one more year of schooling of his or her parents. This measure is derived from a multivariate model that is specified as

$$s_i^c = \beta s_i^p + \boldsymbol{\gamma} \boldsymbol{C_i} + \varepsilon_i, \tag{6}$$

where s_i^c is years of education of the child i, s_i^p is years of education of the child's parents, and β is the degree of IP. $\beta = 0$ represents a case of complete mobility; the educational attainment of children is unrelated to the education of their parents; $\beta = 1$ represents the case in which the education of the children mirrors the education of the parents (an extra year of education of the parents results in one more year of child schooling). A higher value of β represents a lower degree of mobility. $\boldsymbol{C_i}$ is a vector of individual characteristics of the child, the child's parents, and the characteristics of the household when the child was young. However, following Van der Weide and others (2023) and to ensure consistency with the estimates of this measure coming from the

[5] The term "oriented" comes from fact that this mobility measure, while absolute in value, is based on subsets of upward or downward movers.

GDIM, we do not include in our specification any control variable other than a dummy indicator for the survey in which the data were collected (to control for differences in the data collection process).[6]

An additional measure of relative mobility is the intergenerational correlation (IC) in education—the correlation between s_i^c and s_i^p. IC is defined similarly to IP but in terms of the standard deviation of schooling. It measures the increase in standard deviations of a child's education associated with a one standard deviation increase in his or her parents' education. A higher correlation indicates a lower degree of mobility.

4. Educational mobility and economic development: Empirical framework

To analyze the relationship between educational mobility and economic development, we rely on a framework similar to that of Neidhofer and others (2023). Our main empirical specification is the following:

$$Y_{ct} = \omega_c + \tau_t + \beta M_{ct} + \boldsymbol{\delta_x X}_{ct} + \boldsymbol{\delta_h H}_{ct} + \boldsymbol{\delta_i I}_{ct} + \varepsilon_{ct}, \tag{7}$$

where Y_{ct} is the level of income in country c in year t; ω are country fixed effects; τ are year fixed effects; M_{ct} is the aggregate level of mobility in country c in year t, calculated using maternal education;[7] $\boldsymbol{X}_{ct}$, $\boldsymbol{H}_{ct}$, and $\boldsymbol{I}_{ct}$ are vectors of control variables; ε is a residual; and β and $\boldsymbol{\delta}$ are parameters to be estimated. As control variables, we include contemporary country-level variables ($\boldsymbol{X}_{ct}$), such as income inequality (measured by the Gini index) and the log of population size (which we include with a quadratic polynomial). We also include a set of cohort-level variables ($\boldsymbol{H}_{ct}$), such as the average years of education of the workforce and its standard deviation. These two variables aim to control for different levels and allocations of human capital, respectively. We also include

[6] Including any control variable that relates to individual or household characteristics would then result in estimates of IP conditional on those characteristics. This could be desirable depending on the objective of the study. In our current setting, where we are interested in comparing the correlation between differences in mobility across countries and differences in country-level economic outcomes, we explicitly do not want to condition the estimates of mobility to individual or household level characteristics.

[7] Several studies note that mothers' years of schooling have a stronger effect than father's years of schooling on the intergenerational educational mobility of both daughters and sons (see Ranasinghe (2015) for Australia; Bjorklund Lindahl, and Plug (2006) for Sweden; Tansel (2015) for Türkiye; and Azomahou and Yitbarek (2016) for eight countries in Sub-Saharan Africa). However, Lam (1999) and Girdwood and Leibbrandt (2009) demonstrate that, in South Africa, the link between children and the father's education is stronger than that of the mother. Also, while maternal education is a stronger determinant of children's achievements in urban China, paternal education plays a more important role in rural China (Wang et al. 2024). The Life in Transition Survey collects information on the education of both parents. Our study is based on mothers' years of schooling; we use specifications with the education of the father and the education of both parents for sensitivity analysis.

a set of variables related to the initial conditions of the birth cohorts in the workforce (Ict)—namely, the log GDP per capita, the population size, and the infant mortality rate in the decade of birth. The initial conditions during childhood may have long-term effects on adult productivity and affect the relationship between mobility and economic development.

The misallocation of talent that results from low educational mobility within a given birth cohort may impact productivity only when this birth cohort enters the workforce. To take this into account, we follow Neidhofer and others (2023) to estimate cohort participation profiles for each country-year. We estimate the aggregate level of mobility in the following way:

$$M_{ct} = \sum_{b=1}^{B} \frac{n_{bct}}{\sum_{b=1}^{7} n_{bct}} m_{bc}, \tag{8}$$

where m_{bc} is the mobility of cohort b (out of a total of B cohorts) in country c, and n_{bct} is the number of employed people in cohort b in country c in year t. The aggregate level of mobility in a country at a given time is thus the weighted mobility of the different cohorts, where the weights are the share of each cohort in the country's labor force at that point in time. We apply this same weighting procedure to the cohort-specific variables in equation (7).

5. The data

This paper combines data from two main sources: the Life in Transition Survey (LiTS) and the Global Database on Intergenerational Mobility (GDIM).

LiTS is used as the primary data source for deriving intergenerational educational mobility in the countries of Europe and Central Asia. LiTS has been implemented by the European Bank of Reconstruction and Development (EBRD) and the World Bank. The survey covers the transition economies of Europe and Central Asia[8] and several comparator countries in Western Europe, the Middle East, and North Africa (EBRD 2023). The first round of the LiTS was carried out in 2006, the second in 2010, the third in 2016, and the fourth in 2022–23. This study uses the second, third, and fourth rounds, which provide comparable information on parental education.[9] The survey

[8] Our definition of Europe and Central Asia includes all the countries of the former Soviet Union, Türkiye, and the former planned economies of Central and Eastern Europe. Northern, Southern, and Western Europe are not included, and belong to the group of countries we define as High Income countries.
[9] The classification of parental education in the first round of the LiTS is not comparable to that of the following rounds. We therefor exclude it from our study.

included a nationally representative sample of around 1,000 households per country in the second and fourth rounds and around 1,500 households per country in the third round. The second round covers 35 countries, the third round 34, and the fourth round 39. The 30 countries that were included in all three rounds used in our study include all the countries that were part of the former Soviet Union except Turkmenistan; Czechia and the Slovak Republic; and Germany, Türkiye, and the remaining countries in Central and Eastern Europe that transitioned from a planned to a market economy during the 1990s.[10] Several countries of Western Europe, the Middle East, and North Africa were included in some (but not all) rounds.[11] For these countries, we estimate intergenerational mobility using GDIM data (discussed later in this section).

The main variable is the educational attainment of the survey respondents and their parents, expressed in years. The second round of the LiTS recorded the educational attainment variable in years; in the third and fourth rounds, educational attainment was recorded in completed levels of education. A country-specific correspondence table between levels of education and years of schooling was used to transform this categorical variable into years of schooling (UNESCO Institute of Statistics 2021). These correspondence tables are based on 2010 data and may not accurately reflect the correspondence between years of schooling and levels of education for past years, particularly for individuals who completed their education several decades ago. The differences are likely to be minor, and, as detailed later, we control for them.[12] Information on the number of observations with non-missing information per country and birth cohort is included in the appendix.[13]

[10] The 30 countries included in the three rounds of the LiTS used in our study are Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czechia, Estonia, Georgia, Germany, Hungary, Kazakhstan, the Kyrgyz Republic, Kosovo, Latvia, Lithuania, Moldova, Montenegro, North Macedonia, Poland, Romania, the Russian Federation, Serbia, the Slovak Republic, Slovenia, Tajikistan, Türkiye, Ukraine, and Uzbekistan.

[11] France, Sweden, and the United Kingdom were included in round 2. Italy and Mongolia were included in rounds 2 and 3. Cyprus was included in round 3. Greece was included in rounds 3 and 4. Algeria, Jordan, Lebanon, Morocco, and the West Bank and Gaza were included in round 4.

[12] The differences relate primarily to the duration of primary education, which in many countries was extended at the expense of lower secondary in the 1970s. Thus, an individual who completed primary education (and later dropped out of school) in the 1960s may have completed five years of education. In contrast, an individual who did so in the 2000s may have completed seven years. Given that we use the correspondence tables of 2010, we may be overestimating the years of education of people who completed primary education (and later dropped out) in the 1960s and before.

[13] Table A.1 shows the number of non-missing observations for three selected age cohorts and the total in three rounds of the LiTS by country. As can be expected, the number of observations in the 1940-1949 age cohort decreases rapidly

For countries outside Europe and Central Asia, we use the GDIM dataset, which provides estimates of intergenerational educational mobility for four birth cohorts (individuals born in the 1950s, the 1960s, the 1970s, and the 1980s) across 114 countries (van der Weide and others 2023). It draws on microdata from social and household surveys, which contain retrospective information on parental education. Similarly to the LiTS, the GDIM relies on a correspondence between categorical information on attained levels of education and the equivalent number of years of schooling.

Our empirical analysis includes variables from other sources. GDP per capita and population come from the World Development Indicators (World Bank 2023). Historical GDP per capita and population (used to estimate GDP per capita and population at the decade of birth of the different cohorts) are from the 2020 edition of the Maddison Project Database (Maddison Project Database 2020; Bolt and van Zanden 2020). Historical infant mortality rates from 1950 onward are estimated by the United Nations' World Population Prospects Population Division (UNDESA 2022); rates for 1930–50 are from various historical sources.

Our cross-country panel of educational mobility and economic outcomes includes 1,419 country-year observations in the period 2000-2020, covering 108 countries. However, we have 10 or more non-missing country-year observations only for 68 countries.[14] This sub-panel of 1,244 country-year observations is the primary sample of our empirical analysis. Table 1 presents the descriptive statistics of the main variables of our analysis for the cross-country sample.

6. Educational mobility across countries and generations

This section describes the patterns of intergenerational educational mobility observed across countries and generations, using the enlarged sample of 115 countries for which we have estimates of mobility. We start our descriptive analysis by looking into the patterns of the upward mobility gap, the new oriented mobility measure that we apply in this work.

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by rounds of the LiTS. The oldest respondents from this cohort were 70 years old in the second round of the survey, 76 years in the third, and 83 in the last round of the LiTS. The numbers are especially low in Kazakhstan (29), Uzbekistan (37), and Azerbaijan (45). Sample sizes of younger cohorts, however, are large and more stable.

[14] These are 18 countries in Europe and Central Asia, 16 countries in Latin America and the Caribbean, 24 high-income countries not elsewhere included, and 10 other developing countries in Asia and Africa.

The average upward mobility gap for the 1980s birth cohort varies from 0.8 (in Uzbekistan, with respect to fathers) to 9.1 (in Tunisia, with respect to mothers). When looking at the 1950s birth cohort, the upward mobility gap varies from 0.7 (in Mauritania, with respect to fathers) to 8.3 (in Viet Nam, with respect to mothers). While the upward mobility gap calculated with respect to fathers and the one calculated with respect to mothers are correlated (figure 1), the values with respect to mothers are, in most cases, above those calculated with respect to fathers. This results from the lower average educational attainment among mothers.

High values of the upward mobility gap usually occur when the share of children having more education than their parents is high (the horizontal axis in figure 2), and the increase in years of education among children who are more educated than their parents is large (the vertical axis in figure 2). For the 1980s birth cohort, the median share of upward movers (calculated relative to their mother's education) is 61 percent (58 percent relative to their fathers'). The median increase in years of education is 5.7 relative to mothers' education and 5.3 years relative to fathers'.

