Upward Mobility in Developing Countries

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Abstract. This article provides an overview of the literature on mobility in developing countries. Explicit distinctions are drawn between directional and non-directional measures, absolute and relative measures, and combinations thereof. We note that the scarcity of panel data has hindered the measurement of mobility for many countries. We pay particular attention to the recent development of panel-free mobility measures, which allows us to measure upward mobility in 122 countries. Finally, we discuss some central themes in the literature.[1]

1 Introduction

This article reviews the literature on socioeconomic mobility across ranked categories such as income, wealth, or education in developing countries. We recognize at the outset that mobility is a broad and many-faceted concept, and we do not pretend to cover all its varied aspects here. For instance, we do not make much of the distinction between mobility *within* generations and mobility *across* generations. As stressed by Jäntti and Jenkins (2015), the same conceptual issues arise whether we are interested in intergenerational or intragenerational mobility.

In section 2, we review the theoretical literature on the measurement of mobility. As just noted, our review deliberately refrains from being even-handed. Specifically, we restrict ourselves to ranked categories throughout and do not discuss the subject of mobility across unranked categories such as geography, religions or occupations. Rather, we emphasize *directional* or *upward* mobility, which takes full account of the hierarchical nature of ranked categories.

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As discussed in section 3, most measures of income mobility require panel information. As a result, while we have decent estimates of educational mobility, much less is known about income mobility in developing countries. But recent advances in the literature break the ground for new research on mobility in developing countries. In particular, Ray ⓡ Genicot (2023) propose a measure of upward mobility that is panel free. In section 3, we apply this measure to the World Inequality Database (2021) data, thereby obtaining estimates of upward mobility for 122 countries. Section 4 reviews the empirical correlates of directional mobility found in the literature.

2 Concepts and Measures of Mobility

There is a large theoretical literature on the measurement of mobility. The mere presence of many contributions is reflective of the fact that the notion of mobility is built from several components. Indeed, it is far from clear that all these aspects should be expressed in a single measure, as this could lead to disagreement or confusion surrounding the core ideas of mobility.

Perhaps the most important conceptual divide is between mobility measures that are "non-directional" versus those that emphasize the direction of movement along ordered or ranked categories. In its extreme form, the former is only sensitive to pure movement and places no weight at all on the category in question. Geographical mobility represents an extreme example. The very fact that individuals move in and out of various locations makes the situation more "mobile." The locations have no comparative value per se. In contrast, a directional measure places value on a ranking underlying the relevant categories. A wealth category of $1,000 is worth less than a wealth category of $10,000, so the direction of movement matters as well. Such measures do not reward pure movement just for the sake of it.

There is also a distinction to be made between "absolute" and "relative" measures of mobility. Absolute measures are those in which all impacts on mobility stem from individual changes in intrinsic economic standing, independently of changes in the positions of others. In contrast, relative measures are only concerned with changes in *comparative* individual standings. The entire system might be growing or shrinking, but a fully relative measure would not record such absolute changes.

This second distinction is largely (though not entirely) orthogonal to our first point concerning directional and non-directional measurement, namely, the distinction based on ranked categories. A non-directional measure can equally be relative or absolute. In contrast, a directional measure might have relative features, but it will rarely lose all its absolute characteristics because changes in some directions rather than others could have intrinsic mobility value, even when those changes are balanced across everyone in society.

2.1 Non-Directional Measures

As already mentioned, non-directional measures are equally responsive to movements in any direction, sometimes even when the underlying categories are clearly ranked in social or economic terms. Many of these non-directional, relative measures are entirely based on the transition matrix or the copula characterizing the joint distribution of socioeconomic characteristics for an individual or family across time or generation (see box 2.1).

Consider two periods $t \in \{1,2\}$ and a set of entities I. These entities can represent individuals, households, dynasties, or percentiles, depending on the applications. Let $\boldsymbol{s}_t = \{s_{it}\}_{i=1}^{I}$ denote a vector of socioeconomic indicators for all entities i in period $t \in \{1,2\}$.

