Journal of Development Economics 166 (2024) 103167

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

Regular Article

Intergenerational mobility around the world: A new database☆

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ARTICLE INFO

JEL classification:
D31
D63
I24
J62
O15

Keywords:
Intergenerational mobility
Inequality
Education
Poverty

ABSTRACT

Using individual data from over 400 household surveys, this paper compiles a global database of intergenerational mobility in education for 153 countries covering 97 percent of the world's population. Intergenerational mobility in education is estimated to be lower in the average developing country than in the average high-income country. Children in the developing world have been less successful at surpassing their parents' education, despite the lower levels of parental education. The poorer the country, the more likely it is that individuals born to parents who do not have an education lack the means to get an education. The world as a whole is estimated to be less mobile than the average country in it, which highlights the importance of the country in which one obtains his/her education.

1. Introduction

Intergenerational mobility (IGM) is the extent to which an individual's success is independent of the success of his or her parents. Low mobility could conceivably lead to unrealized human potential and a misallocation of resources and talent. The main contribution of this paper is to offer estimates of intergenerational mobility in education for 153 countries representing 97 percent of the world's population born in the 1980s. For 114 countries, or 87 percent of the world's population, estimates of mobility span four decades: from those born in the 1950s to those born in the 1980s. The 1980s cohort represent the youngest generation of adults who would have completed their education at the time of data collection (as most survey data used are from 2010 or later).

A first large cross-sectional database of IGM was compiled by Chetty et al. (2014) which offers estimates of income mobility for 741 subnational regions of the United States. Corak (2021) and Connolly et al. (2021) obtain similarly disaggregated estimates of income mobility for Canada. This made it possible to characterize the variation in intergenerational mobility, establish how large differences in IGM can get, and build an understanding of what the determinants of IGM are. The subnational regions with comparatively high rates of mobility are found to be less residentially segregated, have lower inequality, higher quality public school systems, stronger social networks, and stronger family structures. If the geographic patterns observed across the regions of the United States and Canada are also observed across countries, then the least mobile countries are more likely to be found in the developing world.

Cross-country evidence on IGM however is scarcer and biased towards high-income world (see e.g., Black and Devereux (2011), Corak (2013) and Jäntti and Jenkins (2015) for reviews of the literature). Current evidence for the developing world includes a study by Alesina et al. (2021) on Africa, studies by Asher et al. (2018) and Hnatkovska et al. (2013) on India, and a cross-country study on Latin America by Neidhöfer et al. (2018). The largest cross-country study on intergenerational mobility prior to this paper is Hertz et al. (2007) who provide estimates for 42 countries.

☆ The authors would like to thank Alexandru Cojocaru, Miles Corak, Francisco H. G. Ferreira, Berk Özler, Silvia Redaelli, Bob Rijkers, Carolina Sánchez-Paramo, and Stefan Thewissen for their generous comments and inputs. We gratefully acknowledge financial support from the UK government through the Data and Evidence for Tackling Extreme Poverty (DEEP) Research Programme.

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https://doi.org/10.1016/j.jdeveco.2023.103167
Received 29 November 2021; Received in revised form 16 July 2023; Accepted 5 August 2023
Available online 12 August 2023

Our Global Database on Intergenerational Mobility (GDIM) significantly expands the evidence base on intergenerational mobility in education – and makes it possible, for the first time, to paint a truly global picture of intergenerational mobility.[1] This in turn allows us to test whether insights from the existing literature, which has mostly focused on developed countries, generalize to developing countries. We focus on mobility in education for two reasons.[2] First, intergenerational data on education is more widely available than on income. Second, unlike income, the level of education does not change once acquired, meaning that it is unlikely to introduce a lifecycle bias when elicited at a point in time (Nybom and Jan, 2016). A limitation of focusing on education mobility is that it does not capture distortions in the labor market, such as the extent to which access to good jobs is contingent on the parental background one is born into.

Measuring intergenerational mobility in education is subject to several methodological challenges, namely that educational outcomes are bounded below, bounded above, and exhibit bunching. Six different measures of intergenerational mobility are considered that address these challenges in different ways. Specifically, we evaluate: for respondents born to parents in the bottom half of the education distribution, (1) the probability that respondents reach the top quartile and (2) the expected educational rank within their generation (see e.g., Asher et al., 2019), (3) the share of respondents with a completed primary education conditional on neither parent having completed primary education (see e.g., Alesina et al., 2021), (4) 1 minus the correlation coefficient between respondents' and parents' years of schooling as well as (5) 1 minus the corresponding regression coefficient (see e.g., Hertz et al., 2007; Neidhöfer et al., 2018), and (6) the share of respondents that managed to surpass their parents in terms of education.[3]

We test three main hypotheses. First, whether intergenerational mobility is on average lower in the developing world across the different measures of mobility. Second, if there is indeed a mobility gap between the developing world and the developed world, whether that gap is closing over time. Third, whether intergenerational mobility increases monotonically with national income levels. Richer countries have the necessary resources to fund public interventions that compensate for private disadvantages (e.g. provide high quality public education for children born into disadvantaged backgrounds). This would be consistent with the findings of Chetty et al. (2014), who show that lower levels of intergenerational mobility are more likely to be found in the lagging areas of the United States.

We obtain the following empirical findings. First, for the youngest cohort born between 1980 and 1989, intergenerational mobility is lower in the average developing country when compared to the average high-income country. This observation holds true for all six measures of mobility. Second, we observe a convergence in mobility when using measures that are sensitive to changes in education inequality across generations (inequality-sensitive measures), but a divergence in mobility when using measures that are invariant to changes in inequality (inequality-invariant measures) are used.

Third, regarding the relationship between intergenerational mobility and national income, we similarly observe two distinct patterns. Inequality-sensitive measures of mobility show a monotonically increasing relationship, while inequality-invariant measures show a U-shape-pattern with high levels of mobility observed among the richest as well as the poorest countries (arguably for different reasons).[4] Fourth, Sub-Saharan Africa stands out as a region where children have been least successful at surpassing their parents' education, despite the comparatively low levels of parental education. In the poorest countries, the scope for surpassing parents is greatest but the capacity to educate children is lowest. By contrast, in the world's richest countries, the capacity to educate children is greatest but the scope to surpass parents is lowest. In other words, for two individuals with the same parental education background, it greatly matters what country one is born into, which sits well with Milanovic (2015).

Fifth, the world as a whole is notably less mobile than the average country in it. This underscores the importance of the country in which one obtains his/her education. We furthermore observe a modest upward trend in global mobility measured by inequality-sensitive indicators, while global mobility measured by inequality-invariant indicators is more stagnant. This empirical pattern is consistent with a decline in global inequality over time (Lakner and Milanovic, 2016). Sixth, when intergenerational mobility is disaggregated by gender, girls are found to be catching up to boys in the average developing country. Girls have already overtaken boys in the average high-income country for selected measures of intergenerational mobility and if current time-trends prevail, girls are on track for also surpassing boys in the developing world in the coming decade(s).

The remainder of the paper is organized as follows. Section 2 describes our methodology and presents our measures of intergenerational mobility. Section 3 describes the Global Database of Intergenerational Mobility. Section 4 presents the trends and patterns in intergenerational mobility over time across the world. Section 5 provides additional in-depth analysis and Section 6 concludes.

2. Intergenerational mobility in education

The intergenerational transmission of education (or other socio-economic indicators) is commonly described by the following regression equation (see e.g., Hertz et al., 2007; Corak, 2013, 2021; Chetty et al., 2014; and the references therein):

$$y_{ict} = \alpha_{ct} + \beta_{ct} y_{ict-1} + e_{ict}, \tag{1}$$

where y_{ict} denotes the education outcome (either years of schooling or highest grade completed) for individual i of generation t in country c, and e_{ict} denotes an error term with mean zero and variance σ^2_{ct}. The parameters α_{ct}, β_{ct}, and σ^2_{ct} capture different aspects of the intergenerational transmission process. The intercept α_{ct} measures the progress in human capital accumulation between generations *t-1* and *t*, while the regression coefficient β_{ct} measures intergenerational persistence in education.

There is a multitude of measures of intergenerational mobility that can be derived from the transmission process, each with its own interpretation, shortcomings, and advantages. We will use six measures of mobility guided by past literature. Mobility measures are frequently

[1] A preliminary analysis of a prior version of the GDIM is referenced in the World Bank report "Fair Progress: Economic Mobility Across Generations Around the World" (Narayan et al., 2018). In parallel to our study, Brunori et al. (2021) developed the "Equal Chances" database that includes estimates of intergenerational income mobility for 27 countries as well as estimates of inequality of opportunity for 47 countries. Our estimates of intergenerational mobility in education for 153 countries are also included in this database.

[2] Alesina et al. (2021), Neidhöfer et al. (2018), Asher et al. (2018), and Hertz et al. (2007) similarly focus on education, arguably for the same reasons.

[3] When evaluating the share of individuals who managed to surpass their parents' education level, individuals whose parents achieved the highest possible level of education are counted as mobile when they managed to match this level.

[4] A possible explanation for this observation is that in countries where most parents have no education, parental education will be a weak predictor of child education as there is little variation between parents. As countries develop, the gaps between poor, middle-class, and better-off parents become more pronounced. In the absence of public interventions, it will matter whether one is born into a poor, middle-class, or upper-class family, such that intergenerational mobility will start to decline. As countries further increase their national income and can afford public policies aimed at leveling the playing field, intergenerational mobility may increase. We observe a positive correlation between mobility and public spending, particularly public spending on education, which is consistent with this rationale.

classified as absolute or relative measures, but there is no settled definition of this terminology. For reviews of different measures, see e.g., Jäntti and Jenkins (2015) and Fields and Efe (1996, 1999). Therefore, we refrain from using the terms absolute and relative, and will instead explore commonalities and differences in the empirical patterns the six measures generate. Table 1 summarizes the measures of mobility used.

Three main challenges exist in the measurement of intergenerational mobility in education that do not arise in the measurement of intergenerational mobility in income: Education is bounded below, bounded above (rarely do people attain more than 21 years of schooling), and is highly coarse. The latter is in part because not all surveys collect granular data on educational outcomes, and in part because the outcomes themselves are coarse; there is bunching at certain educational categories such as no schooling, completion of primary etc.

The boundedness below mostly concerns low-income countries, where it is not uncommon that a majority of parents have completed zero years of schooling (the parents in our study are born approximately in the 1960s or earlier). By contrast, the boundedness above mostly affects high-income countries, where in younger cohorts, a significant fraction of respondents has obtained tertiary degrees. Middle-income countries are least affected by these measurement challenges. Overall, the boundedness from above is less of a concern than the boundedness from below as even in the richest countries only as minority of the population attains the highest education level.

Our starting point involves two of the most canonical coefficients used to measure intergenerational mobility, the correlation coefficient between respondents' and their parents' outcomes (also denoted *COR*), and the regression coefficient from the intergenerational transmission regression (also denoted *BETA*). Years of schooling is used for the education outcome variable y_{ict}. As *COR* and *BETA* both measure intergenerational persistence, 1-*COR* and 1-BETA are adopted as measures of intergenerational mobility. These measures are used by e.g., Hertz et al. (2007) and Neidhöfer et al. (2018) and many others.

A key feature of the correlation coefficient is that it is invariant to changes in the marginal distributions of respondents' and parents' education (or more precisely, it is invariant to changes in the standard deviations across the two generations). The values of *COR*, however, do not have a natural economic interpretation. The regression coefficient measures what share of an additional year of parental schooling is transmitted to their children on average. While *BETA* offers a natural interpretation, it is sensitive to the marginal distributions in education. This means that changes in *BETA* may in part reflect changes in education inequality across generations rather than changes in the intergenerational dependence structure.[5]

COR and *BETA* are subject to two additional measurement concerns. First, they are sensitive to measurement error in the education outcome data. Years of schooling may be a noisy proxy for human capital, particularly at low levels of education (i.e., it is unclear whether one versus three years of schooling reflects a meaningful difference in human capital). Second, they are measures of overall association without distinguishing between mobility at the top and mobility at the bottom. Intuitively, one might understand intergenerational mobility as the ability of individuals born to parents at the bottom of the distribution to obtain an education.

Two measures used by Asher et al. (2019) address these concerns: (a) the share of respondents who reach the top quartile of years of schooling (in their generation) out of those who were born to parents who ranked in the bottom half of their generation (denoted by *BHQ4*), and (b) the expected rank of a respondent (in the education distribution of her generation) whose parents rank in the bottom half of their generation (denoted by *MU050*). These measures require that each parent can be

Table 1
Mobility measures used.

Name	Description	Formula
1-COR	1 minus the correlation coefficient between respondents' and parents' years of schooling.	$1-\rho, \rho = cor(y_{child}, y_{parent})$
1-BETA	1 minus the coefficient from regressing respondents' years of schooling on parents' years of schooling.	$1-\beta$
MU050	The expected educational rank of respondents born to parents from the bottom half.	$E(rank_{child} \mid rank_{parent} < 50)$
BHQ4	The probability that respondents born to parents from the bottom half reaches the top quartile.	$P(rank_{child} > 75 \mid rank_{parent} < 50)$
AHMP	Share of respondents with a completed primary education conditional on neither parent having completed primary education.	$P(c_{child} \geq primary \mid c_{parent} < primary)$
MIX	Share of respondents with strictly higher educational category than parents if parents do not have tertiary, or with tertiary education if either parent has tertiary.	$P(cat_{child} > cat_{parent}$ or $cat_{child} = tertiary)$

Note: cat refers to the highest educational category completed of the following five categories, (1) less than primary, (2) primary, (3) lower secondary, (4) upper secondary, (5) tertiary. y refers to years of schooling completed. AHMP is taken from the surnames of the four authors of Alesina et al. (2021).

[5] The two measures are related as follows: $BETA = COR * \frac{SD(y_{child})}{SD(y_{parent})}$, where $SD(.)$ denotes the standard deviation.

ranked and assigned to the bottom half of the national distribution. When many parents have completed the same years of schooling, a method to break ties is needed to assign parents to the bottom half. Parents coded with the same level of education may vary in their true (unobserved) educational outcomes, if for example the quality of education varies. In that case, children with parents observed to have the same educational outcome may perform differently in expectation. Asher et al. (2019) derive upper and lower bounds on rank-based mobility measures such as *BHQ4* and *MU*50 that arise from the inability to unambiguously rank parents in terms of their true education. We will use the midpoint of the upper and lower bounds as our point estimate.[6]

We also use a measure that is introduced by Alesina et al. (2021) in their study of intergenerational mobility in Africa, namely the probability that children complete primary school if their parents did not (denoted *AHMP* after the surnames of the four authors of the paper). It should be noted that while completing primary education is fitting for a study of intergenerational mobility in Africa, there are few parents with less than primary school education in high-income countries. This means that the statistical support of the measure tends to be comparatively weak in rich countries.

Our sixth mobility measure evaluates the probability that children surpass the maximum educational attainment of their parents (denoted by *MIX*), which is closely related to the *AHMP* measure. In this case, the education outcome variable will measure the highest grade completed using the following categories (see Section 3 for more details): (i) less than primary, (ii) primary, (iii) lower-secondary, (iv) upper-secondary, or (v) tertiary. Note that in cases where all parents attained less than primary education, *MIX* and *AHMP* will coincide with each other. Note also that this measure is similar to the measure of mobility used by Chetty et al. (2017), which evaluates the share of individuals who managed to surpass their parents in terms of income.

The fact that there is a maximum education category, namely tertiary, introduces a ceiling effect. When both children and their parents have tertiary education, one may not want to classify these children as immobile, which would introduce a mechanical decline in mobility at higher levels of development. For this reason, we consider respondents mobile if they are in a higher educational category than their parents *or* if they have obtained a tertiary degree.

Evaluating intergenerational mobility between parents and children requires specifying which parents and children one is referring to. Unless otherwise specified, all children are considered in the estimation of mobility. Whenever parental education is referred to, the maximum education attained by the parents is used.[7] Our motivation for using maximum parental education is two-fold. Firstly, it provides a more accurate measure of the parental human capital that can be transferred to the children. Secondly, it may provide a more accurate proxy of the household resources that can be invested in the human capital growth of the children. Note also that maximum parental education may be less sensitive to the expansion of female educational attainment and the increasing correlation of educational attainments between parents (i.e. assortative mating).[8]

Alternatively, intergenerational mobility could be evaluated using mother-daughter and father-son pairs. Consider for example a daughter who has obtained primary education, while her mother has no education and her father has completed secondary education. She would be evaluated as (upward) mobile relative to her mother but not relative to her father (or most educated parent). In the Appendix and the database accompanying this paper, mobility estimates using mother-daughter pairs and father-son pairs are included.

3. Data

3.1. Identifying relevant surveys

To construct our Global Database on Intergenerational Mobility (GDIM), a comprehensive review of surveys that ask respondents about their parents' educational attainment was conducted.[9] Eighty percent of the surveys selected were conducted after 2011 such that respondents born in the 1980s had a chance to complete their education by the time the survey data was collected. If more than one relevant survey was found for a country, the survey was selected based on sample size and the quality of the parental education information.

Broadly speaking, three types of surveys are considered. For most developing countries, cross-sectional household income or expenditure surveys are used. For most countries in Europe and Latin America, social surveys such as the European Social Survey (ESS), the Latinobarometro, and the Life in Transition Survey (LITS) are used.[10] For a selected number of high-income countries, annual panels such as the Panel Study of Income Dynamics in the United States and the Labor and Income Panel Study in the Republic of Korea are used. The surveys and years are listed in Table A.1 in Appendix A. The social surveys tend to have smaller sample sizes, so when multiple waves of the same survey contain relevant information on educational attainment, these waves are pooled. This includes three waves of the ESS (from 2010 to 2014), six waves of the Latinobarometro (from 2008 to 2015), and two waves of the LITS (2006 and 2011).

For several countries, including some of the developing world's largest countries such as Bangladesh and a notable number of countries in Sub-Saharan Africa, there are no surveys with retrospective data on parental education. In these cases, high-quality household surveys without retrospective data are used instead. Information on parental

[6] If the bounds are wide, then using the midpoint of the bounds does not necessarily address the concern that the input data are coarse. In Table A.2 we report the width of the bounds of BHQ4 and MU50 by country. The median width of the bounds of MU50 is 1.9 and the interquartile range is 0.8–3.7. The median with of the bounds of BHQ4 is 0.07 and the interquartile range is 0.04–0.10.

[7] Estimates using fathers and mothers separately, as well as estimates based on parents' average years of schooling are available in the online version of the Global Database of Intergenerational Mobility. For two countries, information on fathers' years of schooling but not on mothers' years of schooling is available (Benin and Democratic Republic of Congo). In these cases, it is assumed that the maximum value of parental years of schooling is equivalent to the father's years of schooling.

[8] The existing literature on earnings mobility tends to focus on father-son mobility in large part because of the low levels of female labor force participation observed during the periods when this literature originated, and to avoid the associated selection bias. Since then, female employment has increased substantially, which has weakened the argument of focusing on father-son pairings.

[9] For early users of a prior version of the GDIM, see e.g., Engzell and Tropf (2019), Aiyar and Ebeke (2020), and Leone (2019).

[10] Like Neidhöfer et al. (2018), Latinobarometro is used instead of Lapop, which is another social survey covering the Americas. Lapop only asks for mother's education. Conversely, Latinobarometro records the highest education level of father and mother, which is the variable used in this paper.

Table 2
Coverage.

Income group/region	Number of countries covered		Percent of population covered	
	With retrospective data	Total	With retrospective data	Total
High-income countries	38	38	93%	93%
Developing countries	76	115	86%	98%
East Asia and Pacific	8	18	92%	99%
Europe and Central Asia	20	20	99%	99%
Latin America and the Caribbean	15	16	95%	97%
Middle East and North Africa	6	10	51%	83%
South Asia	5	8	89%	100%
Sub-Saharan Africa	22	43	72%	97%
World	114	153	87%	97%

Note: The table shows the number of countries our database covers, and the population share that these countries account for.

education is obtained for respondents who reside in the same household as their parents – so-called co-residents.[11]

Since co-residing adults need not be representative of the target population, estimates derived from this type of data may be subject to co-residence bias (Emran et al., 2017). The magnitude of this bias depends on the share of adults who co-reside with their parents and the extent to which co-residing adults differ from adults who live away from their parents. With that in mind, samples are restricted to co-residents aged 21–25 at the time of the survey. These respondents, who are part of the 1980s cohort, tend to be old enough to have had a chance to complete their education yet young enough such that a large fraction still co-resides with their parents. For the countries where we rely on co-residents, the share of 21-25-year-olds who co-reside with their parents ranges from 11% to 66%, with the median being 33% and the interquartile range being 21%–40%. Since co-resident surveys only allow us to estimate mobility for this cohort, we are unable to track mobility over time (i.e., across cohorts) for these countries. When time trends are analyzed, the same set of countries is used throughout, so these countries are dropped.