Figure 3 plots the values of upward mobility for every birth cohort, calculated with respect to mothers' education (a similar pattern is found when mobility is calculated with respect to fathers' education). For Europe and Central Asia, we plot the values ranging from the 1930s birth cohorts to the 1990s birth cohorts, using all the information available from LiTS. For the remaining regions of the world, for which we use information from GDIM, we plot the values from the cohorts born between the 1950s and the 1980s. In almost every country, upward mobility is lowest for the younger generations. The patterns of upward mobility across the world are heterogeneous. In South Asia, the Middle East and North Africa, Sub-Saharan Africa, and East Asia and the Pacific, the younger generation have witnessed an increase in upward mobility. In Latin America, in high-income countries, and particularly in Europe and Central Asia, younger generations have lower upward mobility than older generations. In Europe and Central Asia, the median upward mobility of the cohort born in the 1990s was about 40 percent less than those born in the 1930s or 1940s.[15] The secular increase in education levels might explain part of this movement in the more educated

[15] The largest differential in upward mobility between people born in the 1930s and the 1990s is in Kazakhstan, where upward mobility for the youngest generation was almost 85 percent lower than for the oldest generation. In this country, while older generations had established careers and resources from the Soviet era, young people faced a collapsing economy, high unemployment, and dismantled social safety nets. The rapid shift to a market economy, coupled with industrial decline and disrupted education reforms that were adapted to fit local political agendas rather than embracing their intended purposes, left the youth ill-equipped for new economic realities (Silova 2005).

regions: as the average education of parents increased over time, the gap between parental and children's education decreased.[16]

The patterns of upward mobility across generations can be explained by changes in the share of upward movers (figure 4), while in most regions, the average difference in years of schooling for upward movers (figure 5) remained stable. In South Asia, for instance, about 36 percent of people born in the 1950s have more education than their mothers, with an average difference of 6.5 years of education. For people born in the 1980s in the same region, the median share of upward movers is 68 percent, with a median difference of 7.4 years of education. A similar pattern holds for mobility relative to the father's education. In Europe and Central Asia, the median share of upward movers (with respect to mothers) in the 1950s birth cohort was 73 percent, with a median difference of 5.3 years of education. The median values for the 1980s birth cohort were 44 percent and 4 years of education.

The upward mobility gap can be compared with the probability that a child of parents who did not attain higher education does so or upward mobility in higher education (figure 6). Unlike the upward mobility gap, upward mobility in higher education has increased over generations across all regions. There are, however, significant differences in levels, with the upward mobility in higher education considerably higher in high-income countries than in other regions of the world.

The upward mobility gap can also be compared with the more standard relative mobility measures, such as IP and IC. Panel a of figure 7 compares the upward mobility gap with IP; panel b compares the upward mobility gap with IC. In both cases, mothers' education is used as a measure of parental education. The correlation between these indicators of relative mobility and the upward mobility gap is very low. The cross-country correlation between IP and the upward mobility gap has a value of $\rho = 0.17$, and between IC and the upward mobility gap has a value of $\rho = 0.16$. Countries with low IC (high relative mobility) can have both small (Kyrgyz Republic) or large (Tunisia) upward mobility gaps. Similarly, countries with high IC can have small (Hungary) or large (Cyprus)

[16] This is also the result of a "ceiling effect", as years of schooling can have an upper bound, with individuals rarely exceeding 21 years of schooling (Narayan et al. 2018). This effect is mitigated by focusing on the subset of individuals whose parents have lower education, as done for the measure of upward mobility in higher education, discussed later in this section.

upward mobility gaps. This pattern suggests that absolute and relative mobility may not necessarily be correlated across countries.

Figures 8 and 9 look at changes in IP and IC, respectively. In the case of IP, in all regions except for Europe and Central Asia and Sub-Saharan Africa, the younger generations have lower values of persistence (and, thus, higher relative mobility) than older generations. In the case of IC, the changes have been more muted and more common across regions – the correlation between mothers' education and their children's education has slightly increased over generations (indicating a decrease in relative mobility) for all regions. As pointed out by Van der Weide and others (2023), the difference in the mobility trends across these two indicators results from their different association with educational inequality. IP is sensitive to changes in educational inequality within cohorts, while IC is not. For a given level of IC, persistence increases as the dispersion in the children's education increases and decreases as the dispersion in parents' education increases. The decrease of IP across generations witnessed in some regions in the context of a relatively stable IC is most probably the result of underlying changes in the distribution of education within cohorts.

The patterns shown by the different mobility measures do not necessarily align. In Europe and Central Asia, upward absolute mobility has been declining across birth cohorts, while relative mobility did not change significantly, suggesting that an absolute reduction in intergenerational mobility in education may be common across the entire education distribution. Other regions, such as South Asia, have seen increases in both absolute and relative mobility, while Latin America has seen little changes in absolute mobility but increases in relative mobility.

7. Educational mobility across countries and development

In this section, we present the results of the empirical analysis of the relationship between educational mobility and development. We focus on the subset of 68 countries for which we have non-missing data for the main specification in at least 10 of the 21 years from 2000 to 2020.

Panel "a" of table 2 presents the basic specification of equation (7), with no controls other than country and year fixed effects. The results show no significant correlation with the logs of per capita GDP for any of the four mobility indicators except IP, which is positively associated with per capita GDP, implying that *lower* relative mobility is associated with *higher* income. Panel "b" interacts mobility indicators with regional dummies to uncover geographic heterogeneity.[17] The positive association of persistence with income is driven mostly by high-income countries, and by developing countries in Asia and Africa to a lesser degree – with no statistically significant association present in the case of Europe and Central Asia or Latin America. In the case of IC, the lack of a strong association with GDP per capita is common across all the regions, although there is a mildly significant *positive* relationship in Europe and Central Asia and Latin America.

When it comes to indicators of absolute mobility, the upward mobility gap is positively correlated with income in Latin America and in developing countries of Asia and Africa (higher mobility, *higher* income), but it is negatively correlated with income in Europe and Central Asia (higher mobility, *lower* income). For upward mobility in higher education, the association with GDP per capita is positive and strongly significant (higher mobility, *higher* income) in all regions except high-income countries. These results show no clear pattern across regions in terms of the relationship between mobility and country income levels – this association appears to be region-specific. Overall, higher absolute mobility is correlated with higher income, while the evidence points to a more muted relationship for relative mobility.

The inclusion of control variables reinforces these findings (table 3). The association between mobility and GDP per capita is context-specific. In high-income countries, lower relative mobility -as measured by higher values of IP and IC- is correlated positively and significantly with income levels. In Europe and Central Asia, the upward mobility gap has a negative -although statistically weak- association with GDP per capita, while upward mobility in higher education is strongly and positively associated with income levels. In Latin America and the Caribbean, as well as in the developing countries of Asia and Africa, all absolute mobility indicators are positively associated with income, while for relative mobility, the estimates for IC point to a negative relationship with GDP per capita. These results both coincide and contrast those reported by Neidhofer and others (2023) for Latin America, who find a statistically significant and positive association of all mobility indicators—relative and absolute—with subnational GDP per capita.[18] In our analysis,

[17] As discussed in section 5, in this sample we distinguish four regions: Europe and Central Asia, Latin America and the Caribbean, High Income Countries (not elsewhere included), and other developing countries in Asia and Africa.
[18] The specification estimated by Neidhofer and others (2023) includes income inequality as a contemporaneous control variable. We provide the estimates of this specification in our sample in table A2. The results are qualitatively similar to those in table 3.

the positive relationship of absolute mobility with income is also present, but in the case of relative mobility, higher relative mobility is associated with lower income.[19]

The magnitude of the relationship between mobility and GDP per capita varies across indicators and regions. A one standard deviation increase in the upward mobility in higher education results in an increase in GDP per capita of about 0.9-1.6 standard deviations depending on the region - leaving aside high-income countries where the relationship is not statistically significant. A one standard deviation increase in the IC (implying a *decrease* in mobility) is associated with a 0.5-0.7 standard deviation increase in income levels (excluding Europe and Central Asia). For the upward mobility gap, a one standard deviation increase is associated with a variation in income per capita levels that ranges between -0.4 standard deviations and 0.7 standard deviations. Lastly, only in high-income countries, a statistically significant increase in GDP per capita equivalent to 0.9 standard deviations is associated with a one standard deviation increase in the IP (implying a *decrease* in mobility).

Robustness and sensitivity analysis

To test the robustness of our coefficients to changes in the model specification, we conduct model uncertainty analysis (Young and Holsteen 2017) by varying the set of independent variables in equation (7) to find the range of the coefficient estimates for different indicators of educational mobility that is significant with 95 percent probability. We estimate regressions for all possible combinations (permutations) of our independent variables.[20] We then identify the proportion of negative or positive coefficients and the proportion of statistically significant coefficients. If a large share of coefficients remains significant and of the same sign as in our baseline specification, we can have a fair amount of confidence in the main estimates.

Table 4 displays the results of the model uncertainty analysis for the four mobility indicators. Appendix figure A.1 shows the distribution of the estimated coefficients. Overall, the results confirm the robustness of our estimates under different assumptions and with different model

[19] Tables 2 and 3 provide estimates of the contemporaneous effect of intergenerational mobility on average income. It could well be that there are delayed effects of intergenerational mobility on average income. Table A3 reports estimates of dynamic effects (impulse response) for the time-horizon of 10 years (Plagborg-Møller and Wolf 2021). The estimates shows dynamic results consistent with the contemporaneous effects.
[20] If n is the number of variables in equation (7), the total number of combinations is $2^n - 1$. In our sensitivity analysis, we use 8 variables (we treat year dummies as a single block of variables), which produce 255 unique regression specifications.

specifications, as in all four cases, most of the estimated coefficients align with those of the baseline specification.[21] The most robust associations are those between upward mobility in higher education and GDP per capita, with a robustness ratio exceeding the value of two in all regions except high-income countries. The positive association of income levels with the upward mobility gap in Latin America and IC in high-income countries also appears robust, at least in statistical terms.

We also perform Bayesian Model Averaging to account for the uncertainty of which predictors should be included in our model and the posterior distribution of the regression coefficients of interest (Steel 2020). Appendix figure A.2 shows the posterior density distribution of the coefficients on the four mobility indicators across the four regions. The posterior density of a regression coefficient is a mixture of a point mass at zero, representing the probability of not being included in the model, and a continuous density conditional on being included. The results are consistent with our baseline estimations and model uncertainty analysis results in Table 4, which indicate the presence of a significant association between higher upward mobility in higher education and country income in all regions except high-income countries, a significant negative association between higher relative mobility -as measured by IC- in all regions except Europe and Central Asia, and a more mixed pattern for the case of IP and the upward mobility gap.