For continuous variables, it is typically assumed that there is an underlying joint distribution of the socioeconomic indicators over the two periods $G(\tilde{s}_1, \tilde{s}_2)$ with continuous marginals $F_1(\tilde{s}_1)$ and $F_2(\tilde{s}_1)$. If we transform variables so that the indicator variables are themselves the values of the marginal distributions, then these indicators are uniformly distributed on the interval $[0,1]$, and G can be suitably transformed in turn to reflect the distribution of the socioeconomic indicators in each period. The resulting marginal distributions, together with their joint cumulative distribution function $C(u_1, u_2)$, of $(u_1, u_1) = (F(s_1), F(s_2))$ is known as the *copula* of $(\tilde{s}_1, \tilde{s}_2)$ and fully characterizes G (Sklar 1959). The copula contains all information on the dependence structure between s_1 and s_2. Of course, that continues to be true when distributions are made conditional on some observable characteristics, e.g., race or location.

In the case of discrete variables or ordinal categories, this characterization reduces to the well-known *transition* or *mobility matrix*. First introduced by Prais (1955), such a transition matrix $P = p_{jk}$ has as generic element p_{jk} the probability that an entity initially in socioeconomic class j moves subsequently to socioeconomic class k.

Formby et al. (2004) provides a method to estimate proper variance-covariance matrices for transition matrices, whether the categories are exogenous (e.g., occupations) or endogenous to the distribution (e.g., quantiles).

In its non-directional incarnation, mobility can be viewed as the antithesis of a situation in which socioeconomic achievement in a given period accurately predicts socioeconomic achievement in the next (Atkinson 1981, Bartholomew 1982, Conlisk 1974, Dardanoni 1993, Hart 1976, Sommers and Conlisk 1979, Shorrocks 1978 or Wodon and Yitzhaki 2004). Examples of mobility measures that are based on the transition matrix include the second largest eigenvalue modulus or speed of escape from initial conditions (Sommers and Conlisk 1979), the *Shorrocks index* based on the trace (Shorrocks 1978), or the *Bartholomew index* (Bartholomew 1982). In its extreme form, such mobility is just pure movement. Good examples are the relative mobility measures of King (1983) and Chakravarty (1984) that measure the extent of rerankings in the distribution. Mobility as pure movement is often referred to as *exchange mobility* (see Dardanoni 1993 and Markandya 1982).

As far as intergenerational mobility or IGM is concerned, the most popular measures (of *low* IGM) are the *intergenerational income elasticity* (IGE) obtained by regressing log income of children on log income of parents, the *intergenerational income correlation* (IGC), (among others see Solon 1999; Black and Devereux 2011; Jäntti and Jenkins 2015; Mitnik and Grusky 2020 for surveys of intergenerational economic mobility in developed countries, and the *rank-rank correlation* obtained by regressing the percentile rank of children on the percentile rank of the parents (Dahl and DeLeire 2008, Chetty, Hendren, Kline and Saez 2014a).[2]

[2] The intergenerational income elasticity and correlation are related but differ: the IGE equals the IGC between children and parental income times the ratio of the standard deviations of child income to the standard deviations

In contrast to these relative measures, Fields and Ok (1996, 1999b) propose a non-directional, *absolute* measure of mobility that aggregates — over all individuals — the person-specific distances between their socioeconomic status at the end of the period compared to that at the beginning. It measures the total movement or fluctuation in status, whether or not that status increased or diminished. In a similar fashion, Cowell and Flachaire (2018)'s measure of mobility aggregates absolute individual changes but using a more general measure of distance, and investigate the statistical inference of their superclass of mobility measure.

The various measures described in this section naturally have their differences. For instance, some take on their maximum values when the correlation between the socio-economic indicators across periods is negative (a "reversal of fortune"), while others attain a minimum when the correlation is null ("origin independence").[3] However, a common property is that these measures do not distinguish between gains and losses. By construction, they are increasing in fluctuations and shocks. This is especially relevant for developing countries where income and other socioeconomic indicators can be highly variable (World Bank 2013). In addition, measurement error would also be construed as non-directional mobility (an issue discussed below).

2.2 Directional Measures

In contrast to the measures discussed in the previous section, it has been argued that mobility should be directional (Fields and Ok 1999a, Iversen et al. 2019). To the extent that outcomes are not unordered but distinctly ranked along the lines of desirability (such as income, wealth, or education), mobility should reward upward movement and penalize downward movement. A possible counterargument is that this blurs the distinction between growth and mobility. To that, we would respond that some blurring is unavoidable because socioeconomic mobility does have ethical connotations, both in everyday speech and certainly in policy-speak. To say that a society in which every wealthy family occasionally suffers a plunge into the depths of poverty and occasionally returns — but no one ever grows — is "more mobile" than a society in which everyone is wealthy and slowly grows would be really stretching the ethical underpinnings of the term.