In Appendix Bwe use surveys with retrospective data on parental education to evaluate the co-residence bias. We find that the bias does not generate meaningful re-rankings. Furthermore, our main results are unaltered if we exclude estimates based on co-residents. As an additional robustness check, we also use 18-year-olds (instead of 21-25-year-olds). This maximizes the share of individuals who co-reside with their parents at the expense of introducing a bias in the education outcome data as many individuals have yet to complete their education by the age of 18. Accordingly, this introduces a more notable change in the results.

3.2. Global coverage

In total, the GDIM provides estimates of intergenerational mobility for 153 countries representing about 97 percent of the world's population born in the 1980s (see Table 2). This includes countries for which we rely exclusively on co-residents. For 114 countries, or about 87 percent of the world's population and 75 percent of the countries covered, estimates of mobility rely on retrospective data and span four decades: from those born in the 1950s to those born in the 1980s. In all regions but the Middle East and North Africa, the population coverage is greater than 90%. For the Middle East and North Africa, 83% of the population is covered (51% with retrospective questions).[12]

3.3. Coding of education data

Many of the surveys contain a direct question eliciting years of schooling completed. This is the information we use in four out of the six mobility measures we use (*1-COR,* 1-BETA*, BHQ4, and MU050*). For the surveys where no such variable is available, but only information on education levels completed, we convert the categorical information into years of education using UNESCO sources that contain country- and year-specific mappings on the duration of educational programs.[13]

The years of schooling required to complete a category of the International Standard Classification of Education (ISCED) varies across countries, and changes over time within countries. Individuals are assigned to an educational regime based on their birth year and the school entry age. When reforms occur, it is assumed they apply to individuals who have not yet entered that education level. For example, it is assumed that an extension of lower secondary from 3 to 4 years does not affect children who are already enrolled in lower secondary.[14] Still, in cases when large educational reforms occur, it may be difficult for children to accurately report the educational attainment of their parents.

When years of schooling is reported directly, it is up to the respondent whether to include repeated classes. In some cases, the enumerator might be instructed to tell the respondent to exclude repeated classes. Whenever years of schooling are converted based on highest educational outcome achieved, it is assumed that there are no repeated classes. Years of schooling do not account for differences in the quality of education. A year of schooling in, say, Singapore may be of very different quality than

[11] For a handful of countries, recent surveys with co-resident data and older surveys with retrospective questions were combined; the co-resident data is used for the 1980s cohort and the older survey for the 1950s through 1970s cohorts. This applies to Pakistan, Mauritania, Philippines, Rwanda, and Guinea. For two countries, neither recent co-resident surveys nor retrospective surveys were identified, while older surveys with retrospective questions exist. This concerns New Zealand (2000 survey) and Bhutan (2003 survey). To maximize coverage, these surveys are utilized as well. Tabulations show that in Bhutan most respondents born in the 1980s had completed their education by the time of the survey. For New Zealand, it is assumed that the estimate for the 1980s cohort equals the estimate for the 1970s cohort.

[12] High-income countries are defined using the World Bank's income classification as of July 1, 2019. High-income countries are also referred to as "the developed world" in this paper. The remaining countries, referred to as the "developing world", are split further into geographic regions. More information on the income classifications and geographic regions is available here: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

[13] Two sources of information are used. The first source (http://uis.unesco.org/en/isced-mappings) is not available for all countries and for the most part only conveys the duration of ISCED categories in 1997 and 2011. This source is supplemented with information from UNESCO's online database (http://data.uis.unesco.org/), which outlines the durations of ISCED categories since 1970.

[14] The UNESCO information is not available before 1970, so for individuals who went to school before 1970 the durations from 1970 are applied. When information is missing in the UNESCO sources, additional country-specific information is used or the following rule for converting ISCED categories to completed years of schooling is applied: (i) ISCED 1: 6 years, (ii) ISCED 2: 9 years, (iii) ISCED 3: 12 years, (iv) ISCED 4: 13 years, (v) ISCED 5: 15 years, (vi) ISCED 6: 16 years, (vii) ISCED 7: 18 years, and (viii) ISCED 8: 21 years. In a handful of countries, a years of schooling variable is present, but a categorical variable is not. In these cases, the reverse conversion using the country- and year-specific mappings is used.

a year of schooling in Malawi. Due to a lack of global data on educational quality, especially for the cohorts considered in this paper, no quality adjustments are made in our analysis. This is a limitation of the analysis.[15]

For the *MIX* and *AHMP* measures, a globally harmonized categorical measure of educational attainment is constructed. This measure represents the lowest common denominator in granularity across surveys, thus invariably reducing the amount of detail exploited in some countries. With minor exceptions, all surveys contain the following five categories, which are based on UNESCO's International Standard Classification of Education (ISCED): (i) less than primary (ISCED 0), (ii) primary (ISCED 1), (iii) lower secondary (ISCED 2), (iv) upper secondary or postsecondary nontertiary (ISCED 3–4), and (v) tertiary (ISCED 5–8). The categories refer to the highest education level completed by the respondent. A few high-income countries do not have data on the first of these five categories. Since these countries have mandatory schooling at the primary level, it is assumed that all individuals have completed at least primary in these cases.[16] Respondents who are younger than 21 years are excluded from the analysis because a notable fraction of them have still not completed school. Among respondents 21 and older who are still in school, the ones enrolled in upper secondary or less are excluded as well. The ones enrolled in tertiary are assigned the maximum of their highest educational attainment so far and the lowest tertiary degree (ISCED 5).[17]

If parent education data is missing for either the father or the mother, the individual is not included in the analysis. It could be missing because individuals do not know their parents' education or because they did not know either parent. This happens frequently in certain countries. The median share of respondents without parental information is 9%, with the interquartile range being 2%–16%. Poorly educated respondents are more likely to have missing parental education; among respondents with primary or less, the median share without parental information is 12% and the interquartile range is 1%–28%. For those with upper secondary or more, the median is 7% and the interquartile range is 3%–14%. Table A.2 in the Appendix reports this information at the country level, including the number of unique educational outcomes for children and parents, and the share of parents and children with the educational outcome most frequently observed.

4. Intergenerational mobility around the world

A first glance at how intergenerational mobility is distributed across the world is presented in Fig. 1. The map shows estimates of *MU050* for 153 countries for the 1980s cohort. South America, South Asia, parts of Sub-Saharan Africa, as well as parts of Eastern Europe stand out as regions with some of the lowest levels of intergenerational mobility. We find that 17 of the 25 least mobile countries are either in Sub-Saharan Africa, Latin America, or South Asia. Interestingly, some of the highest levels of mobility are also found in Sub-Saharan Africa and South Asia (Maldives and Niger). Global maps for the five other measures of intergenerational mobility can be found in section 5.2 (map for *MIX*) and Appendix C (maps for *BHQ4*, *AHMP*, *1 – BETA*, and *1 - COR*).

Fig. 2 plots the relationship between intergenerational mobility and national income (real GDP per capita) across countries and across cohorts using local polynomial regressions. National income is lagged by 10 years, so that it corresponds with the time periods during which the children were of school age. The results indicate that intergenerational mobility does not increase monotonically as countries grow richer.

The different measures of mobility are seen to exhibit different relationships with national income. Broadly speaking, two distinct patterns are observed: The top row of Fig. 2, including the measures *1 – COR*, *BHQ4* and *MU050*, shows a U-shape-pattern, where mobility is on average highest in the poorest and the richest countries (arguably for different reasons). The local polynomial regressions presented in the bottom row of Fig. 2, for the measures *1 – BETA*, *AHMP* and *MIX*, show an increasing relationship with national income, where the lowest rates of mobility are observed in the poorest countries. In select cases the relationship approaches an inverted-U-shape, with intergenerational mobility declining slightly among the richest countries. Appendix Table C.1 confirms that the U-shapes from the top row are significant when regressing mobility on a second-order polynomial of log GDP per capita, while the inverse U-shapes from the bottom row are borderline significant. Appendix Figure C.5 confirms that omitting estimates based on co-residents from the regressions does not meaningfully change the results. In Appendix Figure C.6, we show the country-level estimates colored by region.

What do the measures from each group have in common? A key feature that separates the two groups of mobility measures is their sensitivity to changes in the marginal distributions across generations, i.e., changes in inequality. The measures shown in the top row of Fig. 2 are less sensitive to changes in the marginal distributions than the measures shown in the bottom row. Henceforward, we will refer to the two groups as inequality-invariant (top row of Fig. 2 and inequality-sensitive measures (bottom row of Fig. 2).[18]

The same grouping of mobility measures can be observed when tracking estimates of intergenerational mobility by birth cohort (from 1950s to 1980s) for the average high-income versus lower-income country (see Fig. 3), using the income classification from 2019.[19] Averages are unweighted by population, which means that they represent the average mobility of countries and not of the average individual in each group.

[15] Unobserved school quality could affect estimates of intergenerational mobility in education in several ways depending on how school quality differs across areas and households and over time. If school quality primarily increased over time, then we would underestimate the share of individuals with better outcomes than their parents (which concerns the measures MIX and AHMP). If school quality improved uniformly, then the other measures of mobility would be unaffected. For example, the rank-based measures may not be affected by school quality unless quality affects different ranks differentially. If school quality exhibits within-country heterogeneity however, with access to high-quality schooling reserved for a privileged sub-population of households, then ignoring gaps in school quality means one will overlook the contribution of between-group inequality and over-estimate intergenerational mobility. The corresponding bias is expected to be larger for countries where the between-group variance component is significant, i.e., where the within-country variation in school quality is large. In poor countries where access to high-quality education will be limited, this bias is expected to be small.

[16] This concerns some countries where LITS or ESS is used, as well as the United States; Taiwan, China; the Republic of Korea; Japan; Canada and Australia. In these economies, no category below primary exists. For a few other countries, it was unclear how to code respondents who have completed Koranic or other religious schools. In general, we assume that these respondents completed education corresponding to the primary level.

[17] This assumption may matter for the estimates. If most individuals who are enrolled in tertiary and 21 years or older end up completing a master's degree (ISCED 7), they are assigned too little education. If these individuals, simultaneously, tend to have highly educated parents, mobility is underestimated. On the other hand, if these individuals instead were dropped from the analysis, the data would lose representativeness.

[18] An alternative is to group the measures into growth-sensitive and growth-invariant. Growth-invariant measures are unaffected if all children in a generation increase their years of schooling by a given percentage. This distinction leads to the same grouping. Thus, in times of economic growth, one can expect the inequality-sensitive (and, hence, growth-sensitive) measures to improve. Yet another alternative is to group the measures into 'level-sensitive' and 'level-invariant' – whether measures are affected by all children in a generation increasing their years of schooling by a certain number of years. In this case 1-BETA moves to the invariant grouping, which may explain why it behaves differently from *AHMP* and *MIX* in Fig. 2.

[19] Figure C.7 shows that the results are robust to using an income classification for the 1950s. Figure C.8 contains a version of the figures with the developing world broken down by six geographical regions.

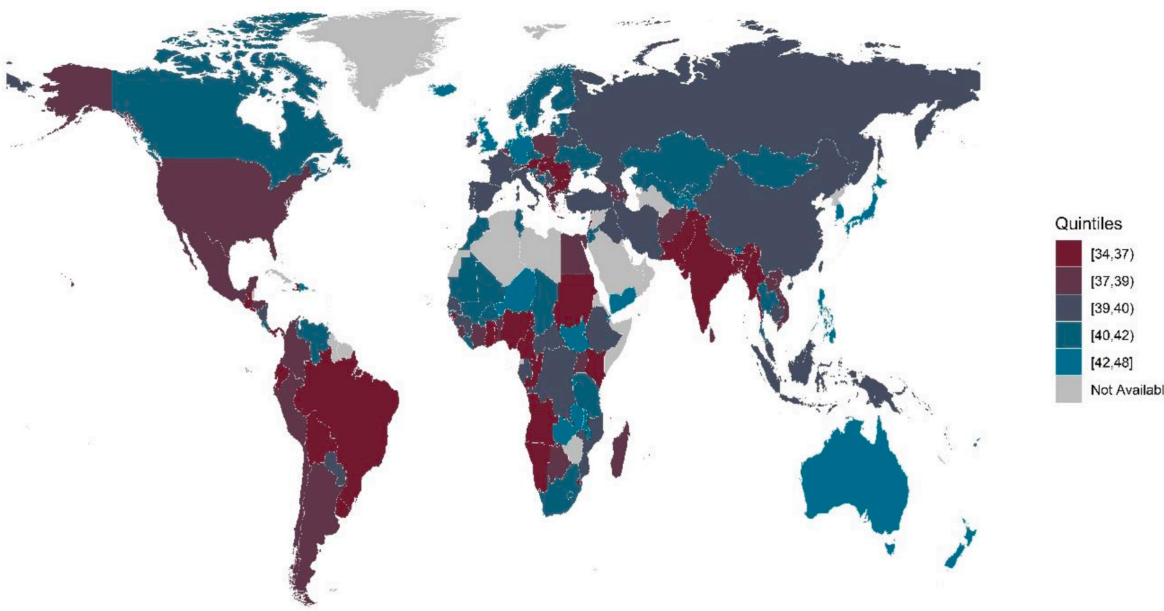

Fig. 1. Intergenerational mobility (*MU050*) around the world (1980s cohort) *Note:* The map shows country-level estimates of *MU050* for individuals born in the 1980s. Countries are classified according to quintiles of the mobility measure. A higher value indicates greater mobility.

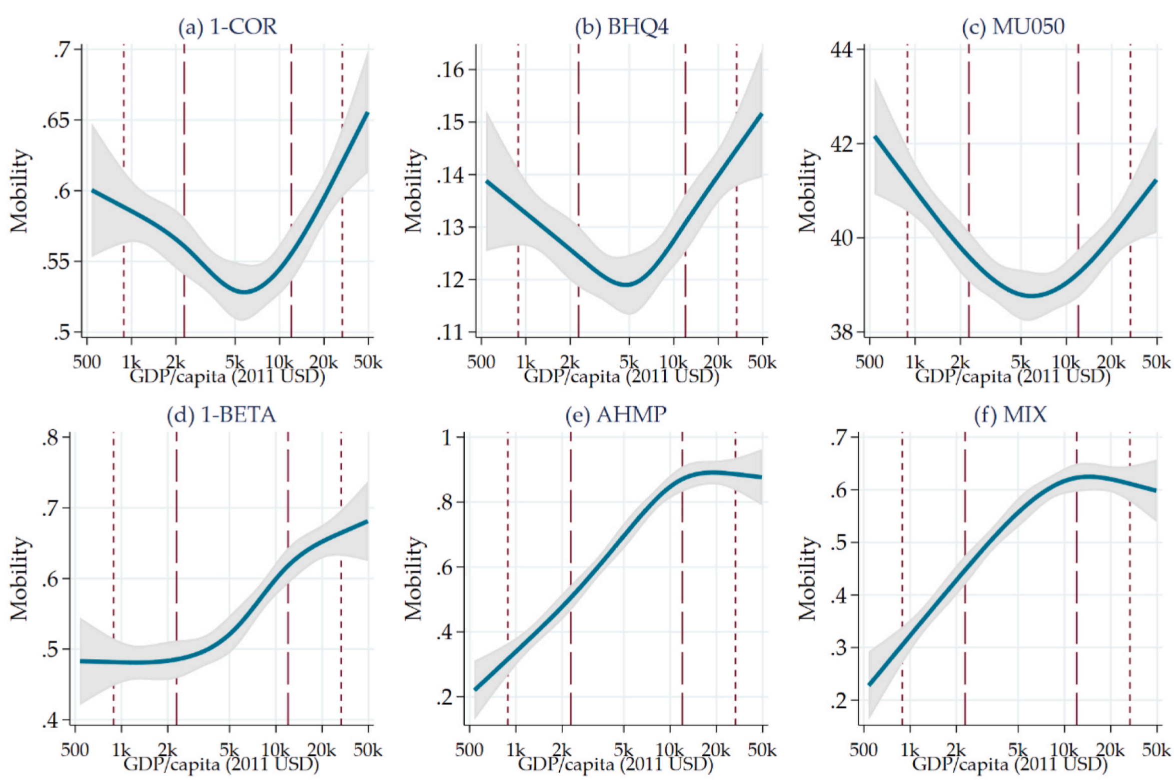

Fig. 2. Relationship between intergenerational mobility and GDP/capita *Note:* The dashed lines indicate the 25th and 75th percentile of the distribution of GDP per capita. The dotted lines indicate the 5th and 95th percentile. GDP data is from the World Development Indicators supplemented with data from the Maddison project where necessary. We match a cohort with the GDP per capita when the cohort, on average, was about to enter school. For example, the cohort born in the 1980s, we match with the GDP per capita from 1990, at which point the cohort on average was five years old.

According to the inequality-invariant (top-row) mobility measures (*1 – COR*, *BHQ4* and *MU050*), the average low-income country reports a decline in mobility, while mobility shows a modest upward trend in the average high-income country. For the cohorts born in the 1950s and 1960s, intergenerational mobility was higher in the low-income world, but arguably for the wrong reasons. These time-trends are consistent with the relationships between mobility and national income observed in Fig. 2.

When intergenerational mobility is measured by the inequality-sensitive indicators (bottom row: *1 – BETA*, *AHMP* and *MIX*), mobility is higher in the average high-income country over the entire 40-year period. Importantly however, mobility is increasing in the average

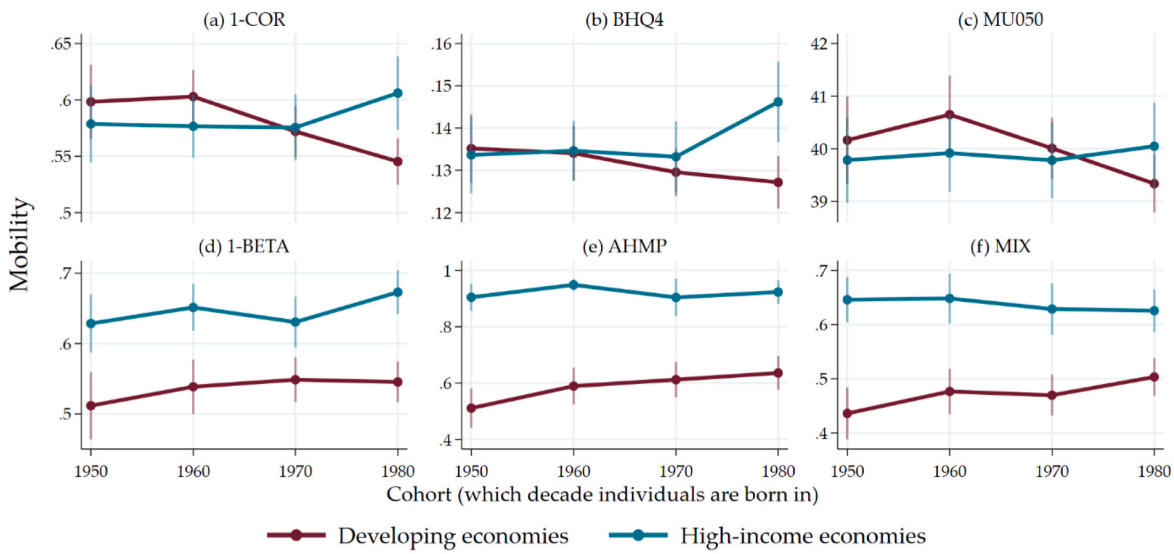

Fig. 3. Intergenerational mobility for 1950s–1980s cohorts *Note:* The figure shows unweighted averages of intergenerational mobility estimates. The vertical bars show 95th confidence intervals. These confidence intervals do not account for the uncertainty of the country-level estimates themselves.

low-income country by these measures, narrowing the gap with mobility observed in the average high-income country. In summary, we observe a convergence in mobility between the low- and high-income world using inequality-sensitive measures, but a divergence in mobility when using inequality-invariant measures.

An empirical observation that is shared by all six measures of mobility is that for the youngest cohort born between 1980 and 1990 (the youngest individuals that will have had the opportunity to complete their education at the time of survey data collection), intergenerational mobility is higher in the average high-income country when compared to the average developing country. Note that this too is consistent with the empirical relationships observed between mobility and national income; whether observing a U-pattern (inequality-invariant measures) or an increasing pattern (inequality-sensitive measures), mobility is found the be highest among the richest countries.