As an extension of our main specification, we consider an autoregressive model in which the level of income in period *t* also depends on the lagged level of income in period *t – 1*:

$$Y_{ct} = \omega_c + \tau_t + \beta M_{ct} + \boldsymbol{\delta_x X}_{ct} + \boldsymbol{\delta_h H}_{ct} + \boldsymbol{\delta_i I}_{ct} + \alpha Y_{ct-1} + \varepsilon_{ct}. \tag{9}$$

Following Neidhofer and others (2023), this specification can be understood as estimating the effects of mobility on growth, as α – 1 can be interpreted as θ in a model in which the dependent variable is $Y_{it} - Y_{it-1}$ (the log growth rate of GDP per capita) and θ is the coefficient associated with lagged GDP per capita. The "de-meaning" method (which subtracts the country mean values of the dependent and independent variables from the respective variables) yields an estimation of equation (9) in a fixed-effect regression that produces a correlation between regressors and the error terms, introducing potential bias in estimated coefficients in (equation 9) (dynamic panel

[21] Appendix figure A.1 shows the distribution of the estimated coefficients across the 255 possible specifications under the analysis.

bias) (Nickell 1981).[22] The standard approach to address such a bias is an estimating model (equation 9) using a dynamic panel data approach by a system generalized method of moments (GMM) estimator that uses lagged regressors as instruments (Arellano and Bover 1995; Blundell and Bond 1998). However, the properties of the system GMM estimator on small samples, like the one we use here ($T = 17$ on average with a minimum of 10 and a maximum of 20) are not well understood (Soto 2009). In particular, the standard errors and auto-correlation tests may be unreliable. Because of these limitations, we present the estimation results of model (9) only to test the sensitivity of our main results to this change in the specification.

Table 5 presents the results of the system GMM estimation of model (9). We use all available lags of the log per capita income ($> t - 2$) and limit the number of instruments by collapsing the instrument set, as recommended by Roodman (2009). The estimates show that the value of α is below one, so the requirement of conditional convergence is satisfied. The Hansen overidentification test is not significant, suggesting that the instrument set is valid. However, the transformed model is not stationary, as the Arellano-Bond AR (2) test is significant. Therefore, the estimations are not fully robust, and we abstain from making further conclusions, other than pointing out the coincidence in the sign of the point estimates between our baseline specification and this estimation for all mobility indicators and regions except the upward mobility gap.

There could be multiple reasons for the endogeneity of mobility to country income levels. For example, richer countries may spend more on public education and targeted transfers to the poor, which, all else equal, may increase intergenerational mobility. While, theoretically, such endogeneity could be addressed through convincing instrumental variable estimates, in practice, finding valid instruments for growth regressions at a country level is notoriously difficult (e.g., Durlauf et al. 2005). So, despite the battery of tests and estimations of alternative specifications, we cannot claim to have estimated the causal effect of intergenerational educational mobility on economic development.

[22] The dynamic panel bias (Nickell 1981) is especially acute in situations when the time dimension of the panel dataset is small and the number of cross-sectional units is large. The dynamic panel bias typically caused underestimation of the coefficients on the lagged dependent variables.

8. Conclusions

This paper analyzes the relationship between intergenerational educational mobility and income levels using panel data covering 68 countries from across the world over the period 2000-2020. The dataset relies on data from the Life in Transition Survey and the Global Database on Intergenerational Mobility. It introduces and applies a new oriented distance-based measure of educational mobility - the upward mobility gap - which improves over the standard absolute mobility measures and provides unambiguous mobility rankings. It compares the patterns of educational mobility over generations and across regions observed by this measure with those observed by other absolute and relative mobility measures. Countries with high upward mobility gaps may have low mobility as measured by relative mobility indicators.

The empirical analysis shows that the relationship between intergenerational educational mobility and country income is region-specific. For instance, the indicators of relative mobility in Europe and Central Asia are uncorrelated with a country's income levels over time, and only a specific dimension of absolute mobility—upward mobility in higher education—shows a positive and statistically robust association with country income across different specifications. In Latin America and the Caribbean countries, higher relative mobility is associated with *lower* income, while higher absolute mobility is associated with *higher* income. These findings suggest that the relationship between social mobility and long-term development may be context-specific, with some aspects of mobility more relevant for economic growth in some contexts but not others.

The reasons behind the heterogeneous relationship between intergenerational mobility and country income over time are potentially manifold. In contexts where growth is driven by investments in capital -be it physical or human- higher absolute mobility may be associated with a greater success in increasing the human capital stock across generations. When growth is driven by increases in total factor productivity, a higher human capital stock across generations will only be associated with higher income levels if such capital leads to the adoption of new technologies or to generate innovations (Akcigit, Pearce, and Prato, 2024; World Bank, 2024). This could be the case in countries with higher upward mobility in higher education. Further research will be needed to understand the mechanisms behind the complex relationship between mobility and development.

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Table 1 Descriptive statistics of the cross-country panel

	Mean	SD	Min	Max	Obs
Mobility indicators (with respect to mothers)					
Intergenerational persistence (cohort weighted)	0.408	0.134	0.162	0.894	1,244
Intergenerational Correlation (cohort weighted)	0.418	0.096	0.212	0.645	1,244
Upward mobility gap (cohort weighted)	3.909	1.343	1.323	8.512	1,244
Upward mobility in higher education (cohort weighted)	0.233	0.120	0.023	0.633	1,244
Mobility indicators (with respect to fathers)					
Intergenerational persistence (cohort weighted)	0.400	0.125	0.189	0.807	1,244
Intergenerational Correlation (cohort weighted)	0.440	0.094	0.259	0.649	1,244
Upward mobility gap (cohort weighted)	3.473	1.225	1.220	7.795	1,244
Upward mobility in higher education (cohort weighted)	0.224	0.116	0.023	0.613	1,244
Socio-economic variables					
Log GDP per capita	10.194	0.699	8.348	11.514	1,244
Log population	16.499	1.513	12.547	19.619	1,244
Average years of schooling (cohort weighted)	11.191	2.358	4.589	15.618	1,244
Standard deviation of schooling (cohort weighted)	3.599	0.713	1.931	5.454	1,244
Population at birth (cohort weighted)	24.799	37.003	0.148	207.414	1,244
Log GDP per capita at birth (cohort weighted)	8.877	0.729	4.822	10.138	1,244
Infant mortality rate at birth (cohort weighted)	49.814	33.653	9.995	148.961	1,244

Note: the sample includes all the countries for which there are at least 10 non-missing observations in the period 2000-2020. This amounts to a total of 68 countries.

Table 2 Basic specification of the model

Panel a

Dependent variable: Log GDP per capita	(1)	(2)	(3)	(4)
Intergenerational persistence	1.9437***			
	(0.7224)			
Intergenerational correlation		1.2317		
		(0.7810)		
Upward mobility gap			–0.0321	
			(0.0358)	
Upward mobility in higher education				-0.0359
				(0.4997)
R^2	0.985	0.985	0.984	0.984
Number of observations	1244	1244	1244	1244
Number of countries	68	68	68	68

Panel b

Dependent variable: Log GDP per capita	(1)	(2)	(3)	(4)
Intergenerational persistence				
× High Income Countries	4.0703***			
	(1.3521)			
× Eastern Europe and Central Asia	1.7261			
	(1.4239)			
× Latin America and the Caribbean	0.5276			
	(0.9445)			
× Other Developing Countries	0.8207*			
	(0.3466)			
Intergenerational correlation				
× High Income Countries		1.4584		
		(2.3473)		
× Eastern Europe and Central Asia		0.3230		
		(1.0612)		
× Latin America and the Caribbean		3.2639*		
		(1.9435)		
× Other Developing Countries		2.6847*		
		(1.5037)		
Upward mobility gap				
× High Income Countries			0.0000	
			(0.0326)	
× Eastern Europe and Central Asia			–0.2903***	
			(0.0694)	
× Latin America and the Caribbean			0.2516**	
			(0.0962)	
× Other Developing Countries			0.2555***	
			(0.0953)	
Upward mobility in higher education				
× High Income Countries				–0.8294
				(0.6392)
× Eastern Europe and Central Asia				4.3389***
				(0.9254)
× Latin America and the Caribbean				3.8166**
				(1.7349)
× Other Developing Countries				6.0788**
				(2.7205)
R^2	0.986	0.985	0.987	0.988
Number of observations	1244	1244	1244	1244
Number of countries	68	68	68	68

Source: All specifications include country and year fixed effects. Standard errors (in parentheses) are clustered at the country level.
*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 3 Full specification of the model

Dependent variable: Log GDP per capita				
Item	(1)	(2)	(3)	(4)
Intergenerational persistence				
× High Income Countries	4.5824***			
	(1.3357)			
× Eastern Europe and Central Asia	1.0773			
	(1.2991)			
× Latin America and the Caribbean	1.2622			
	(1.8260)			
× Other Developing Countries	2.3290			
	(1.4040)			
Intergenerational correlation				
× High Income Countries		3.9513*		
		(2.3518)		
× Eastern Europe and Central Asia		0.6523		
		(0.7874)		
× Latin America and the Caribbean		5.2302**		
		(2.2642)		
× Other Developing Countries		4.8377**		
		(2.1168)		
Upward mobility gap				
× High Income Countries			0.0112	
			(0.0272)	
× Eastern Europe and Central Asia			-0.1942*	
			(0.1110)	
× Latin America and the Caribbean			0.2970**	
			(0.1126)	
× Other Developing Countries			0.3477**	
			(0.1484)	
Upward mobility in higher education				
× High Income Countries				-0.2144
				(0.5208)
× Eastern Europe and Central Asia				5.6392***
				(1.0303)
× Latin America and the Caribbean				5.8244***
				(1.4582)
× Other Developing Countries				9.5098***
				(2.4581)
Year-level controls				
Log population	-1.4247	-0.6160	1.2397	1.9588
	(1.7602)	(1.6649)	(1.7795)	(1.5036)
Log population (squared)	0.0448	0.0141	-0.0408	-0.0690
	(0.0541)	(0.0501)	(0.0557)	(0.0460)
Cohort-level controls				
Average years of education (cohort weighted)	-0.0925 (0.0580)	-0.1697*** (0.0554)	-0.1258** (0.0591)	-0.1826*** (0.0445)
Standard deviation of years of education (cohort weighted)	-0.1785 (0.2252)	-0.1777 (0.1815)	0.1431 (0.1027)	-0.0076 (0.0863)
Cohort-specific initial conditions				
Log GDP per capita at decade of birth (cohort weighted)	0.0112 (0.0591)	0.0254 (0.0567)	0.0014 (0.0542)	0.0010 (0.0446)

Population at decade of birth (cohort weighted)	0.0207*	0.0235**	0.0096	0.0160**
	(0.0110)	(0.0092)	(0.0115)	(0.0076)
Population at decade of birth squared (cohort weighted)	-0.0001**	-0.0001***	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Infant mortality rate at decade of birth (cohort weighted)	-0.0015	-0.0015	-0.0025	0.0046**
	(0.0028)	(0.0025)	(0.0029)	(0.0020)
R^2	0.988	0.988	0.988	0.990
Number of observations	1244	1244	1244	1244
Number of countries	68	68	68	68

Source: All specifications include country and year fixed effects. Standard errors (in parentheses) are clustered at the country level.