This is why empirical studies often zoom in on some specific part of the transition matrix, say, the movement from bottom to upper ranks (Corak and Heisz 1999; Hertz 2006), which implicitly provides a welcome sense of direction. Or they study conditional rank measures in a systematic way. To illustrate, let x and y stand for incomes in neighboring periods or generations, with joint measure μ and marginal CDFs F and G, respectively. Some directional and relative measures used in the literature are:

Directional Rank Mobility (DRM): This measure, introduced by Bhattacharya and Mazumder (2011) expresses the probability that a person's rank in the income distribution is a certain amount higher (or lower) than their initial income rank. It can be calculated unconditionally

of parental income. In contrast, when using rankings, the regression and correlation coefficients coincide because both child and parent ranks are uniformly distributed. These measures are commonly used as indicators of low mobility. In short, IGM is deemed to be higher the lower these measures of persistence are.

[3] More about this distinction can be found in Gottschalk and Spolaore (2002) who provide a welfare framework that that values both reversals and origin independence.

across the distribution or conditional on individuals being at certain ranks or quantiles, to begin with. For instance, the DRM for individuals in quantile r by the extent τ is:

$$D_\tau(r) = \text{Prob}_\mu(G(y) - F(x) > \tau | x \text{ is in quantile } r)$$

Absolute Upward Mobility (AUM): This measure, used by Chetty et al. (2014a), calculates the expected income rank of a person given their initial rank.

$$\mathbb{E}_\mu(G(y) | x \text{ is in quantile } r)$$

Despite the terminology, we would consider this measure as relative as it is unaffected by common growth patterns: scaling up or down parental or children's income will not change the measure.

Two variants of these measures of mobility that are both directional and absolute are :

Directional Mobility (DM): Fields and Ok (1999b) propose a measure that sums individual income growth rates, measured as the average difference in log income.

$$\text{FO}\left(\mathbf{y}, \mathbf{x}\right) = \frac{1}{n} \sum_{i=1}^{n} \left[\ln(y_i) - \ln(x_i)\right].$$

Absolute Mobility (AM): Chetty, Grusky, Hell, Hendren, Manduca and Narang (2017) record the fraction of individuals whose situations have improved relative to their predecessors after a certain number of years or a generation.

$$\text{AM}\left(\mathbf{y}, \mathbf{x}\right) = \frac{1}{n} \sum_{i=1}^{n} 1_{y_i > x_i}.$$

Finally, more recent measures of directional mobility emphasize both absolute and relative growth in income.

Mobility as Pro-Poor Growth: A number of recent measures of mobility propose measures of mobility as a weighted sum of individual income growth rates

$$M = \frac{1}{n} \sum_{i=1}^{n} \omega_i g_i$$

with more weights on either:

- lower absolute baseline incomes: the instantaneous measure in Ray ⓡ Genicot 2023 axiomatically derives weights

$$\omega_i = \frac{x_i^{-\alpha}}{\sum_{i=1}^{n} x_i^{-\alpha}} \tag{1}$$

for some weighting $\alpha > 0$; or
- lower baseline quantiles: ω_i decreasing in initial rank r_i (Jenkins and Van Kerm 2016a, Palmisano and de Gaer 2016 and Berman 2022).

These measures of mobility value growth with higher weights the poorer the individual initially is. In this sense, they are naturally related to a literature that proposes to measure *pro-poor growth* using the growth rates of the mean income for each *quantile* with weights decreasing in the quantile (see Dardanoni 1993, Essama-Nssah 2005, and Ravallion and Chen 2003). The difference is not just the specific weights proposed in Box 2.2, but the use of quantile growth rates versus individual income growth rates (potentially averaged at the quantile level). This particular distinction parallels the contrast made in the literature between the so-called anonymous growth incidence curve, which plots the growth rate of the mean income in the quantile on the quantile (Ravallion and Chen 2003) and its non-anonymous counterpart, that plots instead the growth rate of income of individuals or dynasties starting at a given quantile on the starting quantile (Grimm 2007, Bourguignon 2011, Dhongde and Silber 2016, Palmisano and de Gaer 2016, Palmisano 2018). These authors make the point that the difference between the anonymous and non-anonymous growth incidence curves corresponds to pure exchange mobility as discussed above and connect this literature on pro-poor growth with the convergence literature in macroeconomics (see in particular O'Neill and Kerm 2008, Wodon and Yitzhaki 2005, Bourguignon 2011 and Dhongde and Silber 2016). [4]