Note that the change from a U-shaped-pattern to an increasing relationship with national income for inequality-sensitive measures of intergenerational mobility may in part be mechanical. A comparison of 1-BETA (i.e., the regression coefficient) and *1-COR* (i.e., the correlation coefficient) is illustrative. In the case of 1-BETA, mobility is approximately an increasing function of GDP per capita. By definition, $BETA = COR^{*}SD(y\_child)/SD(y\_parent)$. The standard deviation of years of schooling tends to zero when average years of schooling approaches either zero or the maximum level of education. This suggests that the standard deviation has an inverse-U-shaped-pattern with mean years of schooling. The ratio of standard deviations, which enters directly into the equation for *BETA*, starts off high (when it is near zero for parents and positively higher for their children) and declines as average years of schooling for parents increases. Therefore, for a given correlation between parent and child years of schooling, the regression coefficient peaks among the poorest countries and declines as these countries accumulate human capital and national income. In other words, this transforms the U-shaped-pattern observed for *1-COR* into the increasing pattern observed for 1-BETA.

5. Selected in-depth analyses

5.1. Children surpassing their parents

The share of children who managed to surpass their parents in terms of education, measured by *MIX*, is an intuitive example of an inequality-sensitive measure. Chetty et al. (2017) estimates the share of children who surpassed their parents in terms of income in an application to the United States. They document a considerable decline between the 1940s and 1980s cohorts, mostly explained by a more unequal distribution of income growth over this period rather than a slowdown in average growth rates. This highlights how *MIX* (and other inequality-sensitive measures) capture both the dependence structure between parent and child outcomes, and changes in the marginal distribution across generations. Fig. 4 shows how *MIX* varies across the world.

Sub-Saharan Africa stands out as the region where children have been least successful at surpassing their parents. In some of the poorest or most fragile countries in the region, the share of respondents that have more education than their parents is less than 20 percent, compared to over 80 percent in parts of East Asia. Of the 15 countries in the bottom decile of *MIX*, 12 are in Sub-Saharan Africa, several of them in fragile situations. In the average country of Sub-Saharan Africa, 37 percent of those born in the 1980s have a higher level of education than their parents, as compared to 61 percent of the same generation in the average country of East Asia & Pacific. The share of children who are more educated than their parents for the 1980s cohort is also high in Western Europe, North America, South America, parts of the Middle East, and South Africa. Germany stands out among the high-income countries by having low levels of *MIX*. As also observed in Fig. 3, *MIX* is on average significantly lower in developing (low- and middle-income) countries than in high-income countries.

It becomes increasingly difficult to surpass one's parents as educational attainment increases from one generation to the next. This makes it surprising that *MIX* continues to be much lower in the developing world given that the scope for surpassing the education level of one's parents is much higher in these countries. For example, the tertiary attainment rate among the parents of the 1980s generation in developing countries is comparable to that of the parents of the 1950s generation in high-income countries.

In Fig. 5, we plot the share of children who have more education than their parents against the education of their parents for the average high-income country. As one would expect, this share (conditional on parental education) declines with parental education, and mechanically reaches zero at the highest level of parental education. If the same curve were also to apply to the average developing country, then mobility measured by *MIX* would be higher in the developing world, where parents have lower levels of education.

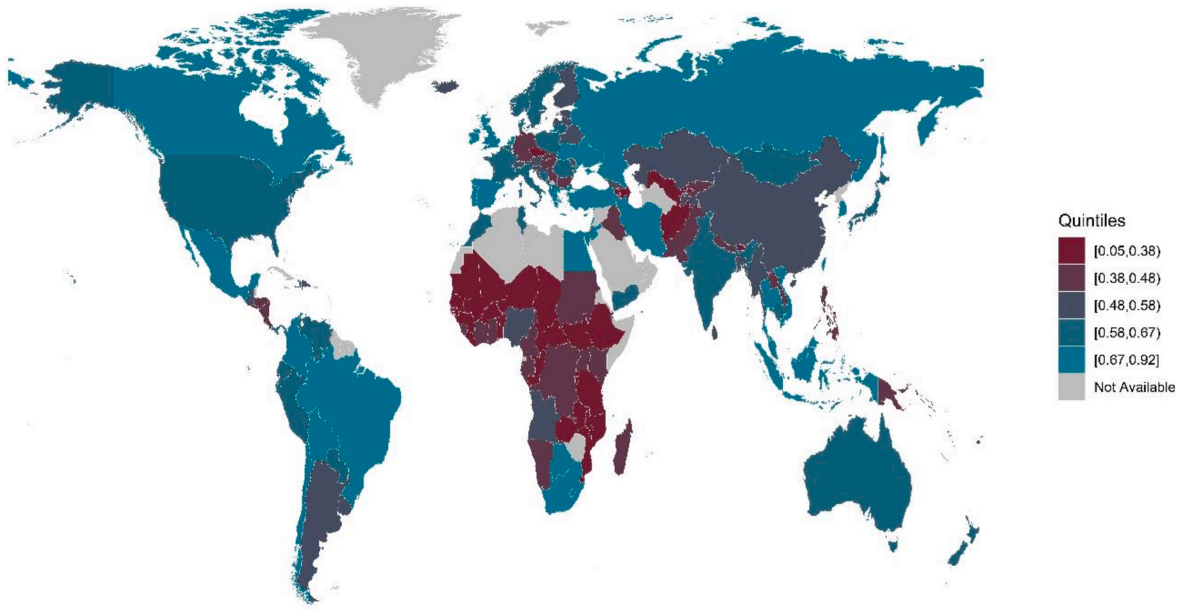

Fig. 4. Mobility measured by *MIX* around the world (1980s cohort) *Note*: The map captures mobility measured by *MIX* for individuals born in the 1980s. A higher value indicates greater mobility.

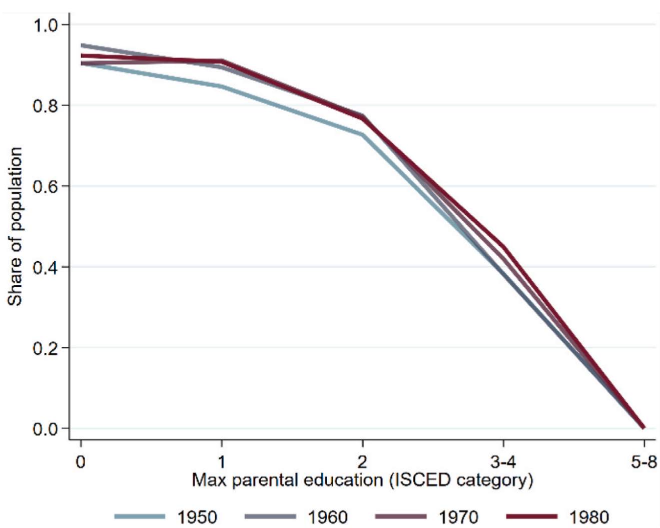

Fig. 5. Share of children surpassing parents, by level of parental education (high-income) *Note:* ISCED category refers to UNESCO's International Standard Classification of Education. ISCED 0 = less than primary, ISCED 1 = primary, ISCED 2 = lower secondary, ISCED 3–4 = upper secondary or postsecondary nontertiary, ISCED 5–8 = tertiary.

The relationship between *MIX* and parental education is seen to take a different shape for developing countries, see Fig. 6. The curve exhibits an inverted-U-shape for the younger generations (1970s and 1980s) in South Asia and Sub-Saharan Africa as well as for older generations (1950s and 1960s) in all developing regions other than Europe and Central Asia. This suggests that individuals with less-educated parents, who are likely to be poorer, are also less likely to be upwardly mobile in most developing countries. That the inverted-U is most pronounced and persistent over time in the two poorest regions, Sub-Saharan Africa and South Asia, is particularly suggestive: the poorer the region, the more likely it is that individuals born to parents who do not have an education lack the means to get an education.

A candidate explanation for this apparent paradox is the lower availability of resources, parental and public, to invest in children in developing countries. In the developing world, children born in poorer (and less educated) households are possibly so constrained in accessing opportunities, that they are unable to take advantage of the greater scope for surpassing their parents. On a positive note, this inverted-U-shape appears to be weakening with each new generation in all regions, as the inverted-U-shape gradually morphs into the pattern observed for the average high-income country.

5.2. Girls are catching up to boys in the developing world

Disaggregated time-trends in intergenerational mobility by gender are presented in Fig. 7. Boys and girls are both compared against their most educated parent. For BHQ4 and MU050, boys and girls are ranked in the national distribution, not in their own-gender distribution. Similar results are obtained when boys are compared with their fathers and girls with their mothers (Appendix C, Figure C.9). For individuals born in the 1950s, boys reported higher rates of mobility than girls in most of the measures, both in the average high-income and average developing country.

Girls are found to be catching up to boys in the average developing country by most measures. In fact, girls have already overtaken boys in the average high-income country when mobility is measured by *MU050*, *BHQ4*, and *MIX*. If current time-trends prevail, girls are on track for also surpassing boys in the developing world in the coming decade(s). We observe increases in mobility for girls in both the average low- and high-income country across most measures of mobility. The trends for boys are more mixed. Overall, the trends and patterns we observe here show less of a distinction between the inequality-sensitive and inequality-invariant measures.

5.3. Long-term steady state value of human capital

Chetty et al. (2020) studies the income differences observed between individuals from different race groups in the Unites States. Assuming the linear intergenerational transmission regression from eq. (1), they derive the implied long-term steady state values for each race group and inspect the factors that shape the rate of convergence in incomes across race groups. In this section, we will adopt this framework to study the projected difference in long-run education levels between the developed and developing world and examine how convergence between the two is

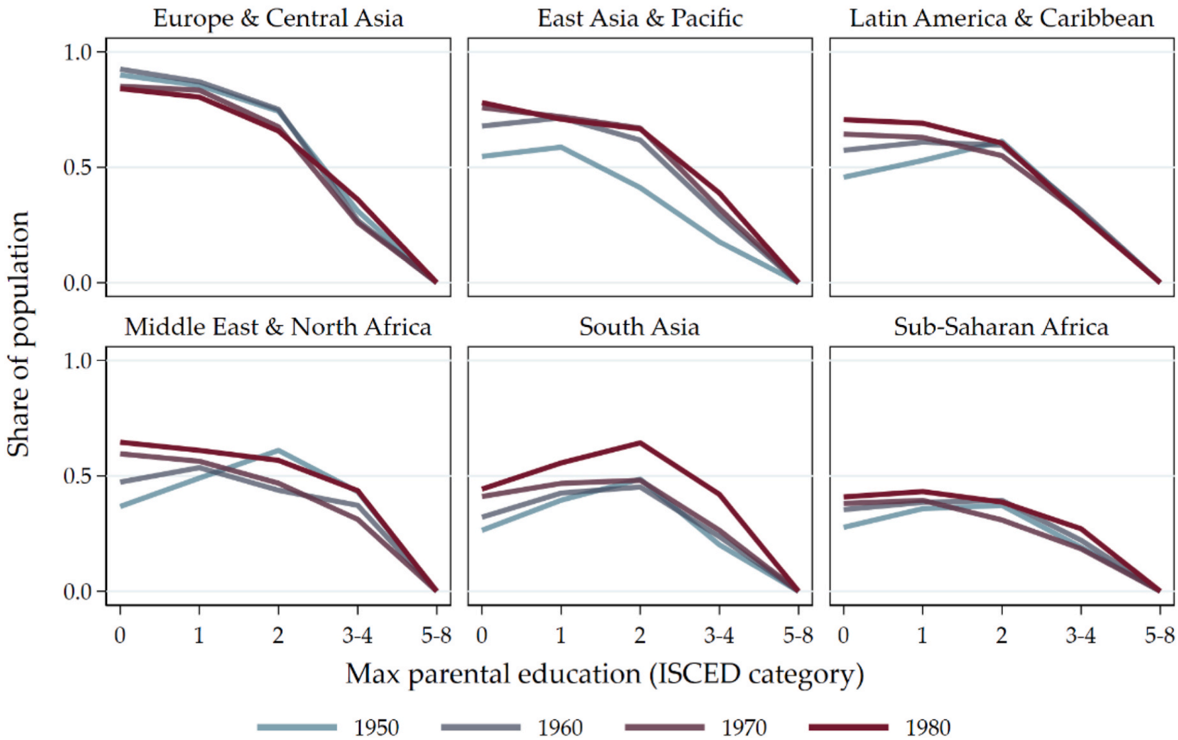

Fig. 6. Share of children surpassing parents, by level of parental education (by developing region) *Note:* See Fig. 5.

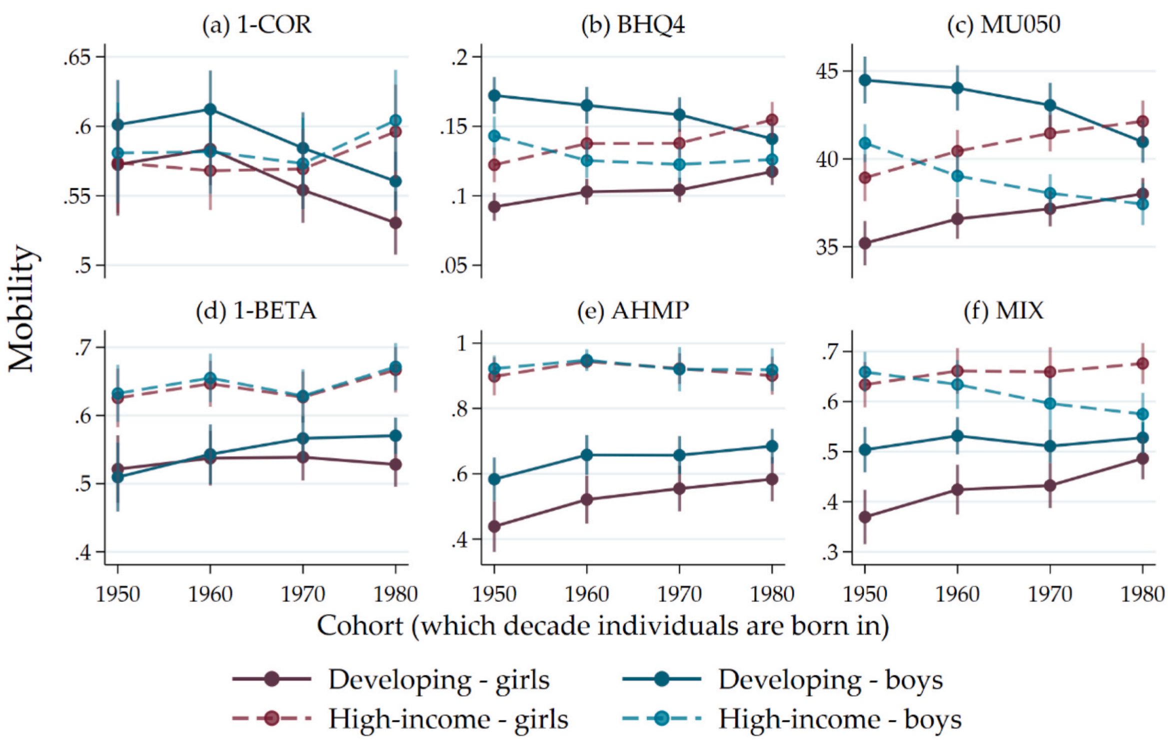

Fig. 7. Intergenerational mobility from the 1950s to the 1980s cohort by gender Note: The figure shows unweighted averages of intergenerational mobility estimates. The vertical bars show 95th confidence intervals. These confidence intervals do not account for the uncertainty of the country-level estimates themselves. For BHQ4 and MU050, boys and girls are ranked in the national distribution, not in their own-gender distribution.

shaped by the intergenerational mobility parameters.

Under the assumed intergenerational transmission process from eq. (1), mean years of schooling satisfies the following autoregressive process across generations:

$$\mu_{ct+1} = \alpha_c + \beta_c\, \mu_{ct}, \tag{2}$$

where μ_{ct} is the population mean for generation t in country c. Evaluating the unconditional expectation on both sides of the transmission equation, and assuming that α_c and β_c are constant with $\beta_c < 1$, yields the following long-run steady state value for years of schooling:

$$\mu_c = \frac{\alpha_c}{1-\beta_c}.$$

Following Chetty et al. (2020), we will focus on between-group differences and inspect the prospects for convergence (between-race differences in Chetty et al. (2020) and between-world differences in our case). Assume that the mobility parameters α_c and β_c primarily vary between (and are constant within) the developed versus the developing world. This assumption finds support in Fig. 8, which plots mean years of schooling for the child versus the parent generation along with linear fits for the high-income and low-income countries (each dot represents a country). High-income countries (indicated by H) and low-income countries (indicated by L) are seen to exhibit markedly different relationships with $\alpha_H > \alpha_L$ and $\beta_H < \beta_L$. Also observe the comparatively high degree of homogeneity within each group.

It follows that the long-run steady state value of the between-world difference in education $\Delta\mu = \mu_H - \mu_L$ equals:

$$\Delta\mu = \left(\frac{\Delta\alpha}{1-\overline{\beta}}\right) + \left(\frac{\Delta\beta}{1-\overline{\beta}}\right)\overline{\mu},$$

where $\Delta\alpha = \alpha_H - \alpha_L$, $\Delta\beta = \beta_H - \beta_L$, $\overline{\beta} = w_H\beta_H + w_L\beta_L$, and $\overline{\mu} = w_H\mu_H + w_L\mu_L$, where w_H and w_L are the population shares for the high- and low-income worlds, respectively. Note that $\overline{\beta}$ equals the mean value of the mobility parameter β which is different from the global mobility parameter for the world at large (which is the subject of the next section).

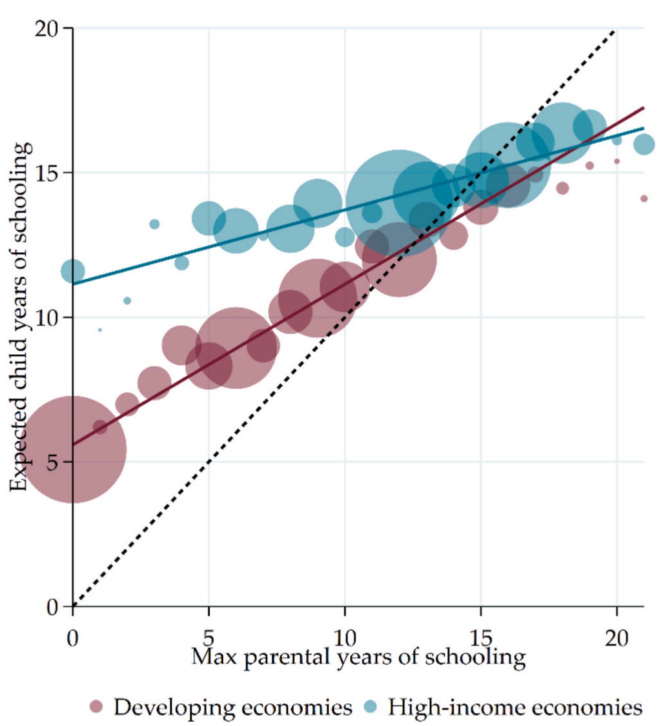

Fig. 8. Expected years of schooling by parental education, 1980s cohort Note: The figure pools all our microdata for the 1980s cohort such that each country's weight sums to its population size. The size of the bubbles is proportional to the share of parents with a given years of schooling. The solid lines indicate linear fitted lines and the dashed line indicates the 45-degree line.

The between-world gap in education is sensitive to between-world differences in the mobility parameters as well as to the overall level of intergenerational mobility. Specifically, smaller gaps can be achieved through lower values of $\Delta\alpha$ and/or $\Delta\beta$ – and for a given level of between-world heterogeneity – through lower values of $\overline{\beta}$ (higher levels of intergenerational mobility). Naturally, convergence in the mobility parameters (i.e., $\Delta\alpha \to 0$ and $\Delta\beta \to 0$) will yield a convergence in outcomes (i.e., $\Delta\mu \to 0$). Note that $\Delta\mu \to 0$ can also be achieved for $\Delta\alpha \neq 0$ and $\Delta\beta \neq 0$. (If either $\Delta\alpha$ or $\Delta\beta$ tends to zero however, as considered in Chetty et al. (2020), then convergence can only be achieved when both $\Delta\alpha$ and $\Delta\beta$ tend to zero.)