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 4 Results of model uncertainty analysis

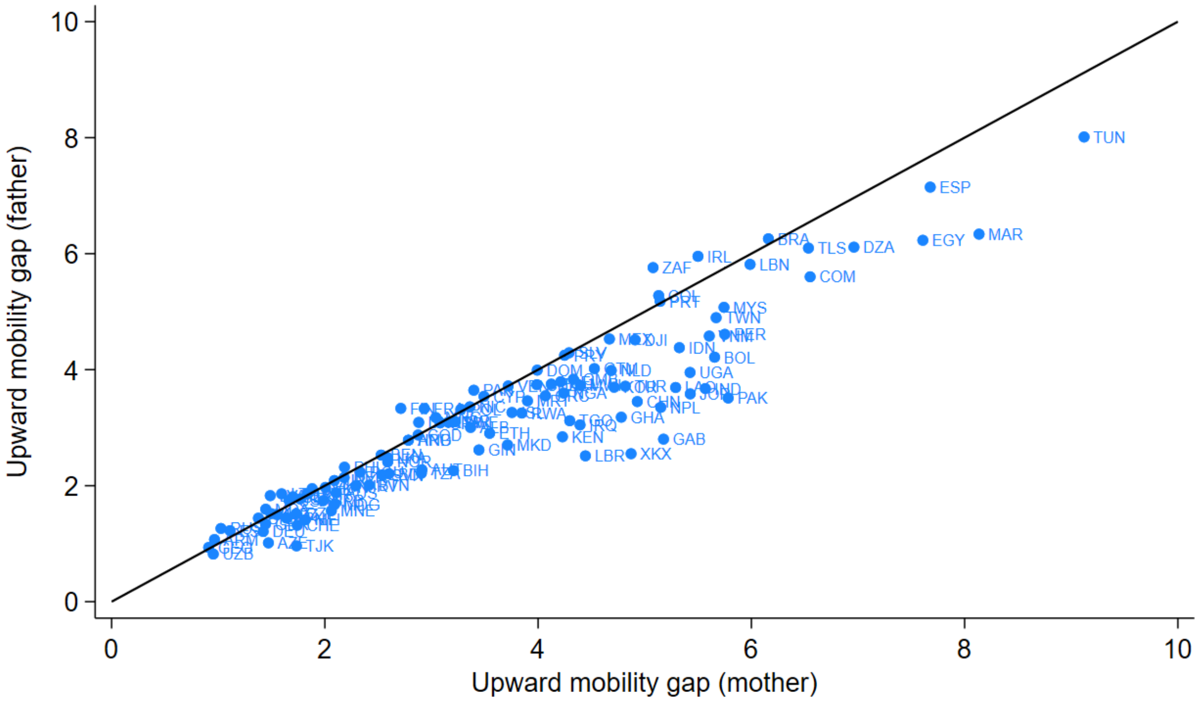
Mobility indicator	Baseline coefficient	Positive (%)	Positive and significant (%)	Negative (%)	Negative and significant (%)	Robustness ratio
Intergenerational persistence						
HIC	4.582	100	100	0	0	2.666
ECA	1.077	100	5	0	0	0.587
LAC	1.262	93	0	7	0	0.543
Others	2.329	100	28	0	0	1.169
Intergenerational correlation						
HIC	3.951	100	0	0	0	1.280
ECA	0.652	76	0	24	0	0.525
LAC	5.230	100	94	0	0	1.879
Others	4.838	100	23	0	0	1.700
Upward mobility gap						
HIC	0.011	75	0	25	0	0.317
ECA	-0.194	0	0	100	76	-1.264
LAC	0.297	100	100	0	0	2.116
Others	0.348	100	95	0	0	1.784
Upward mobility in higher education						
HIC	-0.214	0	0	100	0	-0.244
ECA	5.639	100	100	0	0	3.643
LAC	5.824	100	94	0	0	2.325
Others	9.510	100	86	0	0	2.448

Table 5 System generalized method of moments (GMM) estimation of the model with lagged log per capita income.

Dependent variable: Log GDP per capita	(1)	(2)	(3)	(4)
Intergenerational persistence				
HIC	-0.070 (*0.641*)			
ECA	0.336 (*0.562*)			
LAC	0.483 (*0.892*)			
Others	0.909 (*1.056*)			
Intergenerational correlation				
HIC		-0.016 (*1.334*)		
ECA		0.254 (*0.947*)		
LAC		-0.018 (*0.901*)		
Others		0.886 (*1.877*)		
Upward mobility gap				
HIC			-0.066 (*0.058*)	
ECA			-0.039 (*0.079*)	
LAC			-0.076 (*0.076*)	
Others			-0.046 (*0.129*)	
Upward mobility in higher education				
HIC				-0.085 (*0.556*)
ECA				0.612 (*0.678*)
LAC				-0.419 (*0.896*)
Others				1.106 (*0.972*)
Lagged Log GDP per capita (one year)	0.920^{***}	0.915^{***}	0.974^{***}	0.913^{***}
	(0.078)	*(0.124)*	*(0.071)*	(*0.065*)
Number of observations	1158	1158	1158	1158
Number of countries	68	68	68	68
Arellano-Bond test for AR(1): Prob > χ^2	0.012	0.023	0.015	0.010
Arellano-Bond test for AR(2): Prob > χ^2	0.001	0.001	0.001	0.001
Sargan test for overidentifying restrictions (p-value)	0.714	0.798	0.813	0.813
Hansen test for overidentifying restrictions (p-value)	0.307	0.320	0.365	0.317

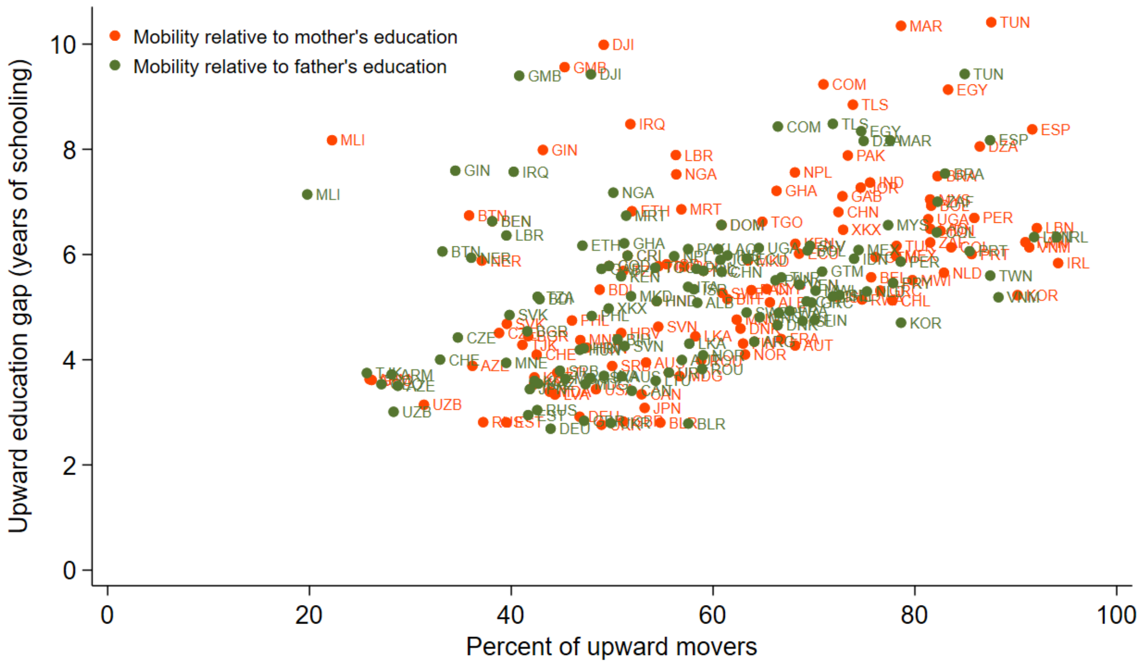
Source: All specifications include country and year fixed effects as well as all of the control variables included in the specifications of table 2. Standard errors (in parentheses) are clustered at the country level.
*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Figure 1 Upward mobility, by country and parent (1980s birth cohort)



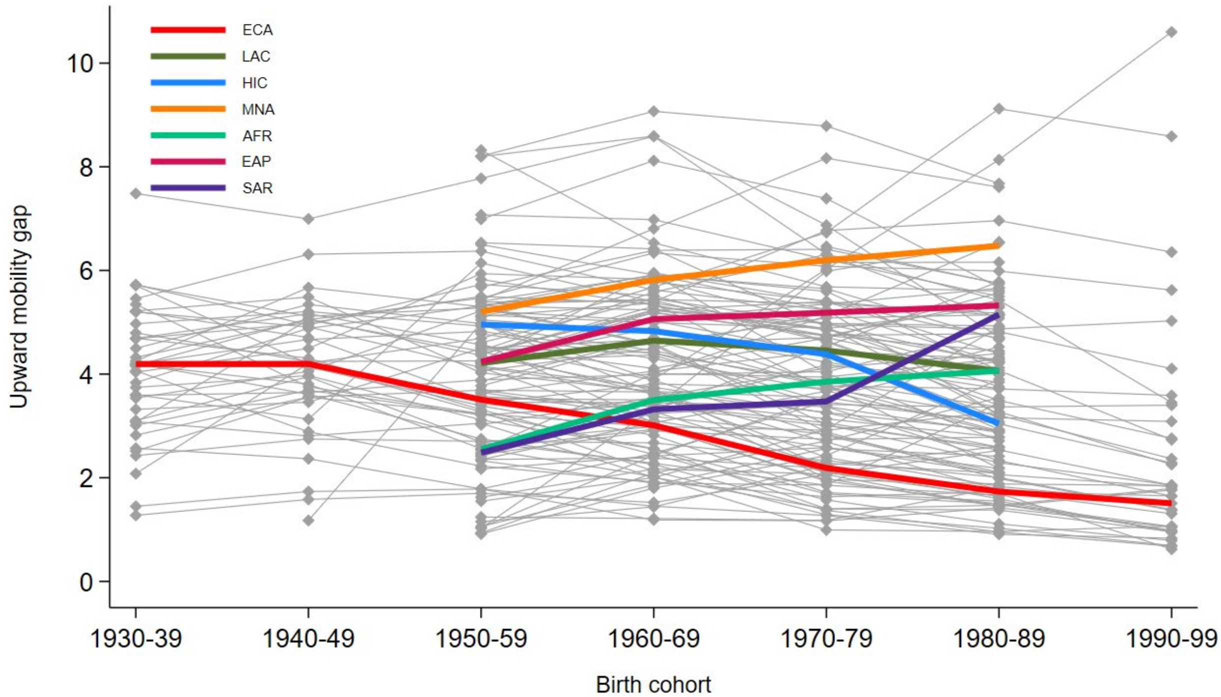
Note: This figure plots the upward mobility gap by parent for the 1980s birth cohort. The vertical axis plots the value calculated with respect to fathers, while the horizontal axis plots the value calculated with respect to mothers. The 45 degree line is plotted in black. The figure is based on data from the Life in Transition Survey (Europe and Central Asia) and the GDIM (remaining regions of the world).