A central issue arises when using individual growth rates: the possibility of income crossings. The greater weight placed on the growth rates of the relatively poor is something that all can agree on. But what should be done when someone who was initially poor becomes richer than her erstwhile poorer counterpart? Note that data available to the researcher are discrete, with income observations separated in time. What if a crossing of income trajectories occurs in between? Should more weight be placed on Bob, who was initially poorer than Ann, but overtakes her between the two survey rounds? It seems reasonable to put more weight on Bob *only* while he is poorer than Ann, switching those weights after the crossing. The problem is exacerbated by the fact that the exact path that connects the two observations. is unknown. There might be no way to know *when* it occurred. Worse still, different unobserved interpolations of intermediate income trajectories may well yield different answers for mobility as a whole (with or without crossings).

This apparently pragmatic issue has deeper conceptual implications. Suppose that the two income trajectories for Ann and Bob are continuous. If we placed greater weight on Bob when he was poorer than Ann, but switch our weights exactly at the time of crossing, then it becomes irrelevant whether it is Bob who moves on ahead thereafter or if Bob and Anne magically switch identities at the crossing, so that the new trajectories now simply bounce off each other, with Ann richer than Bob throughout, except at a single instant of time. If names do not matter when equal incomes are exchanged, the two sets of trajectories — the original and the new pair in which Ann and Bob switch identities at the crossing — *should have exactly the same measure of upward mobility*. That implies, in turn, that panel data can be dispensed with in the measurement of upward mobility, provided we accept that identity switches at identical incomes are meaningless.

[4] Besides the growth incidence curve, other graphical tools have been proposed to illustrate the pro-poorness of growth, such as the income growth profile (Jenkins and Van Kerm 2016b) and the TIM curve (Creedy and Gemmell 2018).

What if there is no smooth crossing, but a discontinuous jump that takes Bob's income above Ann's? This is especially relevant when considering intergenerational mobility, in which the endpoint of a parent's trajectory need not correspond to the starting point of a child's trajectory. However, such jump discontinuities can be approximated arbitrarily closely by a sequence of smooth functions. If we ask for our mobility measure to be continuous in our approximation, then the same argument as before continues to apply.

Ray ⓡ Genicot (2023) formalize this argument. They axiomatize a measure of *instantaneous* upward mobility in (1) that captures pro-poor growth. Armed with this instantaneous measure, they propose to measure upward mobility over an interval of time by imposing two further conditions.The first is that the upward mobility over the interval is fully determined by the collection of all instantaneous upward mobilities during the interval. This condition is that it solves precisely the question of crossings: in our example above, Bob gets a higher weight attached to his income growth than Ann as long as he is poorer than Ann. As soon as his income crosses that of Ann, the weighting tables are turned. The second condition imposes time additivity — upward mobility over the interval is the sum of upward mobility over any pair of exhaustive sub-intervals, weighted by the lengths of the sub-intervals.

The two conditions, along with the linearity of instantaneous mobility in growth rates, result in a straightforward measure of *upward mobility* that is both independent of panel data and completely removes the concept of 'mobility as pure movement':

Upward Mobility (UM): Ray ⓡ Genicot (2023)

$$\mu_\alpha(\mathbf{x}, \mathbf{y}) = \ln \left[\frac{\sum_{i=1}^n y_i^{-\alpha}}{\sum_{i=1}^n x_i^{-\alpha}} \right]^{-\frac{1}{\alpha}} \text{ for some } \alpha > 0, \tag{2}$$

where α is a factor of pro-poorness. If the observations are taken with multiple periods of time in between, the measure of mobility is to be divided by is the number of periods in between the two observations.

And subtracting average growth from this measure gives us the *a relative mobility measure* associated with upward mobility:

$$\rho_\alpha(\mathbf{x}, \mathbf{y}) = \ln \left[\sum_i \left(\frac{y_i}{\bar{y}} \right)^{-\alpha} \right]^{-\frac{1}{\alpha}} - \ln \left[\sum_i \left(\frac{x_i}{\bar{x}} \right)^{-\alpha} \right]^{-\frac{1}{\alpha}}.$$

Appendix 6 provides the asymptotic variances for these measures of upward mobility.