The steady state values for years of schooling can be observed in Fig. 8 by the intersections between the linear fitted lines and the diagonal (45-degree line). High-income countries have a steady state value of 15 years while low-income countries have a steady state value of 12.5 years. At present, that is for the 1980s cohort (the youngest cohort in our database), the mean years of schooling is estimated at 9.4 years for the average developing country and 14.5 years of schooling for the average high-income country. That implies a shortfall of 3 years to the steady state in the developing world (compared to a shortfall of half a year in the developed world).

What factors would facilitate convergence to the steady state values? At generation t, the between-world gap satisfies the following autoregressive process:

$$\Delta\mu_{t+1} - \Delta\mu = \overline{\beta}\,(\Delta\mu_t - \Delta\mu) + \Delta\beta\,(\overline{\mu}_t - \overline{\mu}).$$

It follows that convergence is primarily helped by higher levels of intergenerational mobility $\overline{\beta}$ as well as by a smaller between-world difference in the mobility parameter β.

Let us also disaggregate at the country level and inspect how convergence to steady state varies across national human capital levels. Substituting $\alpha_c = (1-\beta_c)\mu_c$ into eq. (2) gives us:

$$\mu_{ct+1} = (1-\beta_c)\mu_c + \beta_c\, \mu_{ct}.$$

If we subtract μ_{ct} from both sides and re-arrange terms, we obtain:

$$\mu_{ct+1} - \mu_{ct} = (1-\beta_c)\,(\mu_c - \mu_{ct}).$$

Consistent with what we observed for the world aggregated into two groups, higher rates of human capital accumulation (i.e., higher catch-up growth) are predicted for countries whose current mean years of schooling shows a larger gap relative to its equilibrium value, and countries with higher rates of intergenerational mobility (i.e., lower rates of intergenerational persistence β_c). Note that the former condition favors low-income countries, while the latter favors high-income countries.

This is confirmed empirically when we plot mean years of schooling of the current generation, the next generation (predicted), and long-term equilibrium values against national income levels (lagged by 10 years corresponding to the time where individuals were of school age; Fig. 9a) – and against intergenerational mobility measured by $1-\beta_c$ (Fig. 9b). The next generation's projected progress towards the equilibrium value, estimated by $\mu_{ct+1} = \alpha_c + \beta_c\, \mu_{ct}$, is indicative of the speed of convergence. The figures show that (a) larger shortfalls to steady-state years of schooling are observed at lower levels of national income (and intergenerational mobility), and (b) greater convergence to steady-state years of schooling are observed in countries with higher levels of national income and higher levels of intergenerational mobility.

5.4. Global intergenerational mobility

Our database uniquely allows us to evaluate intergenerational

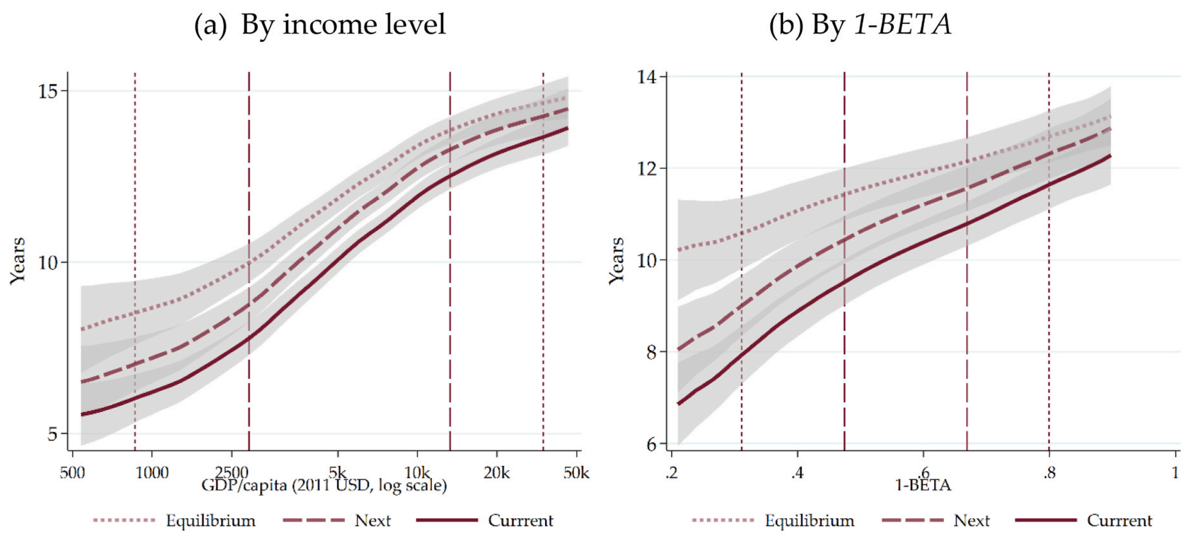

Fig. 9. Steady-state value of years of schooling by income level and mobility, 1980s cohort Note: The dashed lines indicate the 25th and 75th percentile of the distribution of GDP per capita or 1-BETA. The dotted lines indicate the 5th and 95th percentile. We match a cohort with the GDP per capita when the cohort, on average, was about to enter school. For example, the cohort born in the 1980s, we match with the GDP per capita from 1990, at which point the cohort on average was five years old. "Equilibrium" denotes $\overline{\mu}_c$, "Next" denotes μ_{ct+1}, and "Current" denotes μ_{ct}.

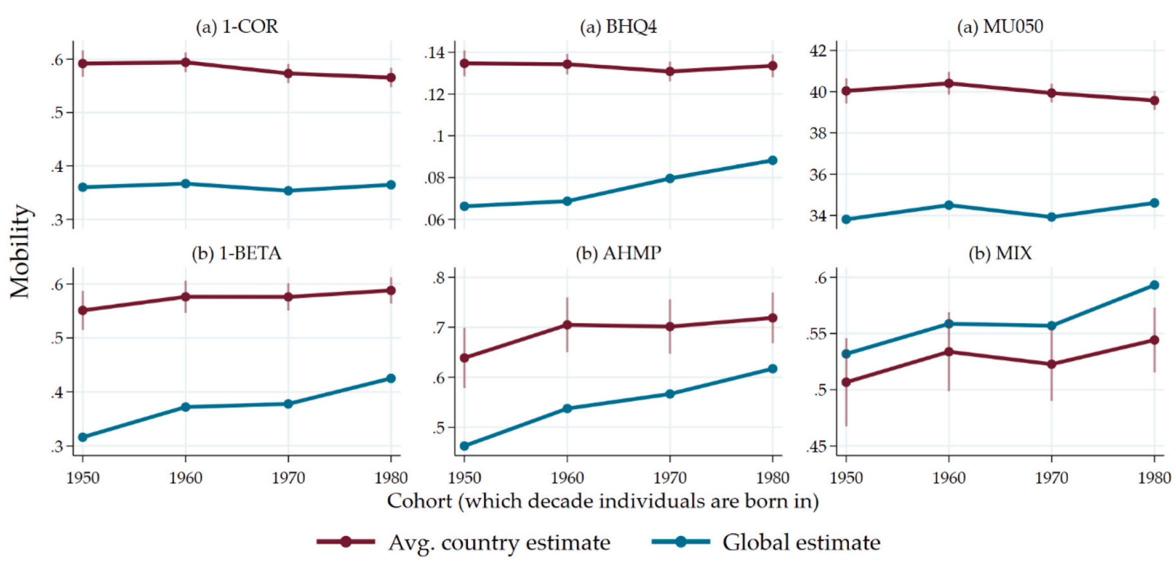

Fig. 10. Intergenerational mobility in the world as a whole *Note*: The red line shows the average mobility estimate per country. The blue line shows intergenerational mobility in the world as a whole (with all country dataset appended and weights rescaled to match country population totals). The vertical bars show 95th confidence intervals. These confidence intervals do not account for the uncertainty of the country-level estimates themselves.

mobility for the world as a whole. Concretely, to calculate global intergenerational mobility, we append all country datasets and rescale the survey weights such that the weight of each cohort in each country sums to the population count of the country at the time the cohort was born. We ignore countries not covered by our database (which amount to about 13% of the global population for the cohort analysis). This allows us to compute all six measures of mobility by treating the world as one large country. Fig. 10 plots our estimates of global intergenerational mobility for the cohorts ranging from the 1950s to the 1980s and compares these against average national mobility (averaged over all 114 countries in our database with retrospective data).

Two empirical observations stand out. First, the world as a whole is less mobile than the average country in it. This is perhaps not surprising and consistent with the fact that individual educational success is determined by private investments (shaped by parental background) and public investments (shaped by the country in which the individual obtained his/her education): Global intergenerational mobility captures both parental and country effects, whereas mobility evaluated at the national level captures parental effects (and neighborhood effects) but not country effects (which are absorbed by the intercept from the intergenerational transmission regression).[20] Second, we observe a modest upward trend in global mobility measured by inequality-sensitive indicators, while global mobility measured by inequality-invariant indicators is more stagnant. This empirical pattern is perhaps more surprising, yet consistent with a decline in global

[20] Note that assume here that the country of residence at the time the survey was conducted is the country in which the individual went to school.

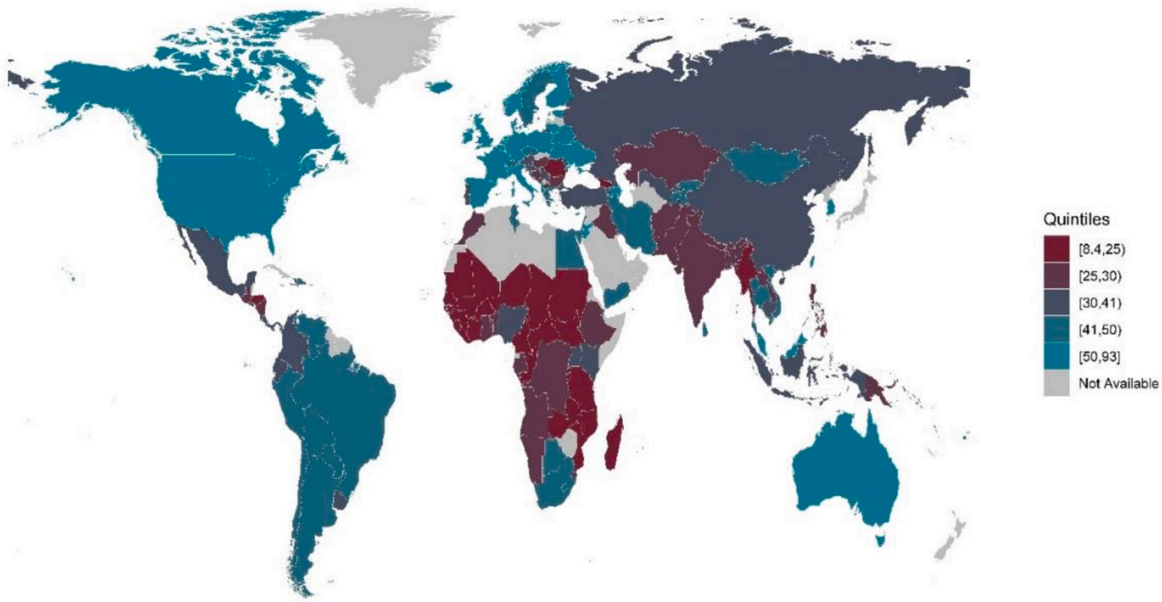

Fig. 11. Expected global rank of individuals born to bottom half of global distribution, 80s cohort *Note*: The map shows a version of the *MU050* measure that evaluates for each country the expected rank in the global distribution of respondents born to parents in the bottom half of the global distribution.

inequality over time (and across generations), also observed in e.g., Lakner and Milanovic (2016).

We also calculate a version of the *MU050* measure that evaluates for each country the expected rank in the global distribution of respondents born to parents in the bottom half of the global distribution.[21] Given that the share of parents who are in the bottom half of the global distribution will vary across countries, this measure will not be inequality-invariant (unlike the regular *MU050*, which identifies parents that are in the bottom-half of each national distribution). Fig. 11 shows how intergenerational mobility is distributed across the world by this measure.

Comparing Fig. 11 to the map of *MU050* (Fig. 1) shows that the United States, Central America, and South America rank high when the global distribution of education is used (for both parents and their children) to evaluate the expected rank of individual years of schooling but rank comparatively low when the national distributions are used. The opposite holds true for parts of Sub-Saharan Africa. This re-iterates that country, in addition to parental background, matters a great deal. Individuals whose parents have low levels of education (bottom half of the global distribution) have a greater chance of achieving higher education in countries with greater public resources.

6. Conclusion

A society with high intergenerational mobility in education is one where an individual's educational success is less dependent on the educational success of his or her parents. Governments have a multitude of reasons for stimulating intergenerational mobility. Low mobility may lead to unrealized human potential and a misallocation of resources as talented individuals from disadvantaged families may get excluded from opportunities. Reducing such inefficiency is arguably good for economic growth. Our newly compiled database provides estimates of intergenerational mobility in education for 153 countries representing 97 percent of the world's population. This enables us to paint a global picture of intergenerational mobility.

Our estimates indicate that intergenerational mobility is higher in the average high-income country when compared to the average developing country across all six measures of mobility considered. The relationship between intergenerational mobility and national income is however, not a monotonic one. Intergenerational mobility measured by inequality-invariant indicators is on average highest in both the richest and the poorest countries. We furthermore observe that: (a) children have lower chances of surpassing their parents' education in the world's poorest countries, despite the comparatively low levels of parent education levels in these countries, (b) the world as a whole is notably less mobile than the average country in it, and (c) that improvements in global intergenerational mobility (measured by inequality-invariant indicators) is stagnating.

Why are some countries more intergenerationally mobile than others? Although causally identifying the determinants of intergenerational mobility is beyond the scope of this study, an analysis of the cross-country correlates of intergenerational mobility may shed some first light on this question. This analysis is presented in Appendix D. To the extent possible we evaluate correlates for the time periods during which the children were of school age, which for the most recent cohort means we will be using data for the early 1990s. On average, countries with higher rates of mobility report (a) larger government expenditures (as a share of national income), especially on education, (b) lower levels of income inequality, (c) higher democracy scores and less conflict deaths, (d) higher migration rates, (e) greater ethnic, linguistic, and religious homogeneity, (f) better child health indicators (such as less stunting and wasting), and (g) more teachers per pupil and less school dropouts. While these correlations provide several interesting hypotheses about the candidate drivers of intergenerational mobility, more work is needed to test these hypotheses. For a comprehensive review of earlier work focusing on the role of family background and public policies, see Bjorklund and Salvanes (2011).

Probing the non-monotonic relationship between intergenerational mobility and national income levels may provide another avenue for future research. At this point we can only speculate as to the underlying mechanisms. One candidate mechanism, which we hope to explore in future work, is the following. In the world's poorest countries, a large majority of parents have no education. While parents' human capital

[21] For six country-cohort combinations, there are not enough parents in the bottom half of the global distribution to reliably compute this measure; this concerns Japan in the 1950s and 1960s, Canada in 1950s, Slovakia in 1960s, Azerbaijan in 1980s, and Bulgaria in 1970s.

presumably still differs in ways unobserved in surveys, the variation is arguably lower when compared to higher levels of development. This makes parent education a relatively weak predictor of child educational success, indicating a high level of mobility. As countries increase their education and income levels, the gaps between parents become more pronounced. Children's education trajectories may eventually start to diverge depending on whether they are born into a poor, middle-class or upper-class family, which would correspond to a decline in intergenerational mobility.[22] We hypothesize that further increases in national income can reverse this trend and increase intergenerational mobility levels when countries invest a share of the higher national incomes into public interventions that will partially compensate for inequalities in private investments.[23] Naturally, differences between low-income and high-income countries go beyond differences in public interventions. More work is needed to evaluate how much of the divergence in intergenerational mobility between the developed world and the developing world can be attributed to differences in public interventions versus other factors.

Finally, future work could probe whether the comparatively high levels of mobility observed among some of the poorest countries may in part stem from unobserved variation between families. There are possibly large opportunity gaps in developing countries between families, even among those with zero education. The most disadvantaged children will grow up malnourished in remote places that offer little access to quality education with lifelong consequences; while other children with similar (observed) parental education background may grow up in conditions that allow for better health outcomes and improved access to education. If that is indeed the case, then mobility could well be lower in these poor countries. New data that provide better variation will be needed to test this.

Author statement

No need to specify credits by author.
(All authors made contributions to all components of the paper.)

Data availability

Our database is publicly available at https://datacatalog.worldbank.org/search/dataset/0050771/Global-Database-on-Intergenerational-Mobility

Appendix E. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2023.103167.

Appendix A. Information on data used

Table A.1
Surveys used

Region	Survey	Sample
East Asia & Pacific		
Cambodia	CSES (2012)	Co-residents only
China	CFPS (2012)	Full sample
Fiji	HIES (2008)	Co-residents only
Indonesia	IFLS (2014)	Full sample
Kiribati	HIES (2006)	Co-residents only
Lao PDR	STEP (2012)	Full sample
Malaysia	KMS (2015)	Full sample
Mongolia	LITS (2016)	Full sample
Myanmar	MPLCS (2015)	Co-residents only
Papua New Guinea	HIES (2009)	Co-residents only
Philippines	ISSP (1999), FIES (2012)	Full sample until 1980s, co-residents only for 1980s
Solomon Islands	HIES (2013)	Co-residents only
Thailand	SES (2012)	Co-residents only
Timor-Leste	LSMS (2007)	Full sample
Tonga	HIES (2009)	Co-residents only
Tuvalu	HIES (2010)	Co-residents only
Vanuatu	HIES (2010)	Co-residents only
Vietnam	STEP (2012)	Full sample
Europe & Central Asia		
Albania	LITS (2016)	Full sample
Armenia	LITS (2016)	Full sample
Azerbaijan	LITS (2016)	Full sample
Belarus	LITS (2016)	Full sample
Bosnia and Herzegovina	LITS (2016)	Full sample
Bulgaria	ESS (2012)	Full sample
Georgia	LITS (2016)	Full sample
Kazakhstan	LITS (2016)	Full sample
Kosovo	LITS (2016)	Full sample
Kyrgyz Republic	LITS (2016)	Full sample
Moldova	LITS (2016)	Full sample
Montenegro	LITS (2016)	Full sample
North Macedonia	LITS (2016)	Full sample
Romania	LITS (2016)	Full sample

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[22] For example, this is the case in Brazil, which exhibits a high degree of dualism between private and public education (Cogneau and Gignoux, 2009).
[23] This explanation and the U-curve in general has parallels to Kuznets' model of dualism and the inverse U-curve of inequality (Kuznets, 1955).