Figure 2 Correlation between share of upward movers and upward education gap, by country (1980s birth cohort)



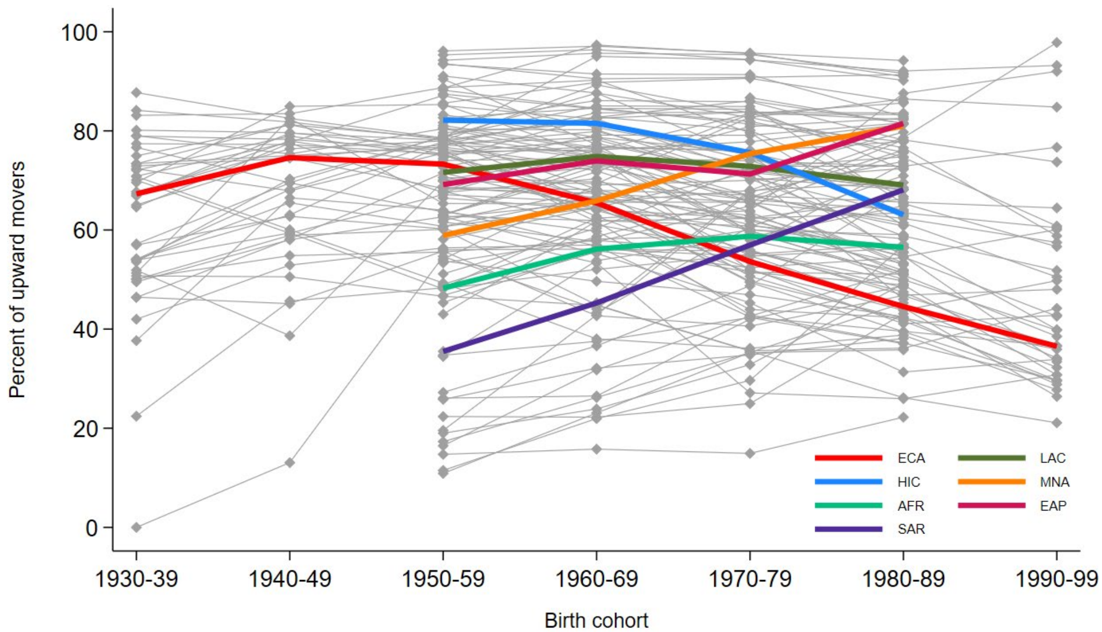
Note: The figure is based on data from the Life in Transition Survey (Europe and Central Asia) and the GDIM (remaining regions of the world).

Figure 3 Average upward mobility (based on mothers' education), by birth cohort



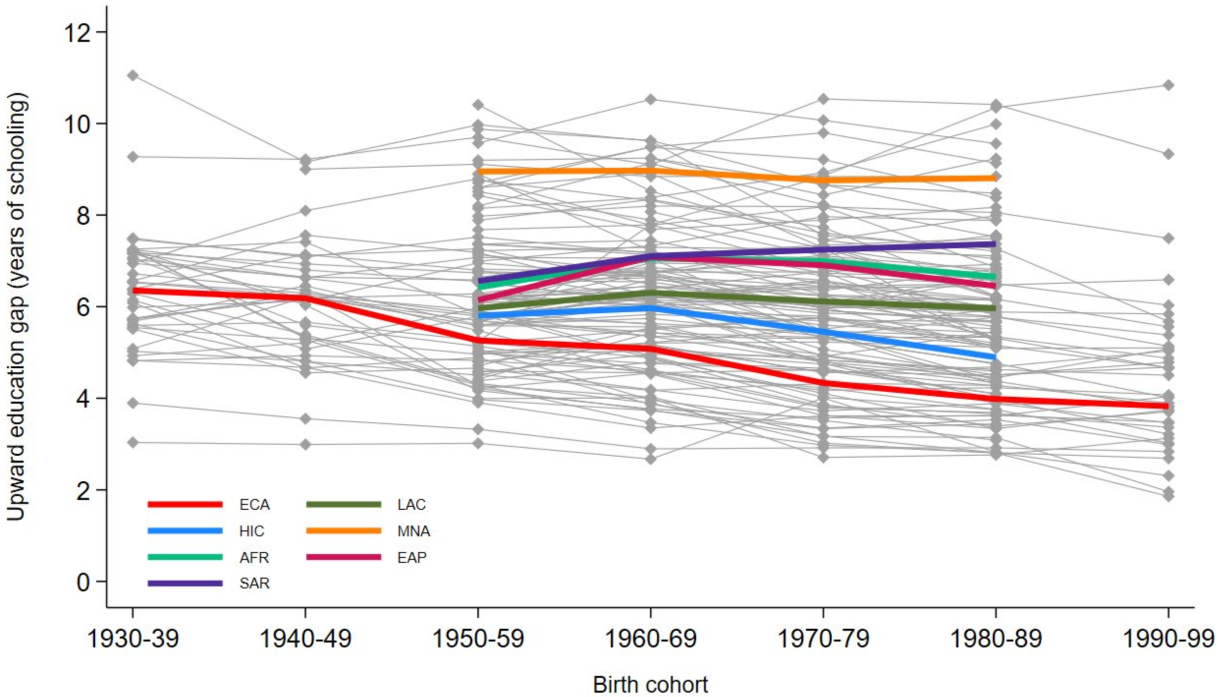
Note: The figure is based on data from the Life in Transition Survey (Europe and Central Asia) and the GDIM (remaining regions of the world). Thick lines indicate regional medians Grey lines plot values for individual countries.

Figure 4 Average share of upward movers (based on mothers' education), by birth cohort



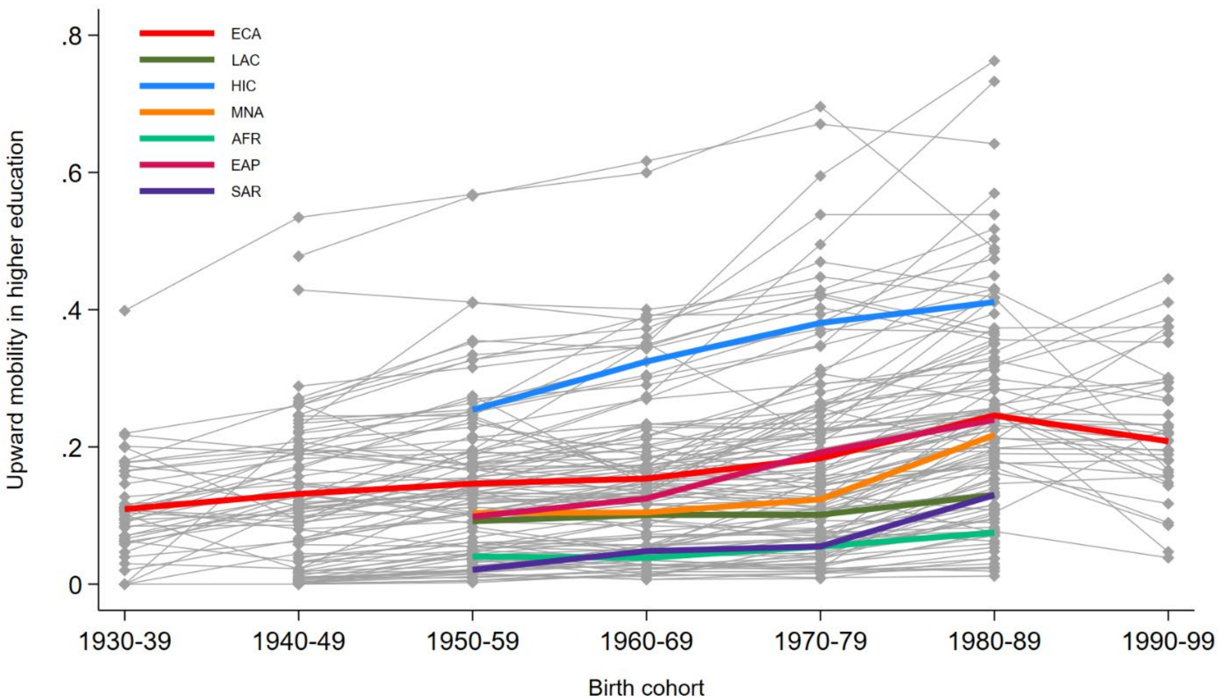
Note: The figure is based on data from the Life in Transition Survey (Europe and Central Asia) and the GDIM (remaining regions of the world). Thick lines indicate regional medians Grey lines plot values for individual countries.

Figure 5 Average upward education gap (based on mothers' education), by birth cohort



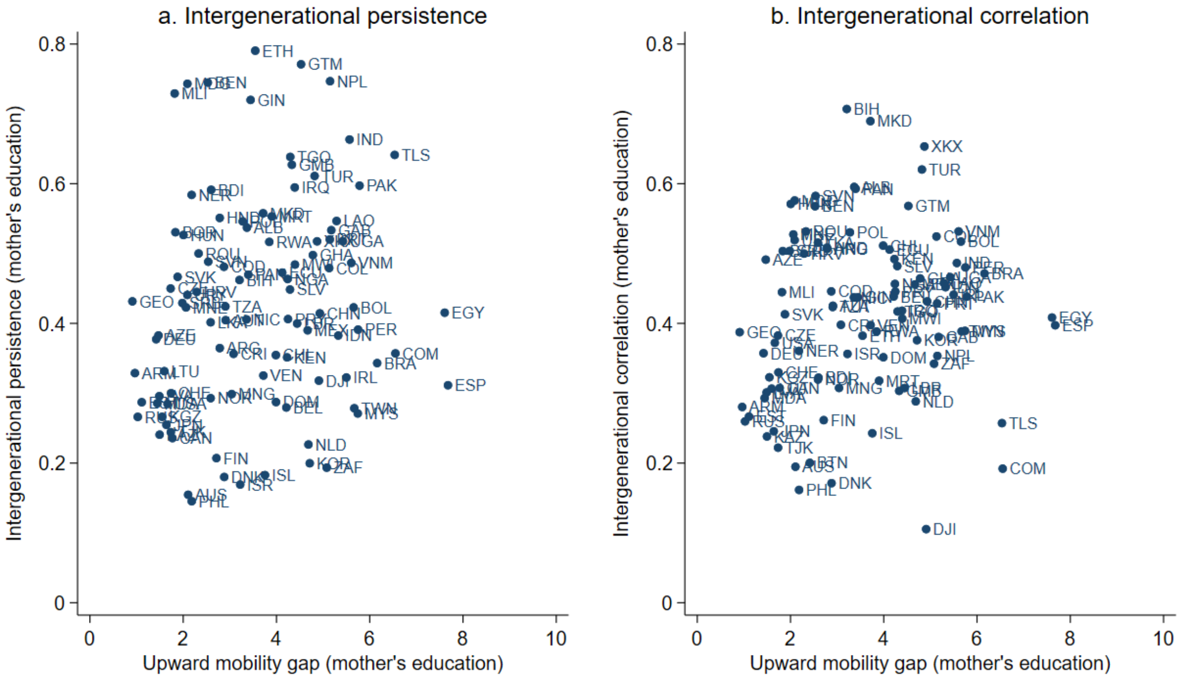
Note: The figure is based on data from the Life in Transition Survey (Europe and Central Asia) and the GDIM (remaining regions of the world). Thick lines indicate regional medians Grey lines plot values for individual countries.

Figure 6 Average upward mobility into higher education (based on mothers' education), by birth cohort



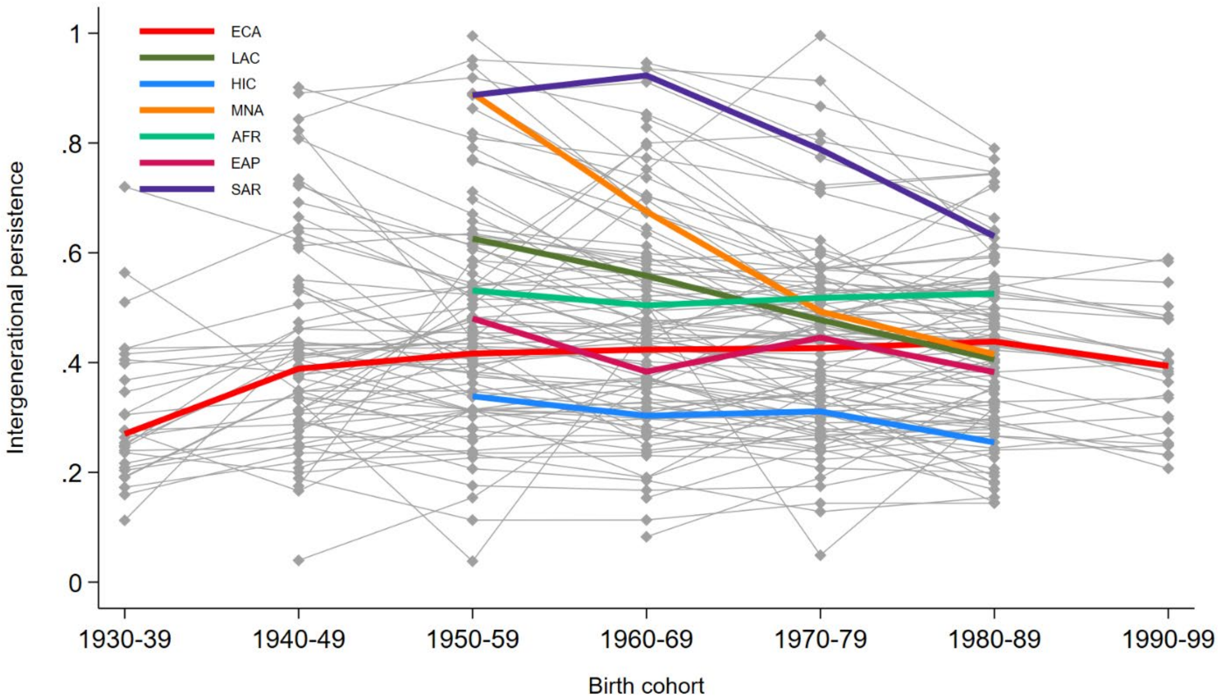
Note: The figure is based on data from the Life in Transition Survey (Europe and Central Asia) and the GDIM (remaining regions of the world). Thick lines indicate regional medians Grey lines plot values for individual countries.

Figure 7 Intergenerational persistence, correlation, and upward mobility gap across countries (1980 birth cohort)



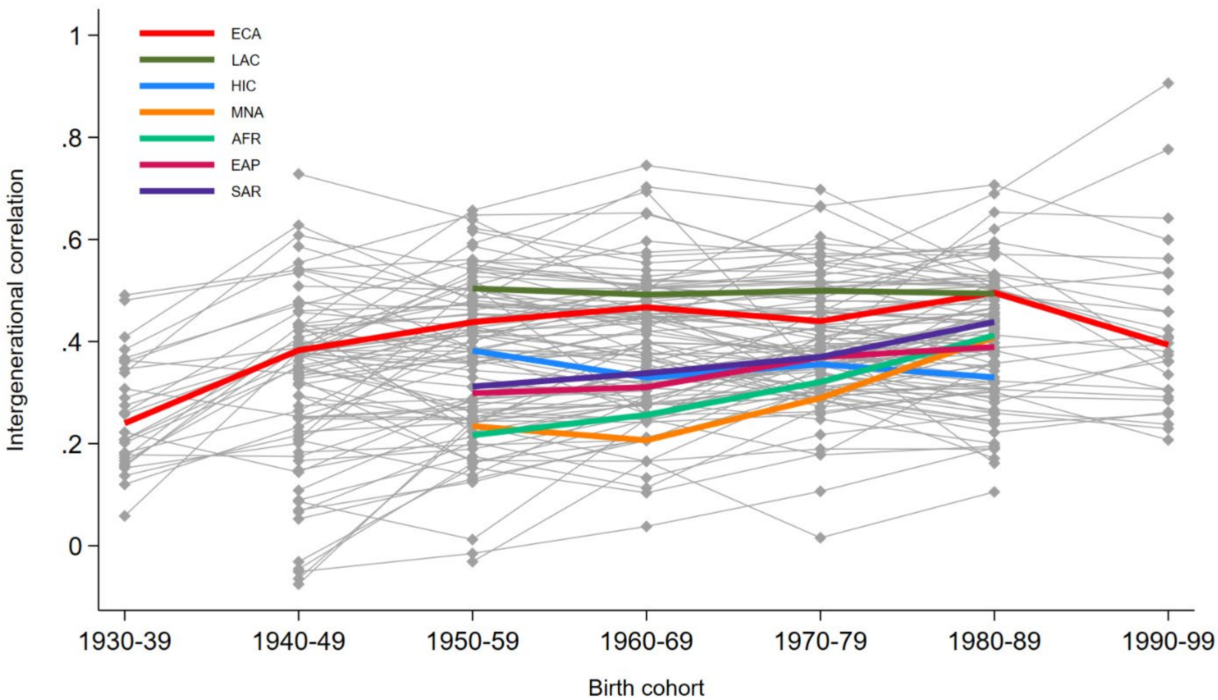
Note: The figure is based on data from the Life in Transition Survey (Europe and Central Asia) and the GDIM (remaining regions of the world).

Figure 8 Intergenerational persistence in education (based on mothers' education), by birth cohort



Note: The figure is based on data from the Life in Transition Survey (Europe and Central Asia) and the GDIM (remaining regions of the world). Thick lines indicate regional medians Grey lines plot values for individual countries.

Figure 9 Intergenerational correlation in education (based on mothers' education), by birth cohort



Note: The figure is based on data from the Life in Transition Survey (Europe and Central Asia) and the GDIM (remaining regions of the world). Thick lines indicate regional medians Grey lines plot values for individual countries.

Appendix tables and figures

Table A.1: Number of non-missing observations in the LiTS sample used in the analysis by selected age cohorts and survey years.

	Age cohorts											
	1940-1949				1960-1969				1990-1999			
Survey year	2010	2016	2023	Total	2010	2016	2023	Total	2010	2016	2023	Total
Country												
Albania	346	330	163	839	714	823	415	1,952	486	813	443	1,742
Armenia	280	366	159	805	553	725	431	1,709	729	668	406	1,803
Azerbaijan	192	116	45	353	601	748	364	1,713	747	1,180	538	2,465
Bosnia and Herzegovina	267	255	142	664	462	734	429	1,625	421	719	253	1,393
Bulgaria	348	441	221	1,010	415	619	339	1,373	250	397	187	834
Croatia	340	323	201	864	378	619	384	1,381	302	497	236	1,035
Czechia	235	359	97	691	405	446	311	1,162	325	296	343	964
Estonia	262	448	170	880	269	427	327	1,023	258	221	174	653
Georgia	303	444	159	906	479	746	368	1,593	506	593	332	1,431
Germany	233	164	69	466	450	568	342	1,360	238	283	239	760
Hungary	344	420	154	918	305	421	340	1,066	263	334	267	864
Kazakhstan	177	175	29	381	487	595	224	1,306	510	622	362	1,494
Kosovo	323	313	147	783	636	912	555	2,103	956	1,302	616	2,874
Kyrgyzstan	201	193	61	455	469	742	365	1,576	849	1,018	493	2,360
Latvia	274	397	236	907	282	491	239	1,012	249	304	166	719
Lithuania	293	338	204	835	380	535	222	1,137	303	329	329	961
Moldova	285	306	161	752	372	524	231	1,127	352	419	176	947
Montenegro	231	263	91	585	504	620	295	1,419	516	632	439	1,587
North Macedonia	363	408	183	954	653	728	398	1,779	563	729	356	1,648
Poland	461	376	132	969	580	404	300	1,284	489	309	285	1,083
Romania	321	411	108	840	376	411	296	1,083	265	300	241	806
Russian Federation	341	179	53	573	472	427	226	1,125	393	429	213	1,035
Serbia	482	404	108	994	617	609	338	1,564	487	410	284	1,181
Slovak Republic	141	413	158	712	495	566	355	1,416	443	442	198	1,083
Slovenia	243	440	223	906	520	532	442	1,494	327	355	280	962
Tajikistan	208	184	70	462	631	799	451	1,881	1,296	1,357	740	3,393
Türkiye	134	54	51	239	472	585	335	1,392	642	951	777	2,370

Note: Column "Total" shows the number of non-missing observations (sum) in the three selected cohorts.

Table A2. Full specification of the model including inequality

Dependent variable: Log GDP per capita Item	(1)	(2)	(3)	(4)
Intergenerational persistence				
× High Income Countries	4.6918***			
	(1.4411)			
× Eastern Europe and Central Asia	1.4544			
	(1.3379)			
× Latin America and the Caribbean	1.4330			
	(1.8857)			
× Other Developing Countries	0.3689			
	(1.5603)			
Intergenerational correlation				
× High Income Countries		3.3693		
		(2.3986)		
× Eastern Europe and Central Asia		1.0608		
		(0.8183)		
× Latin America and the Caribbean		4.3107*		
		(2.3758)		
× Other Developing Countries		7.5284**		
		(3.5323)		
Upward mobility gap				
× High Income Countries			0.0093	
			(0.0248)	
× Eastern Europe and Central Asia			-0.1552	
			(0.1074)	
× Latin America and the Caribbean			0.2957***	
			(0.1095)	
× Other Developing Countries			0.5665**	
			(0.1671)	
Upward mobility in higher education				
× High Income Countries				-0.4609
				(0.3205)
× Eastern Europe and Central Asia				5.8365***
				(1.0608)
× Latin America and the Caribbean				5.3322***
				(1.8470)
× Other Developing Countries				12.5791***
				(3.8729)
Year-level controls				
Gini index (income)	-0.0077	-0.0094**	-0.0081**	-0.0065
	(0.0047)	(0.0045)	(0.0035)	(0.0042)
Log population	-1.9417	-0.6051	1.1437	1.7808
	(2.0193)	(1.8841)	(1.8868)	(1.7730)
Log population (squared)	0.0495	0.0041	-0.0426	-0.0634
	(0.0635)	(0.0580)	(0.0616)	(0.0566)
Cohort-level controls				
Average years of education (cohort weighted)	-0.0881	-0.1912***	-0.1570***	-0.2127***
	(0.0688)	(0.0555)	(0.0466)	(0.0393)
Standard deviation of years of education (cohort weighted)	-0.0874	-0.1097	0.1214	0.0584
	(0.2349)	(0.1892)	(0.1213)	(0.1038)
Cohort-specific initial conditions				

Log GDP per capita at decade of birth (cohort weighted)	0.0202 (0.0454)	0.0328 (0.0449)	-0.0007 (0.0480)	-0.0093 (0.0387)
Population at decade of birth (cohort weighted)	0.0220** (0.0103)	0.0226** (0.0093)	0.0049 (0.0117)	0.0122 (0.0082)
Population at decade of birth squared (cohort weighted)	-0.0001** (0.0000)	-0.0001** (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
Infant mortality rate at decade of birth (cohort weighted)	0.0008 (0.0029)	0.0007 (0.0027)	-0.0022 (0.0031)	0.0048** (0.0020)
R^2	0.988	0.988	0.988	0.990
Number of observations	1015	1015	1015	1015
Number of countries	68	68	68	68

Source: All specifications include country and year fixed effects. Standard errors (in parentheses) are clustered at the country level.
*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