Table A.1 (*continued*)

Region	Survey	Sample
Russian Federation	ESS (2016)	Full sample
Serbia	LITS (2016)	Full sample
Tajikistan	LITS (2016)	Full sample
Turkey	LITS (2016)	Full sample
Ukraine	ESS (2012)	Full sample
Uzbekistan	LITS (2016)	Full sample
Latin America & Caribbean		
Argentina	LATINOBAROMETRO (2017)	Full sample
Bolivia	EH (2008)	Full sample
Brazil	PNAD (2014)	Full sample
Colombia	ENCV (2013)	Full sample
Costa Rica	LATINOBAROMETRO (2017)	Full sample
Dominican Republic	LATINOBAROMETRO (2017)	Full sample
Ecuador	ECV (2013)	Full sample
El Salvador	LATINOBAROMETRO (2017)	Full sample
Guatemala	ENCOVI (2014)	Full sample
Haiti	ECVMAS (2012)	Co-residents only
Honduras	LATINOBAROMETRO (2017)	Full sample
Mexico	EMOVI (2011)	Full sample
Nicaragua	LATINOBAROMETRO (2017)	Full sample
Paraguay	LATINOBAROMETRO (2017)	Full sample
Peru	ENAHO (2014)	Full sample
Venezuela, RB	LATINOBAROMETRO (2017)	Full sample
Middle East & North Africa		
Djibouti	EDAM (2017)	Full sample
Egypt, Arab Rep.	ELMPS (2012)	Full sample
Iran, Islamic Rep.	HEIS (2014)	Co-residents only
Iraq	IHSES (2012)	Full sample
Jordan	JLMPS (2010)	Full sample
Lebanon	HBS (2011)	Co-residents only
Morocco	ENNVM (2006)	Full sample
Tunisia	TLMPS (2014)	Full sample
West Bank and Gaza	PECS (2011)	Co-residents only
Yemen, Rep.	HBS (2014)	Co-residents only
South Asia		
Afghanistan	NRVA (2011)	Co-residents only
Bangladesh	HIES (2010)	Co-residents only
Bhutan	LSS (2003)	Full sample
India	IHDS (2011)	Full sample
Maldives	HIES (2009)	Co-residents only
Nepal	LSS (2011)	Full sample
Pakistan	IHS (1991), PIHS (2013)	Full sample until 1980s, co-residents only for 1980s
Sri Lanka	STEP (2012)	Full sample
Sub-Saharan Africa		
Angola	IBEP-MICS (2008)	Co-residents only
Benin	EMICOV (2011)	Full sample
Botswana	BMTHS (2015)	Co-residents only
Burkina Faso	ECVM (2009)	Co-residents only
Burundi	ECVM (2013)	Full sample
Cabo Verde	QUIBB (2007)	Co-residents only
Cameroon	ECAM-III (2007)	Co-residents only
Central African Republic	ECASEB (2008)	Co-residents only
Chad	ECOSIT-III (2011)	Co-residents only
Comoros	EESIC (2014)	Full sample
Congo, Dem. Rep.	E123 (2012)	Full sample
Congo, Rep.	ECOM (2011)	Co-residents only
Côte d'Ivoire	ENV (2008)	Co-residents only
Eswatini	HIES (2009)	Co-residents only
Ethiopia	LSMS-ISA (2013)	Full sample
Gabon	EGEP (2017)	Full sample
Gambia, The	IHS (2015)	Full sample
Ghana	GLSS (2012)	Full sample
Guinea	EIBEP (2002), ELEP (2012)	Full sample until 1980s, co-residents only for 1980s
Guinea-Bissau	ILAP-II (2010)	Co-residents only
Kenya	STEP (2013)	Full sample
Lesotho	HBS (2017)	Co-residents only
Liberia	HIES (2014)	Full sample
Madagascar	ENEMPSI (2012)	Full sample
Malawi	LSMS-ISA (2013)	Full sample
Mali	LSMS-ISA (2014)	Full sample
Mauritania	EPCV (1995), EPCV (2008)	Full sample until 1980s, co-residents only for 1980s
Mauritius	HBS (2012)	Co-residents only
Mozambique	IOF (2008)	Co-residents only
Namibia	NHIES (2015)	Co-residents only
Niger	LSMS-ISA (2014)	Full sample
Nigeria	LSMS-ISA (2012)	Full sample

(*continued on next page*)

Table A.1 (*continued*)

Region	Survey	Sample
Rwanda	EICV (2000), EICV-IV (2013)	Full sample until 1980s, co-residents only for 1980s
Senegal	ESPS-II (2011)	Co-residents only
Sierra Leone	SLIHS (2011)	Co-residents only
South Africa	NIDS (2014)	Full sample
South Sudan	NBHS (2009)	Co-residents only
Sudan	NBHS (2009)	Co-residents only
São Tomé and Principe	IOF (2010)	Co-residents only
Tanzania	LSMS-ISA (2012)	Full sample
Togo	QUIBB (2015)	Full sample
Uganda	LSMS-ISA (2014)	Full sample
Zambia	LCMS-VI (2010)	Co-residents only
High-income economies		
Australia	HILDA (2015)	Full sample
Austria	ESS (2016)	Full sample
Belgium	ESS (2016)	Full sample
Canada	CGSS (2014)	Full sample
Chile	CASEN (2013)	Full sample
Croatia	LITS (2016)	Full sample
Cyprus	ESS (2012)	Full sample
Czech Republic	ESS (2016)	Full sample
Denmark	ESS (2014)	Full sample
Estonia	ESS (2016)	Full sample
Finland	ESS (2016)	Full sample
France	ESS (2016)	Full sample
Germany	ESS (2016)	Full sample
Greece	LITS (2016)	Full sample
Hungary	ESS (2016)	Full sample
Iceland	ESS (2016)	Full sample
Ireland	ESS (2016)	Full sample
Israel	ESS (2016)	Full sample
Italy	LITS (2016)	Full sample
Japan	JGSS (2012)	Full sample
Korea, Rep.	KLIPS (2014)	Full sample
Latvia	LITS (2016)	Full sample
Lithuania	ESS (2016)	Full sample
Netherlands	ESS (2016)	Full sample
New Zealand	ISSP (1999)	Full sample
Norway	ESS (2016)	Full sample
Panama	ENV (2008)	Full sample
Poland	ESS (2016)	Full sample
Portugal	ESS (2016)	Full sample
Slovak Republic	ESS (2012)	Full sample
Slovenia	ESS (2016)	Full sample
Spain	ESS (2016)	Full sample
Sweden	ESS (2016)	Full sample
Switzerland	ESS (2016)	Full sample
Taiwan, China	TSCS (2015)	Full sample
United Kingdom	ESS (2016)	Full sample
United States	PSID (2015)	Full sample
Uruguay	LATINOBAROMETRO (2017)	Full sample

Note: For some social surveys we pool multiple waves. The table lists the year of the last wave used.

Table A.2 contains information on the granularity and missingness of the years of schooling variable for children and their parents. For certain countries, the share of missing parental education information is high as a result of the survey design. For example, the countries for which we rely on a Skills Toward Employment and Productivity (STEP) survey, Kenya, Lao, Sri Lanka, and Vietnam, one adult household member was randomly selected to be the key person analytical unit of the household and is the sole household member for which we have parental educational information. Likewise, for some countries in Latin America, notably Brazil, Chile, Mexico, and Peru, parental education is only recorded for a subset of household members (and for Brazil only for one member per household).

Table A.2
Information on educational outcomes

Region	*Unique outcomes*		*Share with modal outcome (%)*		*Missing mother or father outcome (%)*			*Width of mobility bounds*	
	Children	*Parents*	*Child*	*Parent*	*Full sample*	*child<= primary*	*Child>=upper secondary*	*mu50*	*BHQ4*
East Asia & Pacific									
Cambodia	19	18	12	10	0	0	0	1	0.06
China	8	8	40	46	12	16	7	3	0.12
Fiji	19	16	23	11	0	0	0	1	0.02
Indonesia	19	14	26	40	24	32	15	2	0.09
Kiribati	5	6	45	30	0	0	0	1	0.06
Lao PDR	13	7	34	68	78	78	75	8	0.16
Malaysia	12	11	45	21	29	49	27	1	0.03
Mongolia	8	13	28	26	18	14	19	2	0.02
Myanmar	6	6	37	25	17	21	5	6	0.05
Papua New Guinea	16	15	20	20	0	0	0	4	0.02
Philippines	16	6	26	21	0	0	0	0	0.06
Solomon Islands	6	6	26	15	20	19	26	1	0.04
Thailand	19	19	23	30	0	0	0	1	0.02
Timor-Leste	17	14	56	91	0	0	0	22	0.26
Tonga	6	6	69	45	1	0	0	5	0.08
Tuvalu	6	6	78	17	13	17	0	0	0.09
Vanuatu	6	5	41	38	7	5	16	7	0.04
Vietnam	14	8	25	25	74	81	70	2	0.03
Europe & Central Asia									
Albania	8	16	36	28	7	11	6	3	0.03
Armenia	8	16	28	22	13	35	8	2	0.04
Azerbaijan	8	15	44	34	18	65	15	2	0.08
Belarus	8	17	38	21	22	45	22	0	0.14
Bosnia and Herzegovina	9	14	36	23	11	22	8	1	0.04
Bulgaria	21	8	29	39	5	20	2	5	0.08
Georgia	8	18	35	19	14	31	12	1	0.04
Kazakhstan	7	16	47	21	20	46	19	1	0.04
Kosovo	8	14	33	27	7	11	5	1	0.06
Kyrgyz Republic	7	17	44	32	5	19	4	1	0.07
Moldova	7	16	38	22	21	46	12	1	0.06
Montenegro	8	12	43	29	12	25	10	3	0.05
North Macedonia	8	14	34	30	5	9	3	2	0.05
Romania	8	16	30	25	15	25	12	1	0.07
Russian Federation	17	8	21	21	23	39	20	1	0.06
Serbia	8	16	41	26	7	15	4	1	0.07
Tajikistan	8	16	44	17	16	47	14	3	0.07
Turkey	8	12	41	44	7	12	3	4	0.07
Ukraine	18	9	18	16	12	31	11	1	0.07
Uzbekistan	7	17	51	28	17	79	14	2	0.05
Latin America & Caribbean									
Argentina	16	16	30	40	9	14	6	1	0.02
Bolivia	21	17	22	38	17	23	13	3	0.07
Brazil	18	7	27	50	88	89	87	3	0.1
Colombia	21	18	23	22	21	30	12	1	0.03
Costa Rica	16	15	32	43	14	16	11	1	0.07
Dominican Republic	16	15	26	50	26	32	15	1	0.08
Ecuador	21	18	26	40	15	21	8	4	0.06
El Salvador	16	15	26	62	12	13	11	3	0.11
Guatemala	20	13	35	64	7	8	5	6	0.12
Haiti	17	16	11	36	0	1	0	0	0.08
Honduras	15	14	37	60	9	9	7	2	0.07
Mexico	21	19	27	41	45	52	38	0	0.04
Nicaragua	15	14	33	62	11	12	8	2	0.11
Paraguay	16	16	25	29	15	19	10	1	0.02
Peru	19	8	26	26	71	67	74	2	0.04
Venezuela, RB	16	16	29	40	15	22	12	1	0.03
Middle East & North Africa									
Djibouti	15	6	73	91	7	7	9	7	0.21
Egypt, Arab Rep.	21	7	34	76	0	0	0	12	0.17
Iran, Islamic Rep.	4	4	44	19	0	0	0	1	0.02
Iraq	10	10	46	79	0	0	0	11	0.2
Jordan	21	7	23	52	0	0	0	3	0.1
Lebanon	16	17	17	11	0	0	0	2	0.02
Morocco	5	6	50	79	5	6	4	7	0.2
Tunisia	20	6	35	74	8	7	9	10	0.17
West Bank and Gaza	21	21	22	6	0	0	0	0	0.04
Yemen, Rep.	20	21	23	57	0	0	0	1	0.07
South Asia									
Afghanistan	19	20	64	60	2	1	3	2	0.09
Bangladesh	17	16	25	46	0	0	0	1	0.09
Bhutan	20	14	75	91	0	0	1	8	0.2

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Table A.2 (*continued*)

Region	*Unique outcomes*		*Share with modal outcome (%)*		*Missing mother or father outcome (%)*			*Width of mobility bounds*	
	Children	*Parents*	*Child*	*Parent*	*Full sample*	*child<= primary*	*Child>=upper secondary*	*mu50*	*BHQ4*
India	17	17	40	55	31	37	21	2	0.1
Maldives	14	12	36	69	4	7	7	0	0.18
Nepal	14	14	60	69	4	4	3	4	0.13
Pakistan	18	17	33	40	0	0	1	0	0.02
Sri Lanka	16	8	26	24	72	79	66	2	0.06
Sub-Saharan Africa									
Angola	17	17	16	12	0	0	0	0	0.01
Benin	21	20	65	88	3	3	6	12	0.22
Botswana	18	18	35	18	2	0	6	1	0.04
Burkina Faso	17	15	69	76	2	1	13	4	0.14
Burundi	19	16	66	81	52	53	41	1	0.14
Cabo Verde	19	15	19	25	0	0	0	0	0.08
Cameroon	19	19	19	26	0	0	0	0	0.09
Central African Republic	15	17	38	20	6	2	20	0	0.06
Chad	7	7	66	72	2	1	10	7	0.17
Comoros	20	17	58	81	69	70	58	3	0.17
Congo, Dem. Rep.	21	21	31	40	7	6	8	0	0.04
Congo, Rep.	15	15	18	9	1	0	2	0	0.09
Côte d'Ivoire	7	7	48	51	2	2	3	0	0.11
Eswatini	19	16	21	19	0	0	0	0	0.03
Ethiopia	17	14	68	83	9	8	6	7	0.19
Gabon	21	11	27	65	35	34	34	5	0.16
Gambia, The	19	15	74	94	3	2	6	30	0.25
Ghana	18	17	33	65	9	7	8	3	0.11
Guinea	6	6	62	67	1	0	3	4	0.11
Guinea-Bissau	15	15	50	57	0	0	0	2	0.09
Kenya	19	7	30	34	56	60	57	6	0.15
Lesotho	19	17	18	7	1	0	3	4	0.05
Liberia	21	11	49	70	4	4	3	3	0.09
Madagascar	21	21	24	32	5	5	3	0	0.03
Malawi	18	13	32	84	13	11	19	9	0.22
Mali	17	12	84	87	13	14	11	7	0.21
Mauritania	17	7	73	58	0	0	0	2	0.11
Mauritius	21	21	31	8	0	0	0	0	0.08
Mozambique	18	16	25	18	1	1	0	1	0.03
Namibia	20	20	25	11	13	12	3	3	0.05
Niger	20	12	62	94	9	9	13	18	0.22
Nigeria	18	17	36	52	4	3	6	1	0.07
Rwanda	18	17	15	15	0	0	0	0	0.01
Senegal	18	19	54	63	1	2	0	1	0.12
Sierra Leone	7	7	54	64	2	1	2	2	0.09
South Africa	18	18	20	44	19	17	17	1	0.03
South Sudan	13	13	83	81	2	2	33	8	0.22
Sudan	14	13	58	60	12	11	13	4	0.12
São Tomé and Principe	15	13	18	12	0	0	0	0	0.01
Tanzania	18	11	51	53	10	11	7	5	0.1
Togo	16	15	49	81	10	10	12	9	0.16
Uganda	16	9	24	72	45	46	45	8	0.16
Zambia	16	17	21	7	2	2	1	0	0.08
High-income economies									
Australia	13	6	35	26	14	34	10	2	0.03
Austria	18	7	24	30	7	21	5	5	0.06
Belgium	21	9	18	22	13	15	11	2	0.03
Canada	8	8	27	21	24		20	1	0.02
Chile	21	21	29	16	49	54	47	0	0.01
Croatia	9	15	44	27	8	10	7	2	0.04
Cyprus	18	7	36	32	2	5	1	3	0.05
Czech Republic	19	9	32	45	6	10	6	4	0.08
Denmark	21	8	15	26	5	7	3	1	0.05
Estonia	18	9	18	21	16	35	14	1	0.03
Finland	17	8	14	29	6	8	5	2	0.04
France	20	9	14	40	18	25	16	4	0.06
Germany	19	8	19	34	16	40	13	5	0.06
Greece	8	7	44	46	1	1	1	4	0.07
Hungary	20	8	23	34	32	40	30	6	0.07
Iceland	18	9	14	22	5	10	4	1	0.05
Ireland	19	9	14	26	13	12	12	1	0.03
Israel	20	9	34	23	20	15	19	1	0.03
Italy	8	19	45	26	11	17	9	2	0.05
Japan	7	6	46	38	25	41	22	2	0.04
Korea, Rep.	18	12	38	30	13	16	13	2	0.06
Latvia	8	17	34	14	27	46	24	1	0.04
Lithuania	18	9	22	26	18	33	16	1	0.03

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Table A.2 (*continued*)

Region	*Unique outcomes*		*Share with modal outcome (%)*		*Missing mother or father outcome (%)*			*Width of mobility bounds*	
	Children	*Parents*	*Child*	*Parent*	*Full sample*	*child<= primary*	*Child>=upper secondary*	*mu50*	*BHQ4*
Netherlands	20	9	14	31	14	27	10	3	0.06
New Zealand	6	6	36	17	16	29	11	1	0.05
Norway	20	9	13	25	5	7	4	1	0.02
Panama	21	17	24	19	18	20	14	1	0.02
Poland	16	8	25	40	10	29	7	4	0.07
Portugal	21	9	31	50	11	13	7	7	0.14
Slovak Republic	18	9	30	48	5	28	5	6	0.08
Slovenia	20	8	24	33	8	25	6	3	0.06
Spain	20	9	14	37	7	9	5	3	0.08
Sweden	19	9	17	20	13	17	12	1	0.04
Switzerland	19	9	33	23	9	12	8	3	0.03
Taiwan, China	19	9	39	34	10	18	7	4	0.07
United Kingdom	21	9	20	48	31	27	30	2	0.1
United States	19	18	30	23	12	44	10	1	0.03
Uruguay	16	16	24	45	11	17	7	1	0.04

Note: The statistics are based on the full samples, i.e. they average over the cohorts used in the analysis. For surveys that rely on co-residents, missingness is evaluated only for co-residents aged 21–25. For the countries where we rely on both a survey for retrospective data before the 1980s, and a survey with co-residents for the 1980s cohort, only the co-resident survey is used. For Benin and Congo, Dem. Rep. the table shows missingness for fathers' education, as these countries do not have data on mothers' education.

Appendix B. Testing for co-residence bias

We can use surveys with retrospective data on parental education to quantify the magnitude of the co-residency bias by estimating mobility with and without only relying on co-residents. Figure B.1 compares mean years of schooling for co-residents aged 21–25 against estimates for all respondents aged 21–25, and the same for mean years of schooling of parents. Mean years of schooling of co-residents and the parents of co-residents are slightly higher than mean years of schooling of all respondents and parents of all respondents. Figure B.2 compares the mobility estimates based on the sample of co-residents aged 21–25 and the sample of all respondents aged 21–25. For the inequality-invariant measures, there appears to be little systematic difference between the estimates from the two samples. For the inequality-sensitive measures, there is some evidence of mobility estimates being a bit larger for the co-resident samples. Still, the two estimates appear highly correlated, and the size of the bias does not seem to be large enough to generate notable re-rankings.

The sample of countries for which we rely on co-residents tends to be less developed than the countries for which we can do this test. For the countries where we rely on co-residents, we can still compare mean years of schooling of co-residents aged 21–25 and the entire sample aged 21–25 (Figure B.1a, grey dots). For these countries, the difference between years of schooling of only co-residents and the entire sample is smaller, compared to the countries for which we rely on retrospective questions. In particular, for countries with less than 12 years of schooling on average, the countries where we use only co-residents on average have 0.75 difference in means years of schooling from the full sample, while for the countries where we rely on retrospective data the difference is 1 year of schooling. This suggests that if we were able to produce Figure B.2 for the countries where we rely on co-residents only, the observed differences may have been smaller.

In Figure B.3, we plot our main mobility estimates for the 1980s cohort (including co-residents) against estimates where we exclusively rely on 18-year-olds and top-code education at secondary school. Under this specification, mobility is generally higher, essentially because we artificially are removing inequalities at the top. For the *MIX* measure, though, mobility goes down because no individuals now have completed tertiary. The only measure that is little impacted by the specification is *AHMP*. This makes sense, as nearly everyone who will complete primary will have done so by age 18. The fact that the results change notably with a lower age group suggests that we should not let our co-resident age group start lower than age 21.

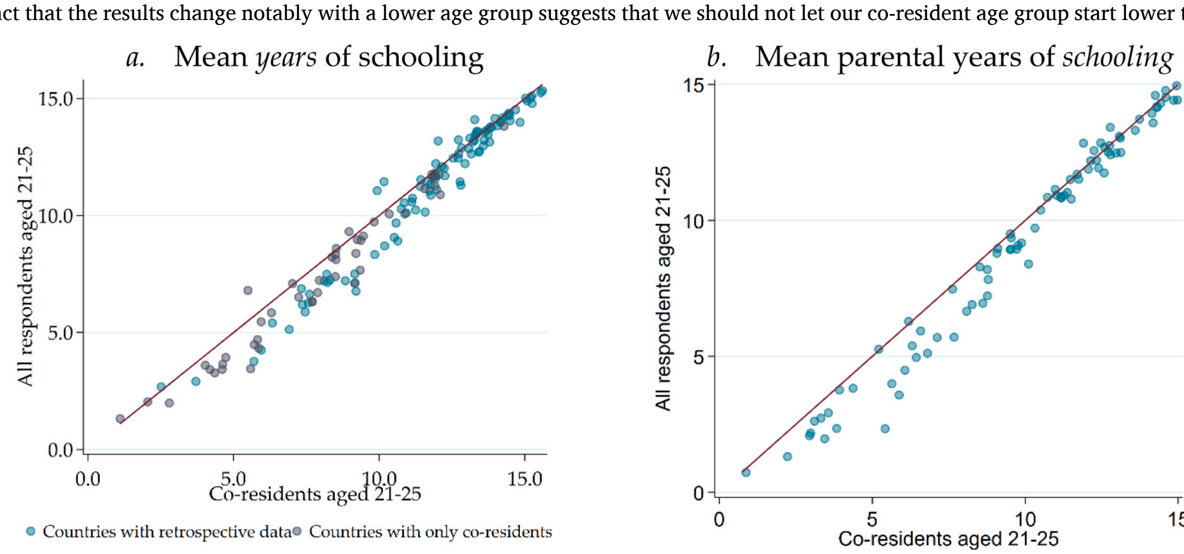

Fig. B.1. Comparing co-residents (aged 21–25) with all respondents (aged 21–25) *Note:* The figures show country-level estimates of mean years of schooling for all respondents aged 21–25 and for respondents aged 21–25 who reside with both of their parents. Panel b reports max parental schooling. The red lines are 45-degree lines.

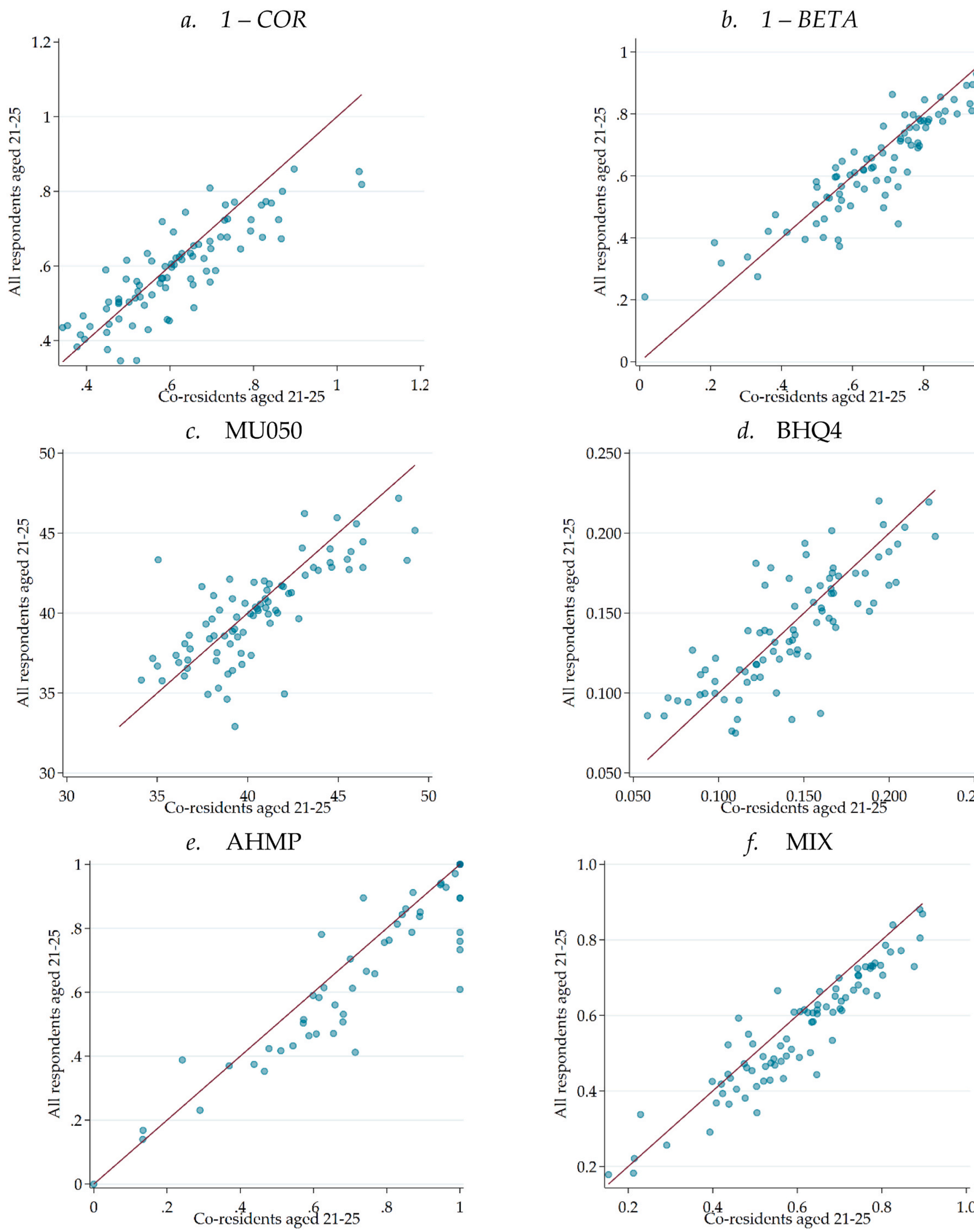

Fig. B.2. Comparing co-residents (aged 21–25) with all respondents (aged 21–25) *Note:* The figures show country-level estimates of intergenerational mobility for all respondents aged 21–25 and for respondents aged 21–25 who reside with both of their parents. Only surveys that include retrospective questions on parental education are included. The red lines are 45-degree lines. For some high-income countries, there are few respondents whose parents have less than primary, particularly if we restrict the sample to co-residents, resulting in cases where all children are coded as mobile according to the *AHMP* measure.

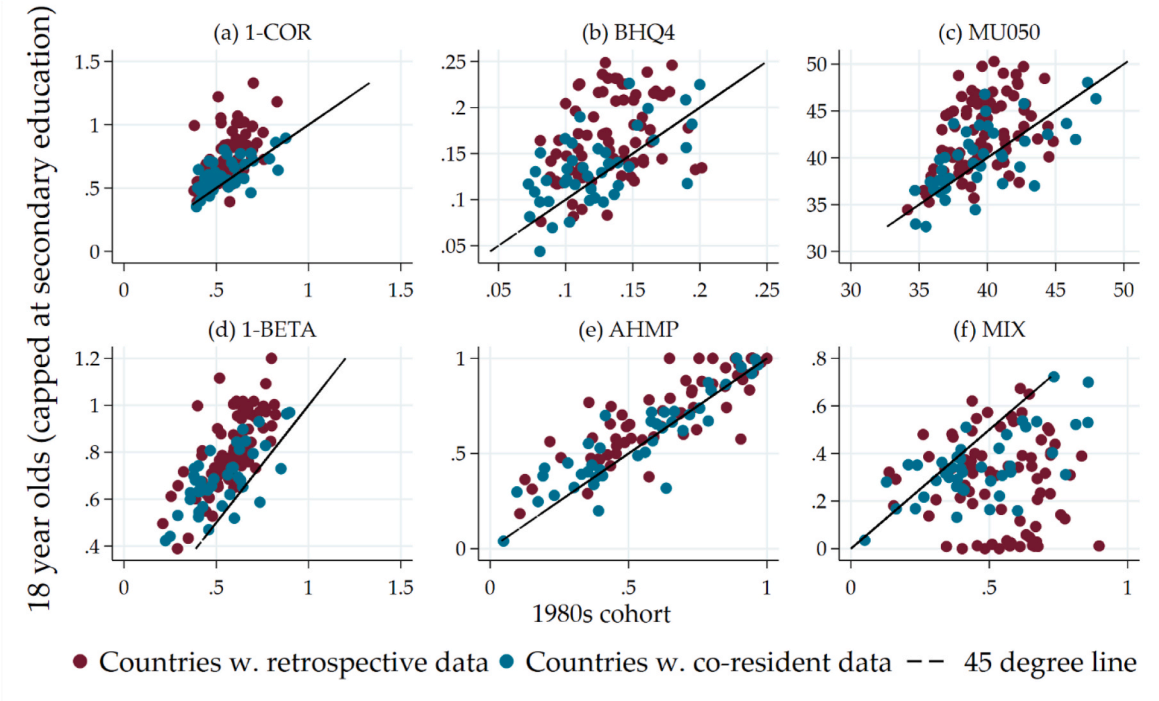

Fig. B.3. Estimates using only 18-year-olds with education top-coded at secondary *Note:* The estimates called the 1980s cohort are from our main specification. For countries with retrospective data, they are based on all respondents born in the 1980s. For the countries with co-resident data, they are based on respondents aged 21–25. These estimates are plotted against estimates based only on 18-year-olds where education is top-coded at upper secondary school.

Appendix C. Additional graphs and tables

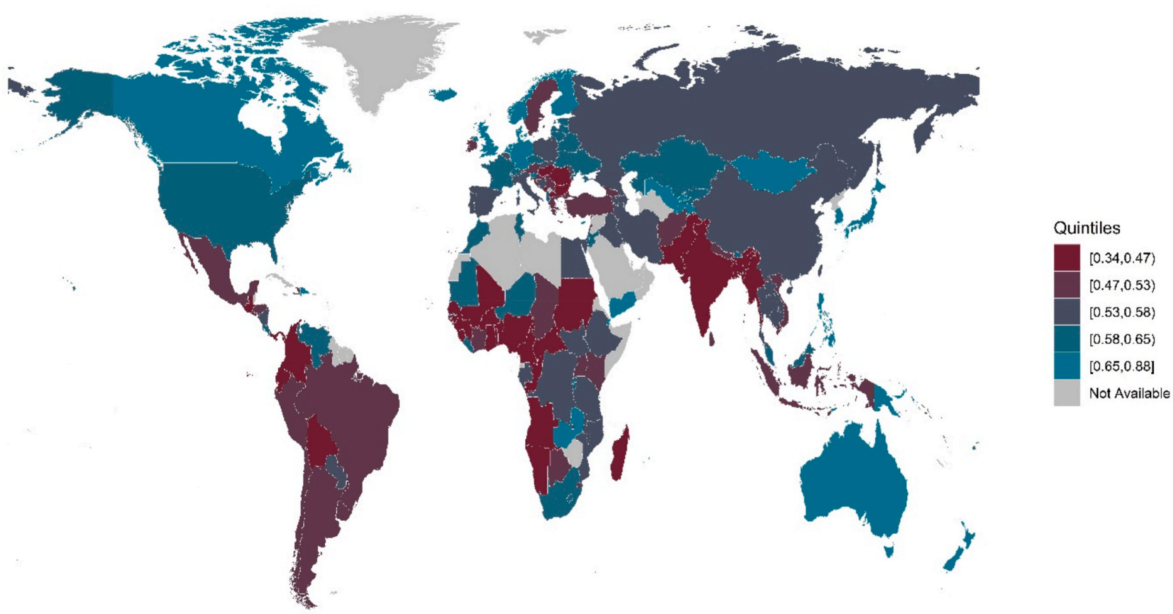

Fig. C.1. Intergenerational mobility (*1-COR*) around the world (1980s cohort) *Note:* The map shows country-level estimates of *1-COR* for individuals born in the 1980s. Countries are classified according to quintiles of the mobility measure. A higher value indicates greater mobility.

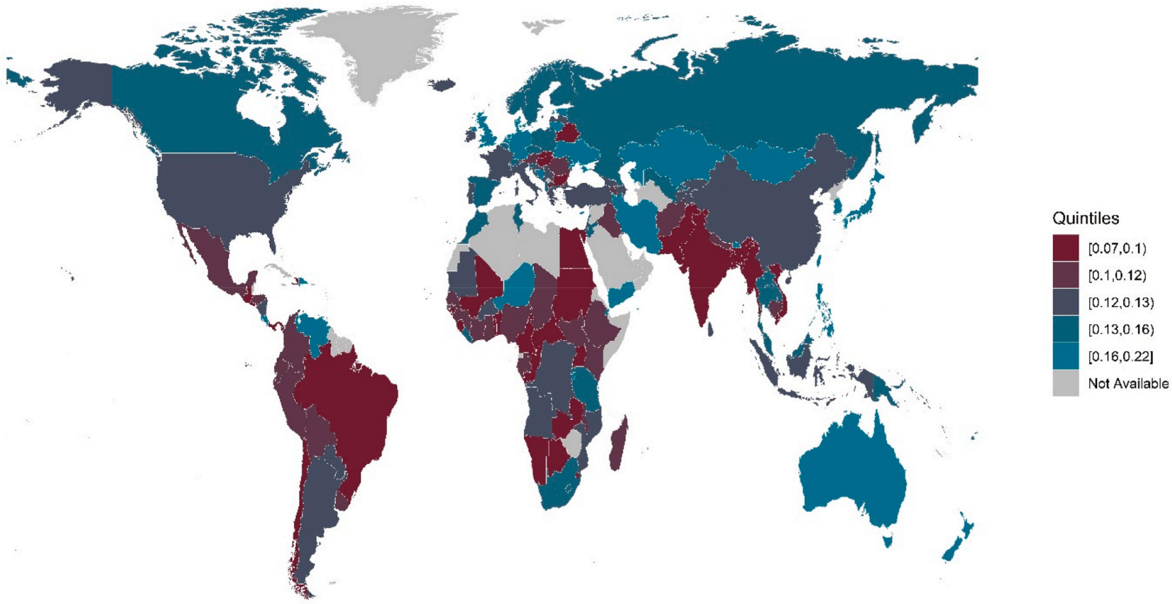

Fig. C.2. Intergenerational mobility (*BHQ4*) around the world (1980s cohort) *Note:* The map shows country-level estimates of *BHQ4* for individuals born in the 1980s. Countries are classified according to quintiles of the mobility measure. A higher value indicates greater mobility.

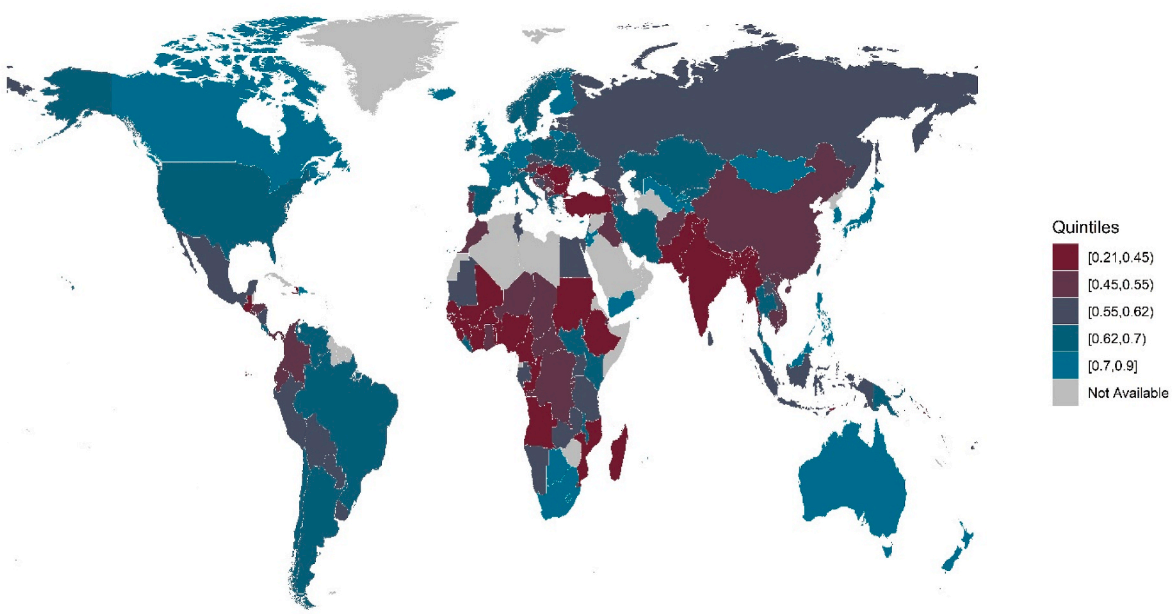

Fig. C.3. Intergenerational mobility (1-BETA) around the world (1980s cohort) *Note:* The map shows country-level estimates of 1-BETA for individuals born in the 1980s. Countries are classified according to quintiles of the mobility measure. A higher value indicates greater mobility.

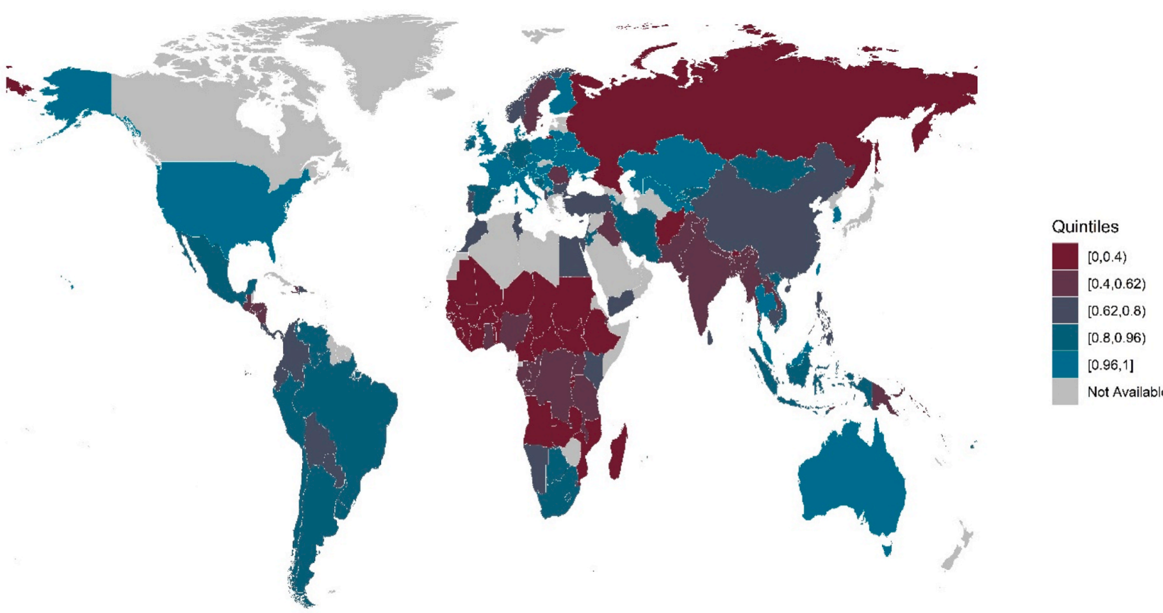

Fig. C.4. Intergenerational mobility (*AHMP*) around the world (1980s cohort) *Note:* The map shows country-level estimates of *AHMP* for individuals born in the 1980s. Countries are classified according to quintiles of the mobility measure. A higher value indicates greater mobility. This measure cannot be calculated for all countries due to absence of parents without primary education in the sample. This concerns 10 countries including Canada and Japan.

Table C.1
Regressions of mobility on polynomial of log GDP/capita

	Inequality-invariant			Inequality-sensitive		
	1-COR	*BHQ4*	*MU050*	1-BETA	*AHMP*	*MIX*
ln(GDP/capita)	−0.436***	−0.104***	−12.705***	−0.205	0.854***	0.524***
	(0.103)	(0.029)	(2.808)	(0.14)	(0.245)	(0.176)
ln(GDP/capita)^2	0.061***	0.015***	1.649***	0.047**	−0.058*	−0.041*
	(0.014)	(0.004)	(0.368)	(0.019)	(0.033)	(0.023)

Note: Each column shows coefficients and standard errors (in parenthesis) from regressing a mobility measure on a second-order polynomial of ln(GDP/capita). We match a cohort with the GDP per capita when the cohort, on average, was about to enter school. For example, the cohort born in the 1980s, we match with the GDP per capita from 1990, at which point the cohort on average was five years old. Standard errors are clustered at the country-level but do not account for the uncertainty of the mobility estimates themselves. P-values less than 0.1, 0.05, and 0.01 are marked with *, **, and ***.