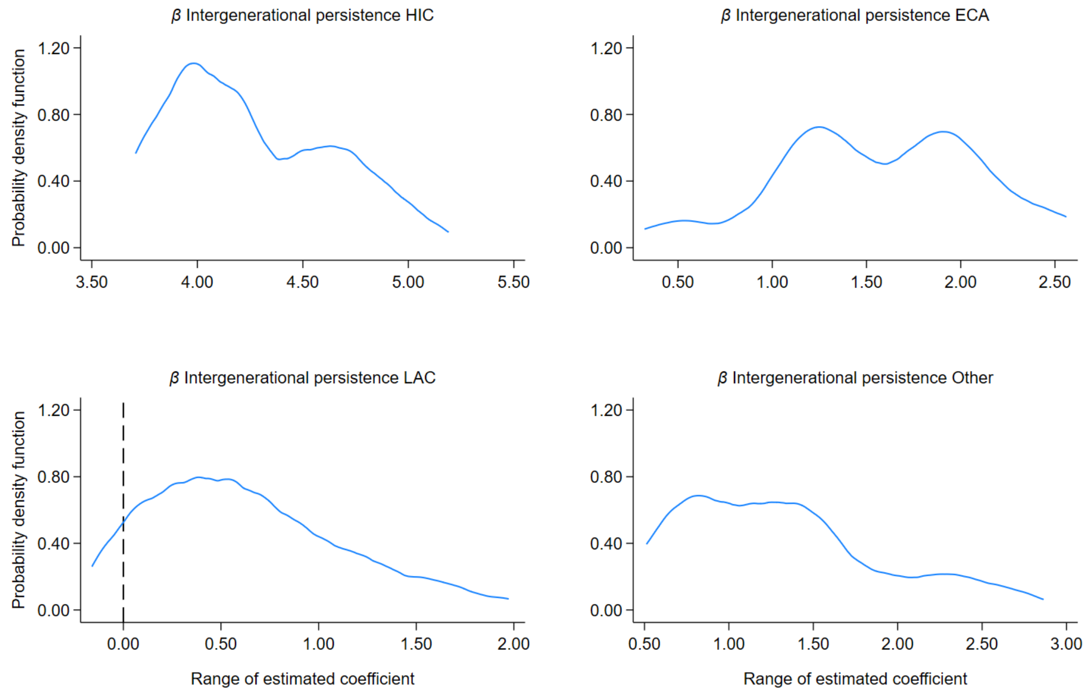
Table A3: Impulse response dynamic effects of various measures of intergenerational mobility on per capita GDP.

	Intergenerational persistence		*Intergenerational correlation*		*Upward mobility gap*		*Upward mobility in higher education*	
	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*
High income countries								
Contemporaneous effect	-0.106***	*0.032*	-0.078**	*0.037*	-0.001	*0.002*	0.077***	*0.029*
Horizon 1	-0.183***	*0.041*	-0.138***	*0.047*	-0.003	*0.003*	0.115***	*0.037*
Horizon 2	-0.255***	*0.048*	-0.191***	*0.055*	-0.006**	*0.003*	0.153***	*0.044*
Horizon 3	-0.315***	*0.053*	-0.231***	*0.062*	-0.008**	*0.003*	0.187***	*0.049*
Horizon 4	-0.365***	*0.056*	-0.265***	*0.065*	-0.009**	*0.004*	0.208***	*0.052*
Horizon 5	-0.411***	*0.057*	-0.297***	*0.067*	-0.010***	*0.004*	0.221***	*0.053*
Horizon 6	-0.455***	*0.057*	-0.326***	*0.067*	-0.010***	*0.004*	0.234***	*0.053*
Horizon 7	-0.500***	*0.057*	-0.354***	*0.068*	-0.011***	*0.004*	0.255***	*0.054*
Horizon 8	-0.551***	*0.061*	-0.400***	*0.073*	-0.011***	*0.004*	0.278***	*0.058*
Europe and C. Asia								
Contemporaneous effect	-0.024	*0.027*	0.004	*0.030*	0.009***	*0.003*	0.281***	*0.048*
Horizon 1	-0.062*	*0.034*	-0.015	*0.039*	0.009**	*0.004*	0.406***	*0.061*
Horizon 2	-0.106***	*0.040*	-0.037	*0.045*	0.008	*0.005*	0.507***	*0.071*
Horizon 3	-0.142***	*0.044*	-0.055	*0.051*	0.007	*0.006*	0.581***	*0.079*
Horizon 4	-0.170***	*0.047*	-0.068	*0.054*	0.006	*0.006*	0.622***	*0.084*
Horizon 5	-0.194***	*0.048*	-0.082	*0.055*	0.006	*0.006*	0.640***	*0.086*
Horizon 6	-0.205***	*0.047*	-0.082	*0.055*	0.008	*0.006*	0.678***	*0.086*
Horizon 7	-0.214***	*0.048*	-0.080	*0.056*	0.011*	*0.006*	0.755***	*0.088*
Horizon 8	-0.216***	*0.051*	-0.084	*0.060*	0.015**	*0.007*	0.867***	*0.094*
Latin America and C.								
Contemporaneous effect	-0.103***	*0.028*	-0.076**	*0.035*	-0.002	*0.003*	0.113*	*0.062*
Horizon 1	-0.158***	*0.035*	-0.113**	*0.045*	-0.004	*0.004*	0.208***	*0.079*
Horizon 2	-0.210***	*0.041*	-0.143***	*0.053*	-0.006	*0.005*	0.294***	*0.092*
Horizon 3	-0.249***	*0.045*	-0.164***	*0.059*	-0.008	*0.005*	0.355***	*0.103*
Horizon 4	-0.274***	*0.048*	-0.176***	*0.063*	-0.009	*0.006*	0.387***	*0.110*
Horizon 5	-0.290***	*0.049*	-0.183***	*0.064*	-0.009	*0.006*	0.408***	*0.112*
Horizon 6	-0.302***	*0.048*	-0.183***	*0.064*	-0.008	*0.006*	0.432***	*0.113*
Horizon 7	-0.330***	*0.049*	-0.200***	*0.065*	-0.008	*0.006*	0.441***	*0.115*
Horizon 8	-0.390***	*0.052*	-0.271***	*0.069*	-0.011*	*0.006*	0.362***	*0.123*
Other developing								
Contemporaneous effect	-0.130***	*0.036*	-0.102**	*0.048*	-0.003	*0.003*	0.059	*0.065*
Horizon 1	-0.208***	*0.046*	-0.156**	*0.061*	-0.006	*0.004*	0.138*	*0.083*
Horizon 2	-0.289***	*0.054*	-0.208***	*0.072*	-0.010*	*0.005*	0.186*	*0.097*
Horizon 3	-0.353***	*0.060*	-0.250***	*0.080*	-0.013**	*0.006*	0.207*	*0.108*
Horizon 4	-0.396***	*0.063*	-0.278***	*0.085*	-0.016***	*0.006*	0.206*	*0.115*
Horizon 5	-0.415***	*0.064*	-0.286***	*0.086*	-0.016***	*0.006*	0.221*	*0.118*
Horizon 6	-0.426***	*0.064*	-0.282***	*0.087*	-0.015**	*0.006*	0.263**	*0.119*
Horizon 7	-0.453***	*0.065*	-0.297***	*0.088*	-0.014**	*0.006*	0.318***	*0.121*
Horizon 8	-0.501***	*0.069*	-0.367***	*0.094*	-0.016**	*0.007*	0.299**	*0.129*

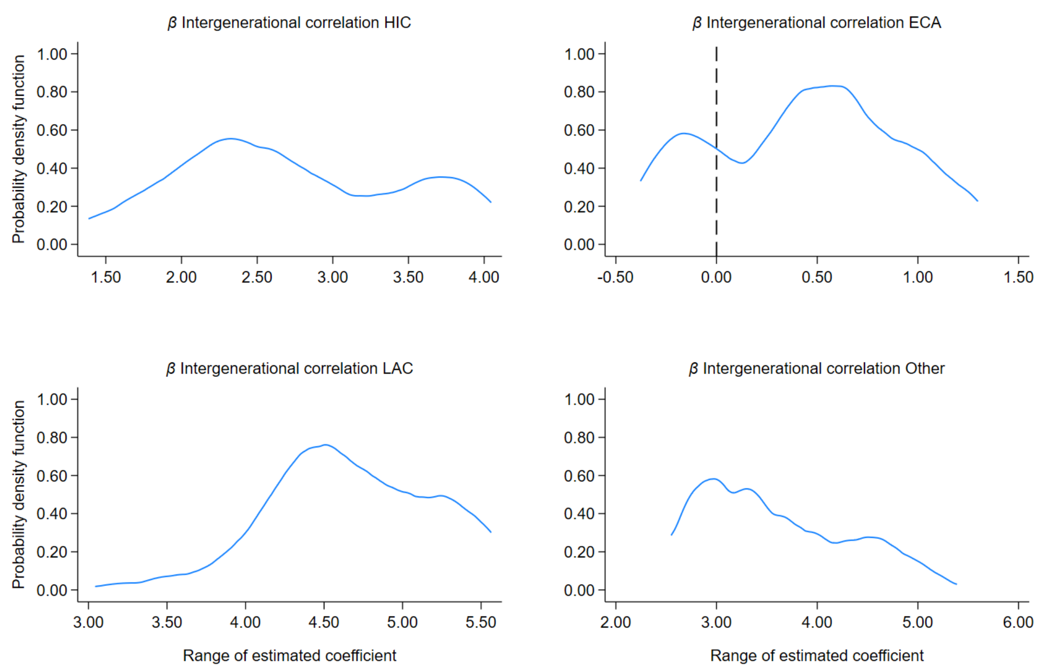
Note: Standard errors are calculated with a small-sample degrees-of-freedom adjustment.*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Figure A.1 Distribution of estimated coefficients in model uncertainty analysis