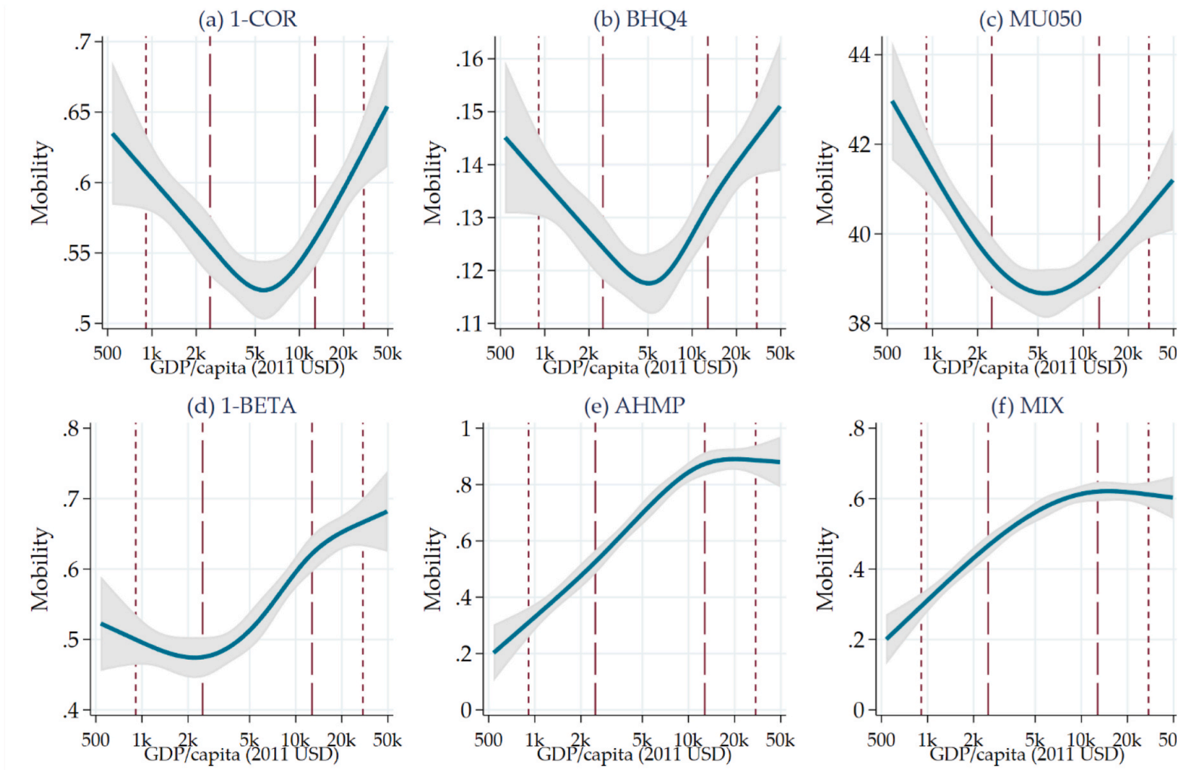

Fig. C.5. Mobility as a function of income when excluding estimates based on co-residents *Note:* The dashed lines indicate the 25th and 75th percentile of the distribution of GDP per capita. The dotted lines indicate the 5th and 95th percentile. GDP data is from the World Development Indicators, supplemented with data from the Maddison project where necessary. We match a cohort with the GDP per capita when the cohort, on average, was about to enter school. For example, the cohort born in the 1980s, we match with the GDP per capita from 1990, at which point the cohort on average was five years old.

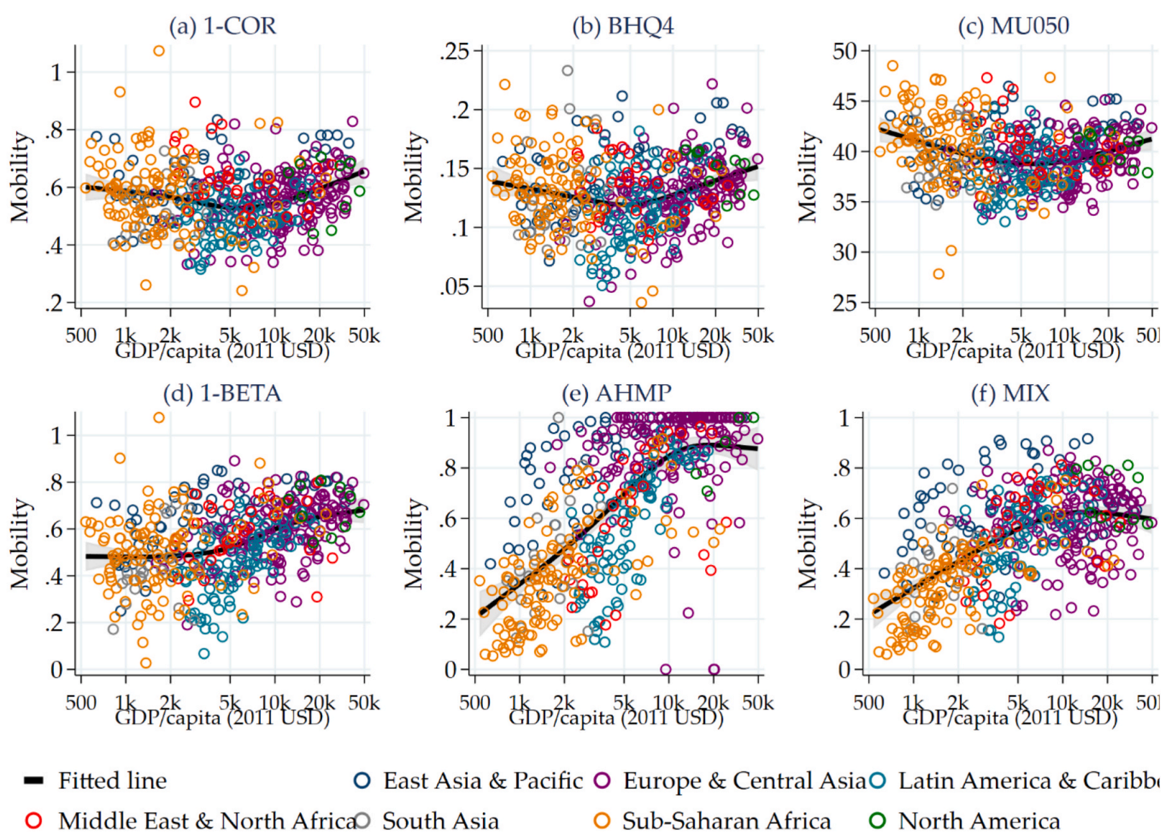

Fig. C.6. Relationship between mobility and GDP per capita *Note:* GDP data is from the World Development Indicators, supplemented with data from the Maddison project where necessary. We match a cohort with the GDP per capita when the cohort, on average, was about to enter school. For example, the cohort born in the 1980s, we match with the GDP per capita from 1990, at which point the cohort on average was five years old.

In the main part of the paper, we categorized countries into high-income and developing based on countries' recent status. Below we see what the results would be if we instead had used a categorization based on countries' income level in the 1950s. Unfortunately, the income classifications we are using did not exist before 1988, so we have constructed what an income classification in the 1950s would have looked like if the 1988 definition is brought backwards. The definition from 1988 is that high-income countries have a GNI per capita greater than 6000 USD. We use data from the Maddison database to calculate the growth rate in real GDP per capita from the 1950s to 1987 (which is the year of the data used in the 1988 classification). We assume that the growth in GNI is identical to growth in GDP, infer countries' average GNI in the 1950s, and categorize countries by whether their real GNI per capita in the 1950s (in 1987 prices) is below or above 6000 USD. With this approach only Australia, Denmark, Great Britain, Luxembourg, the Netherlands, Norway, New Zealand, Sweden, and the United States would be high-income countries in the 1950s. A few countries lack GDP data for some years, in these cases we inspect the data for the years available to judge if they might plausibly belong to the high-income group in the 1950s. Based on this, we add Canada to the list above.

Our main qualitative results remain unchanged when using this classification (Figure C.7): For the 1980s cohort, mobility is greater for high-income countries than developing countries; inequality-invariant mobility has declined for developing countries and increased recently for high-income countries; inequality-sensitive mobility has increased for developing countries and remained flat for high-income countries.

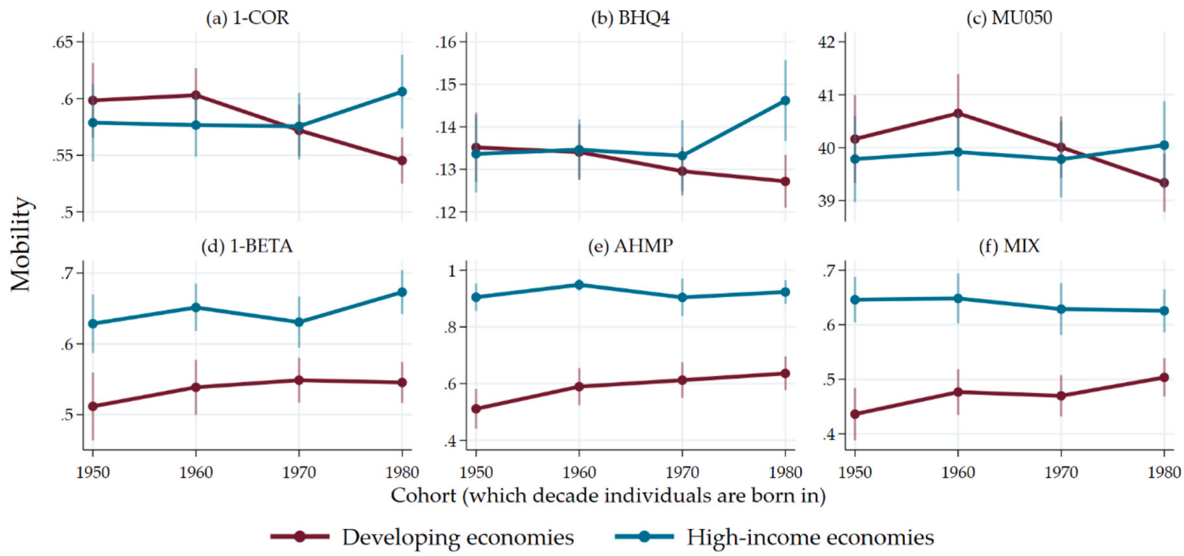

Fig. C.7. Mobility based on an income classification from the 1950s *Note:* The figure shows unweighted averages of intergenerational mobility estimates. Countries are categorized into high-income and developing based on their income level in the 1950s, in contrast to the main text which used the current income classification. The vertical bars show 95th confidence intervals. These confidence intervals do not account for the uncertainty of the country-level estimates themselves.

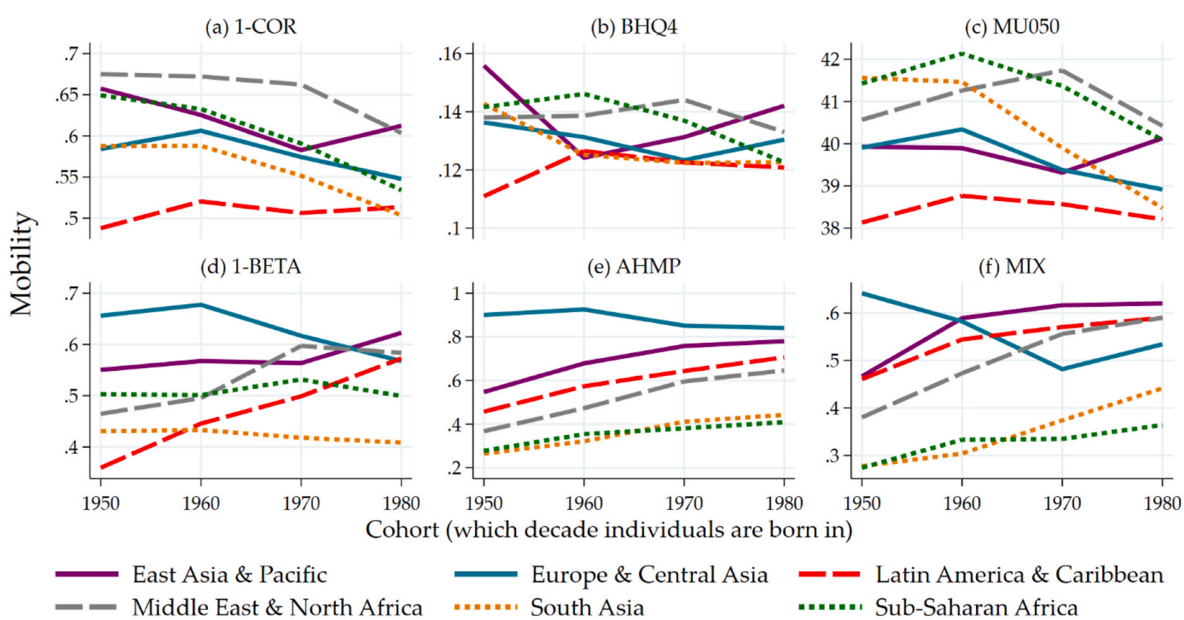

Fig. C.8. Mobility over time by region

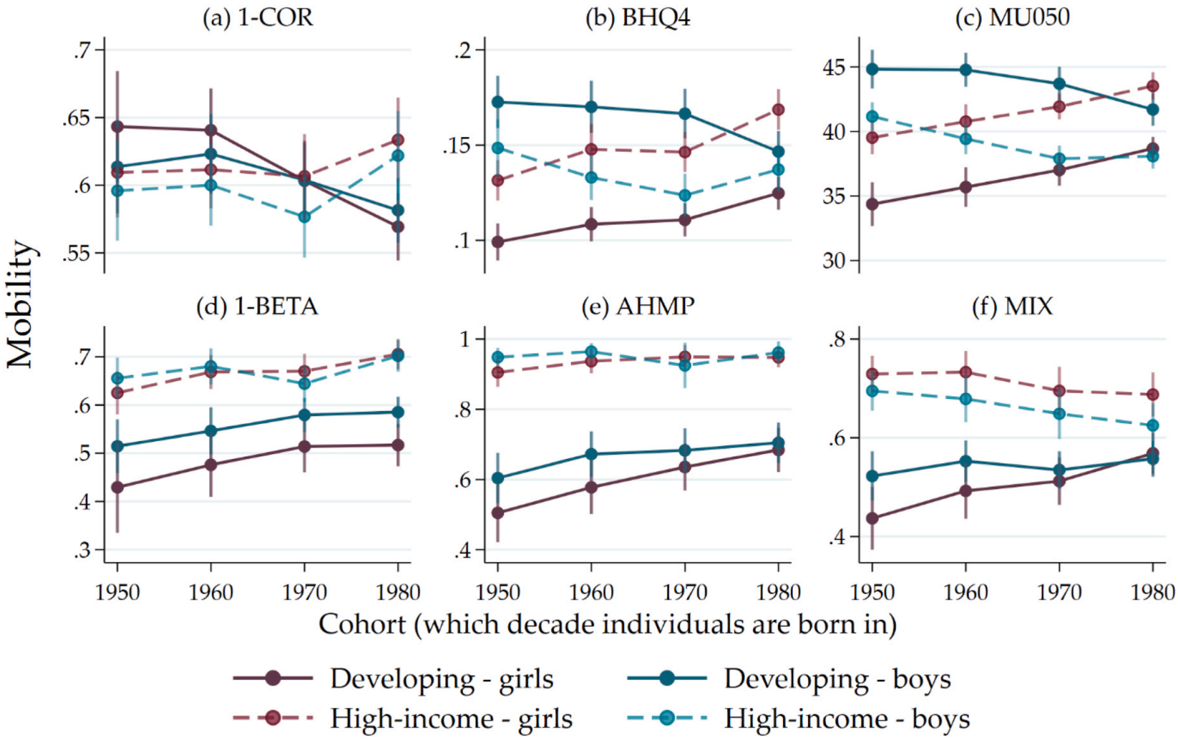

Fig. C.9. Intergenerational mobility from the 1950s to the 1980s cohort by gender *Note*: The figure shows unweighted averages of intergenerational mobility estimates by region. Boys are compared against their fathers and girls are compared against their mothers. The vertical bars show 95th confidence intervals. These confidence intervals do not account for the uncertainty of the country-level estimates themselves.

Appendix D. Correlates of intergeneration mobility

In this appendix we examine factors beyond national income that may correlate with intergenerational mobility. While causally identifying the determinants of intergenerational mobility is beyond the scope of this study, correlating our estimates of intergenerational mobility with a set of salient country characteristics may shed some light on why some countries are more intergenerationally mobile than others. We evaluate the correlates for the time periods during which the children were of school age, which for the most recent cohort means we will be using data for the early 1990s. When relevant, we also provide references to the literature studying the effectiveness of these policies. For a recent and exhaustive review of the empirical literature see e.g. Mogstad and Torsvik (2021), and the references therein.

We consider correlates related to the economy, education, health, labor market, demography, infrastructure, and governance. The selection of correlates is guided by data availability and prior studies, notably Alesina et al. (2021), Asher et al. (2018), and Chetty et al. (2014). Figures D.1 and D.2 plot the coefficients from regressions with intergenerational mobility (standardized to have mean 0 and variance 1) as the dependent variable and a given correlate (also standardized to have mean 0 and variance 1) as the independent variable. Figures D.3 and D.4 add country fixed effects. Following the above-mentioned studies, we focus on the results obtained without fixed effects. Overall, fixed effects reduce the significance of the results (which is not surprising given that temporal variation is limited in some of the regressors), but generally does not affect the sign of significant effects.

We hypothesize that public interventions are a plausible channel through which intergenerational mobility increases as countries become richer. The success with which public spending may shape a positive relationship between intergenerational mobility and national income will presumably depend on the magnitude of public spending relative to private spending and on how governments allocate their public investments.[24] Public investments that try to equalize opportunities for poor children include policies to promote public school quality, education subsidies, and campaigns to improve aspirations of disadvantaged youth. This would reduce the importance of parental background in determining an individual's human capital (Kearney and Levine, 2016; Lee and Seshadri, 2019). Public interventions are found to be most effective when they focus on early childhood (Restuccia and Urrutia, 2004; Herrington, 2015; Blankenau and Youderian, 2015; Lee and Seshadri, 2019). The more resources the government dedicates to leveling the playing field, the larger the positive effect on intergenerational mobility will be.[25]

Beyond a country's national income, we identify four groups of factors that are significantly correlated with intergenerational mobility. First, lower

[24] It will also depend on a host of other factors, such as the degree to which intergenerational persistence is due to nature versus nurture. The former – where persistence can be explained by genetics – is more challenging to overcome by means of public policies. Black et al. (2020) find that for adopted children in Sweden, educational attainment is more related to the years of schooling of their biological parents rather than their adoptive parents, suggesting that nature plays an important role.

[25] What may matter more than overall spending is the extent to which investments produce key inputs into improving access to and quality of education. The existing literature observes that public interventions are more likely to increase mobility when: (a) public investments are sufficiently large (Iyigun, 1999), (b) are targeted to benefit disadvantaged families/neighborhoods (Mayer and Lopoo, 2008; Herrington, 2015; Blankenau and Youderian, 2015), (c) focus on early childhood (Herrington, 2015; Blankenau and Youderian, 2015; Millan et al., 2020), and (d) when political power is not captured by the elites unless the rich have the interests of the poor at heart (Anderson et al., 2015; Uchida, 2017).

income inequality and a larger government are associated with greater mobility. Higher tax revenue as a share of GDP is significantly associated with greater mobility in five out of the six mobility measures, government expenditure as a share of GDP is associated with higher mobility in five of the six measures, government expenditure on education as a share of GDP is associated with higher mobility in all six measures, and a lower Gini coefficient is associated with greater mobility in four of the six measures. Log GDP/capita is associated with higher mobility in all inequality-sensitive measures but none of the inequality-invariant measures. As we have shown in the main text, inequality-sensitive measures of mobility exhibit a U-pattern relationship with log GDP/capita.

The positive association between tax revenue and expenditure with mobility is consistent with other studies in the literature. Azomahou and Yitbarek (2021), in their empirical study of nine countries from Sub-Saharan Africa, observe a strong positive relationship between redistributive policies and intergenerational mobility. Holter (2015) similarly observes a strong positive cross-country correlation between intergenerational mobility and measures of tax progressivity and level. Using data for Mexico's PROGRESA/Oportunidades conditional cash transfer program, Behrman et al. (2011) find that the human capital investments linked to public transfers (targeting the poor) have long-lasting positive effects on schooling and intergenerational mobility in education. Public investments in education that target children from poorer families may furthermore achieve a multiplier effect as these interventions help make these children better future parents and thereby improve the educational and employment outcomes of their children (Devereux 2019).

The second group of factors shown in Figure D.1 to D.4 relate to education and health. These indicators are correlated with inequality-sensitive mobility but not with inequality-invariant mobility. For health and education, we construct two indices that aggregate the selected indicators in these groups.[26] These indices are highly significantly correlated with all inequality-sensitive measures considered. In contrast to the existing literature (see below), we do not observe a significant relationship between years of compulsory schooling and mobility.

There is a very large literature on the impact of educational investments on intergenerational mobility, especially the effects of educational expansion. Increasing the years of compulsory schooling and expanding the coverage of primary schooling through the construction of new schools have been shown to lead to improvements in educational outcomes of subsequent generations and increase mobility (Black et al., 2005; Oreopoulos et al., 2006; Mazumder et al., 2019). Azomahou and Yitbarek (2021) identify the expansion of secondary education as a key positive determinant of intergenerational mobility in nine Sub-Saharan African countries, while Binder and Woodruff (2002) observe a positive correlation between the expansion of schooling and intergenerational mobility in Mexico. Using data from Jordan, Assaad and Saleh (2018) similarly find that greater availability of basic public schools has a positive effect on intergenerational mobility, while the effect of secondary public schools is found to be insignificant. In contrast to these results for lower levels of education, the evidence on tertiary education is more mixed. Using longitudinal data from the United States, Bloome et al. (2018) find that the expansion of higher education has had a positive effect on intergenerational mobility as it helped low-income children achieve a college degree. In a cross-country study, Holter (2015) however observes and rationalizes a strong negative correlation between intergenerational earnings persistence and public expenditure on tertiary education.

Other aspects of educational investment that have received attention in the literature relate to school quality, teacher pay and school finances. Arenas and Jean (2020) find that unequal access to good schools is associated with lower intergenerational mobility and that mobility can be increased by means of school equalization interventions and desegregation policies (see also Hassler et al., 2007; Lee and Seshadri, 2019). Using tax returns data from Italy, Acciari et al. (2022) estimate intergenerational income mobility at the subnational level and find that mobility is higher in provinces with higher school quality. Card et al. (2022), in an empirical application to the United States, find that intergenerational mobility is strongly tied to teacher wages. In another study on the United States, Kwon (2017) estimates the causal effect of public-school spending on intergenerational mobility by exploiting U.S. school finance reforms and finds that greater reform-induced spending has a positive effect on intergenerational mobility (with larger gains for advantaged children).

Among the third group of correlates we find that countries with a large agricultural sector and lower access to electricity are less mobile. Most notably, the share of employment in industry and services is highly correlated with mobility while the reverse applies to the share employed in agriculture. This applies to five of the six mobility measures. The share of the urban population shows mixed results: For inequality-invariant measures, the relationship is insignificant, while it is highly significant for inequality-sensitive measures. For electricity, the results are more clear-cut. Greater access to electricity is associated with more mobile societies according to five out of six measures, particularly the inequality-sensitive measures. Population is negatively correlated with inequality-invariant mobility, meaning that smaller countries are on average more mobile. In larger countries it may be more difficult and more costly (in per capita terms) to provide uniform public services, i.e. equal access to quality healthcare, schooling, transport and communication infrastructure.

The final group of indicators relates to homogeneity and migration. Greater homogeneity, democracy, and safety tend to be associated with higher mobility. Homogeneity here refers to the probability that two randomly selected individuals from a country share the same ethnicity, religion, or language. Overall, these findings apply to five of our mobility measures and suggest that in peaceful and democratic times, it is easier for the bottom to rise. The positive correlation between intergenerational mobility and homogeneity is consistent with the results obtained by Alesina et al. (2016). We find that the stock of international migrants is positively associated with mobility according to five out of six measures. This could reflect the fact that migrants may be more likely to migrate to countries that are more mobile and by extension offer greater opportunities. This sits well with a recent study by Abramitzky et al. (2021), who find that "children of immigrants from nearly every sending country have higher rates of upward mobility than children of the US-born" and that "immigrants achieve this advantage in part by choosing to settle in locations that offer better prospects for their children".

[26] These indices are the sum of each of the standardized education and health correlates, respectively, upon which the index itself is standardized.

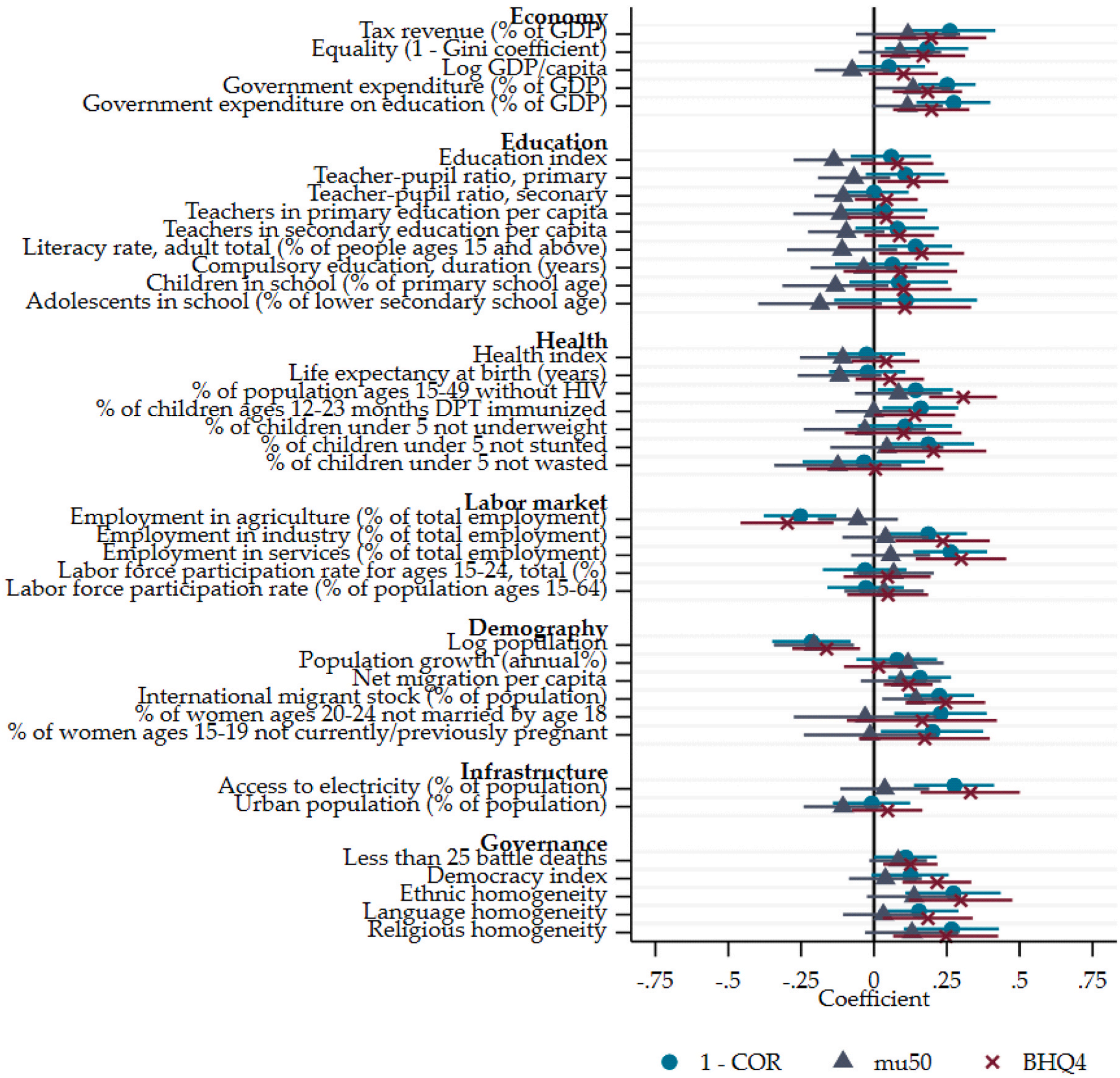

Fig. D.1. Correlates of intergenerational mobility (inequality-invariant measures) *Note:* The figure plots the coefficients from regressing a measure of intergenerational mobility (standardized to have mean 0 and variance 1) on the covariate in question (standardized to have mean 0 and variance 1). The dots show the point estimate while the lines show the 95 percent confidence intervals where standard errors have been clustered at the country level. The confidence intervals do not account for the uncertainty of the mobility estimates themselves. The health index and education indices are constructed as the mean value of the health and education variables, respectively, and then standardized to have mean 0 and variance 1. The covariate data come from the World Development Indicators with four exceptions: (1) the equality indicator comes from *All the Ginis* dataset, (2) the battle death indicator comes from the Uppsala Conflict Data Program, (3) the democracy index we obtain from the V-Dem Dataset, and (4) the homogeneity variables we obtain from Montalvo and Reynal-Querol (2005) and Alesina et al. (2016). We match intergenerational mobility estimates for a given cohort with correlate data from around the time the cohort was in primary or secondary school. As an example, we match data for the cohort born from 1980 to 1989 with correlate data for 1990–1999.

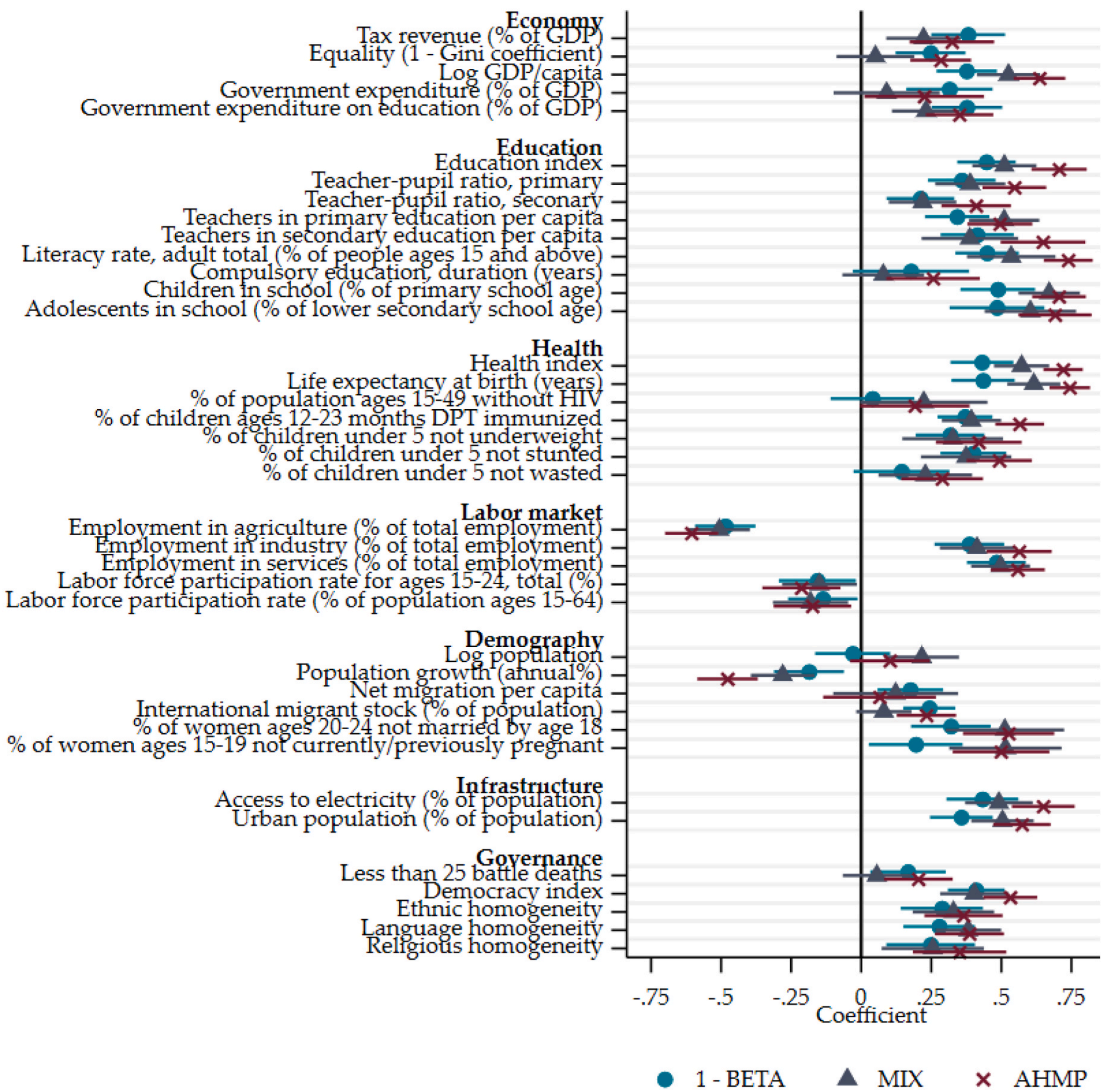

Fig. D.2. Correlates of intergenerational mobility (inequality-sensitive measures) *Note:* See Figure D.1.

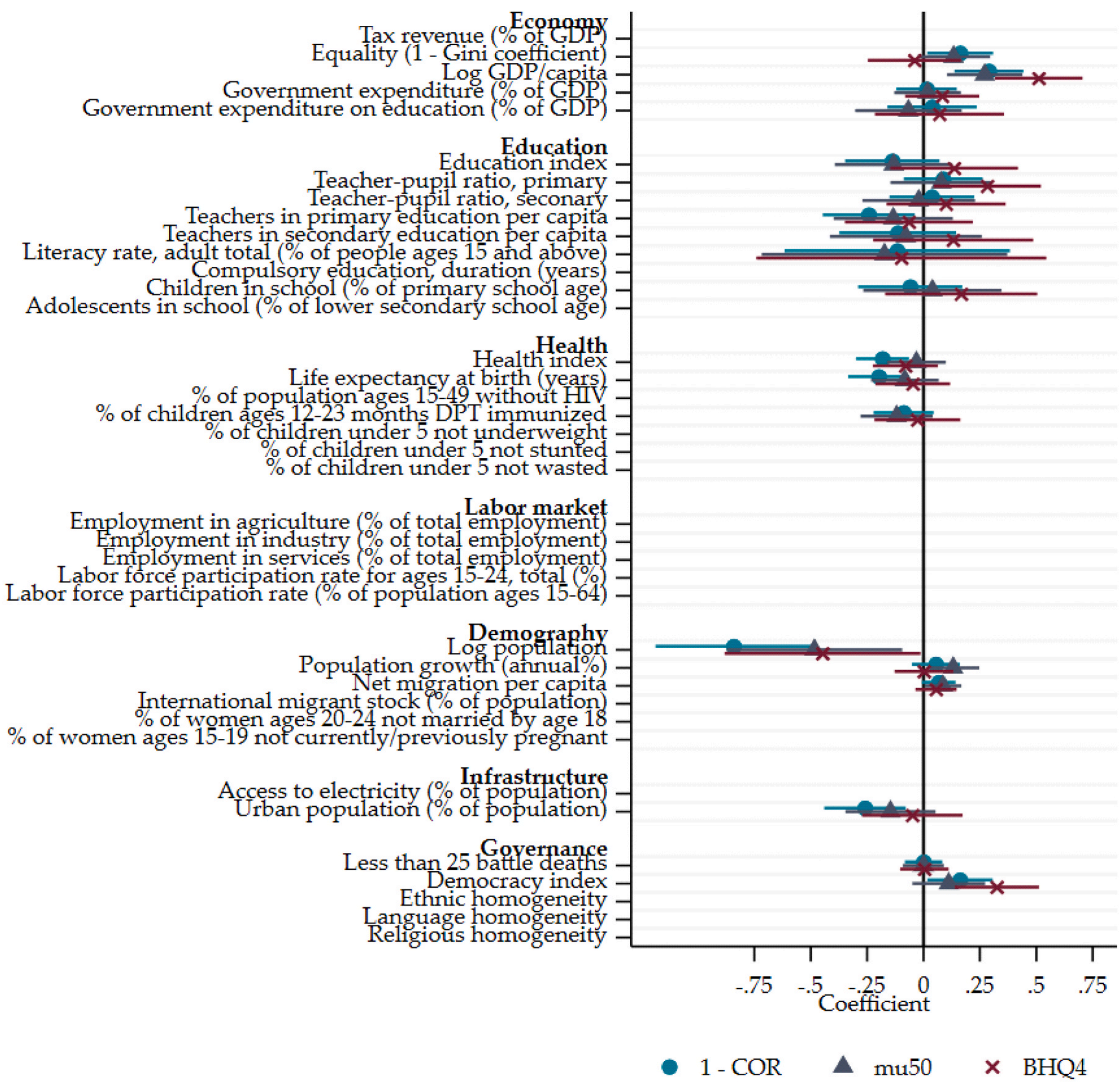

Fig. D.3. Correlates of intergenerational mobility, fixed effects (inequality-invariant measures) *Note:* The figure plots the coefficients from regressing a measure of intergenerational mobility (standardized to have mean 0 and variance 1) on the covariate in question (standardized to have mean 0 and variance 1). The dots show the point estimate while the lines show the 95 percent confidence intervals. The confidence intervals do not account for the uncertainty of the mobility estimates themselves. Only covariates with data on at least 50 countries are plotted. See note to Figure D.1 for a description of the covariates.

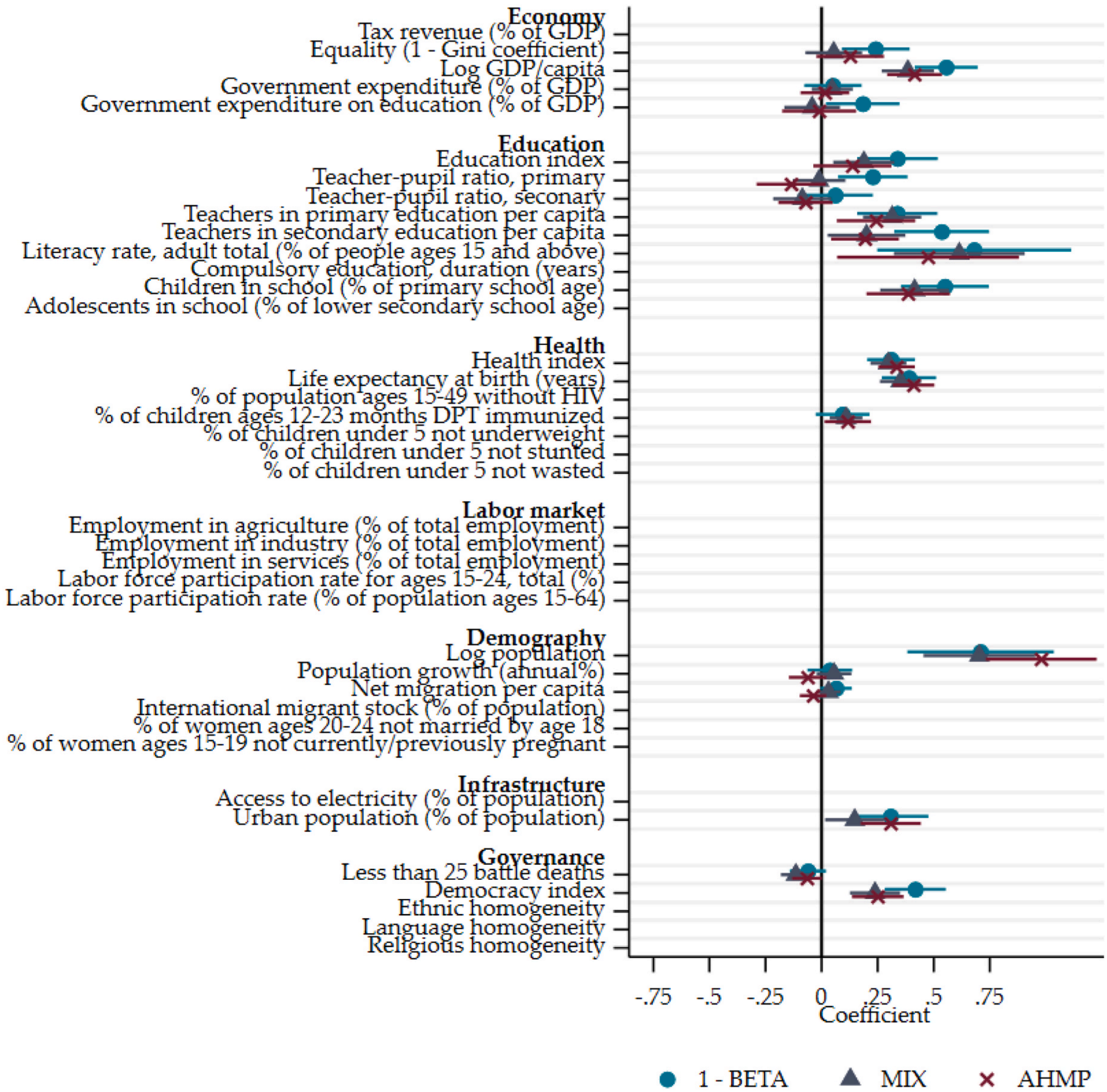

Fig. D.4. Correlates of intergenerational mobility, fixed effects (inequality-sensitive measures) *Note:* The figure plots the coefficients from regressing a measure of intergenerational mobility (standardized to have mean 0 and variance 1) on the covariate in question (standardized to have mean 0 and variance 1). The dots show the point estimate while the lines show the 95 percent confidence intervals. The confidence intervals do not account for the uncertainty of the mobility estimates themselves. Only covariates with data on at least 50 countries are plotted. See note to Figure E.1 for a description of the covariates.

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