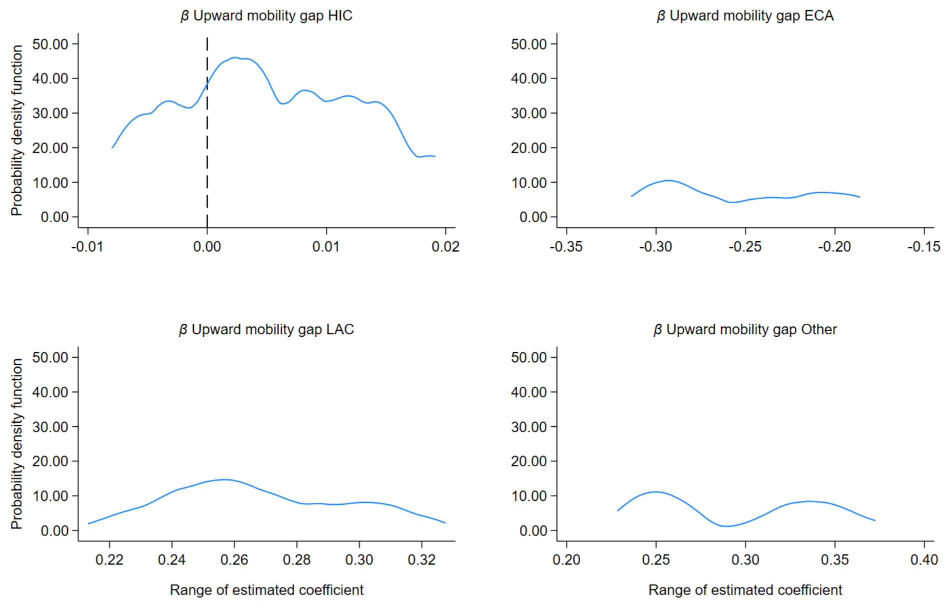
a. Intergenerational persistence



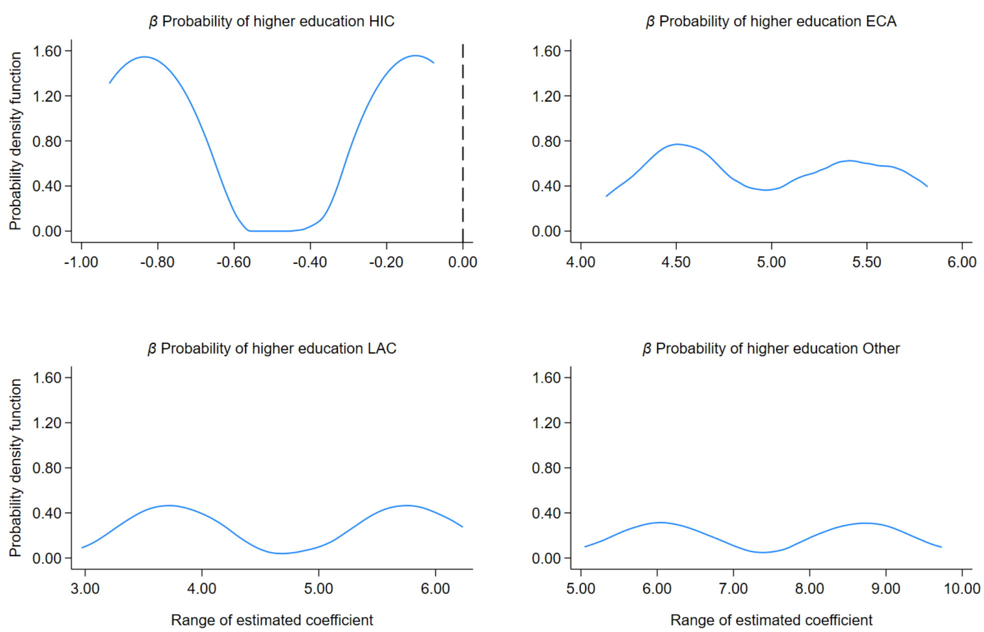
b. Intergenerational correlation



c. Upward mobility gap



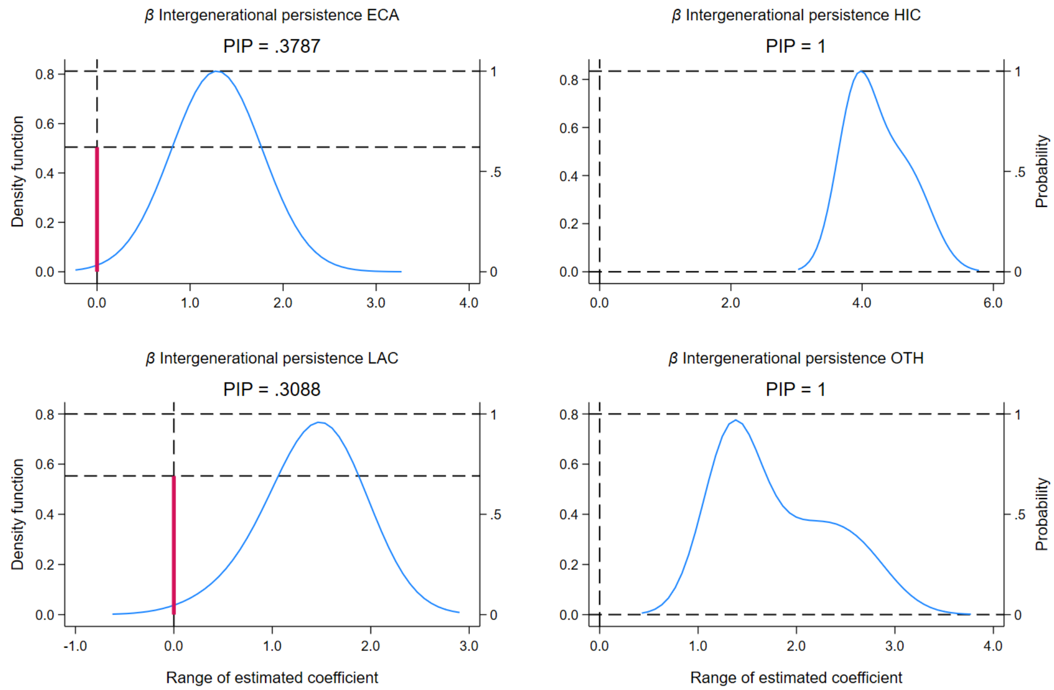
d. Upward mobility in higher education



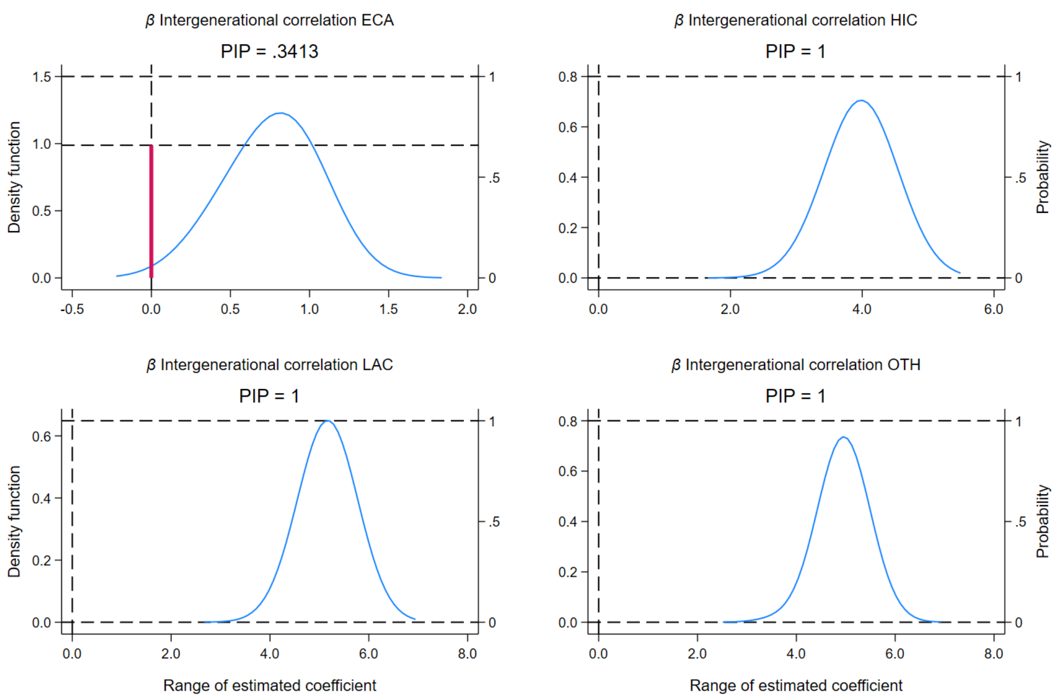
Note: The figure plots the distribution of the estimated coefficients for each of the four regions resulting from the model uncertainty analysis proposed by Young and Holsteen (2017). The distribution is derived from the estimation of 255 possible specifications of equation (7), reflecting all combinations of control variables.

Figure A.2 Posterior density plots of estimated coefficients in the Bayesian Model Averaging Analysis

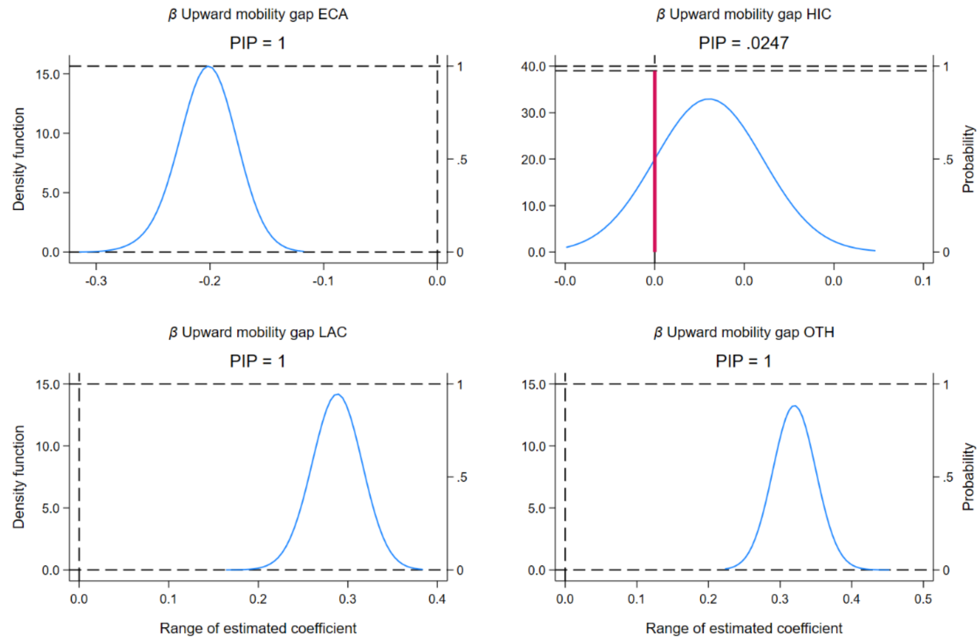
a. Intergenerational persistence



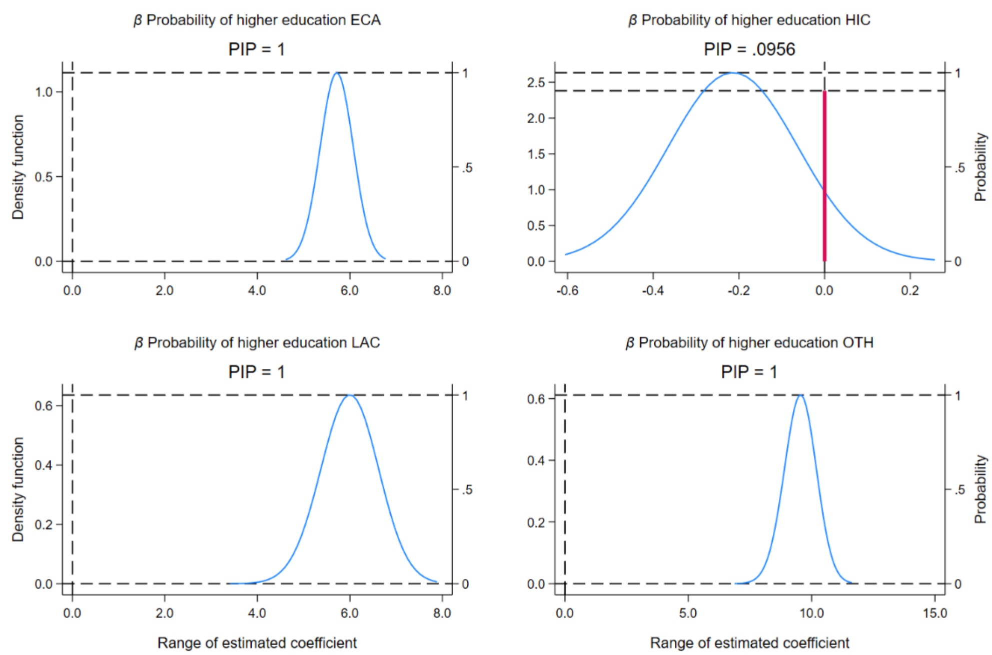
b. Intergenerational correlation



c. Upward mobility gap



d. Upward mobility in higher education



Note: The figure plots the posterior densities in the Bayesian Model Averaging linear regression for each of the four mobility indices.