This last measure is related to another group of mobility measures that measure mobility as an equalizer of income. Chakravarty, Dutta and Weymark 1985, Maasoumi and Zandvakili 1986, and Fields 2010 developed measures that compare the inequality of individual incomes aggregated over a longer period of time compared to individual income over a shorter period of time.

In closing this section, we note that while each measure discussed so far has its own specific properties, measures of the same type tend to co-move in practice. For instance, Berman (2022) finds a correlation of between 0.93 and 1 among four standard measures of relative mobility based on the copula when applied to 28 copulas measured for different cohorts, different countries, and different definitions of incomes. Deutscher and Mazumder (2020) showed for Australia that the measures within the same categories (e.g. relative, absolute directional, etc) tend to be highly correlated. Comparing different measures of intergenerational mobility, Checchi (2002) finds a strong correlation *within* relative ordinal measures and within absolute measures of mobility, though the two sets of measures can diverge. In what follows, we will consider the upward mobility measure introduced in Box 2 in greater detail.

3 Measuring Upward Mobility in Developing Countries

In Sections 3.3 and 3.4, we will review the existing findings in developing countries regarding upward mobility of education and income respectively. However, before proceeding, we shall briefly discuss some of the prevalent data challenges. We do so in Sections 3.1 and 3.2.

3.1 Scarcity of Panel Data

Many of the measures of mobility discussed in the previous section require panel data with good-quality income data, a scarce commodity in developing countries. As a result, researchers have also developed a number of methods to proxy panel data.

Synthetic Panels. First, it is possible to create synthetic panels by matching individuals to the same time-invariant characteristics over consecutive cross-sections. These have been proposed as a substitute for panel data (Dang and Lanjouw 2013; Moreno et al. 2021). This method has been used, in particular, to assess the likelihood of escaping or falling into poverty. Such measures can be viewed as simple measures of directional mobility. Examples of this approach can be found in Ferreira et al. (2012); Foster and Rothbaum (2015); Beegle et al. (2016); Li et al. (2019); Bourguignon and M. (2020) (see Dang et al. 2019 for a recent survey).

Hybrid Approach. Second, researchers have proposed to combine information from panel data with information from other surveys. For instance, Chetty et al. (2017) combine the copula of the parent-child income distribution, estimated from a unique panel of tax records (Chetty et al. 2014b), with estimates of the marginal income distributions by generation using the CPS and decennial Census data in the United States.

Copula Approximation. Researchers have proposed approximations for the copula or transition matrix. Berman (2022) shows that the long-term evolution of absolute mobility in the United States appears to be relatively insensitive to variations in the copula. In other words, replacing an estimate of the copula with estimates from other high-income countries or time periods does not significantly alter the overall patterns observed in Chetty et al. (2017)

If we assume a bivariate lognormal distribution for the income of parents and children, then five parameters characterize the distribution: the means and standard deviations of the two marginal distributions (obtainable from cross-sectional data) and the correlation between children and parents log-incomes (which requires panel data). This last correlation coefficient is hard to obtain, but empirically its exact value appears to matter little. Berman (2022) proposes to use the US value of 0.3 for this correlation to estimate absolute mobility in other developed countries, where the marginals come from the World Inequality Database (2021). In addition to a bivariate lognormal distribution for the income of parents and children, Kraay and van der Weide (2022) also assume that individual incomes follow an autoregressive lognormal process with individual fixed effects. They show that, under these assumptions, one can use the aggregate moments (the mean and variance of the country's income) from repeated cross-sections to estimate bounds for the correlation coefficient and, therefore, the IGE.

However, as already noted, not all measures require panel data. Ray ⓡ Genicot (2023) propose a measure of upward mobility that does not require panel data for its implementation. This is not an empirical assertion, as in the work of Berman (2022), but a conceptual one. It can be therefore be used for most countries, at least those in which comparable cross sections of income distributions are available over different years and for a fixed set of reasonably detailed quantiles. In Section 4, we discuss some applications of this measure.

3.2 Other Data Issues

Emran and Shilpi (2019) provides a good review of the limitations to measuring IGE in developing countries. Apart from the absence of a panel structure, the additional difficulties of mobility-related data from developing countries can be classified under the following headings.

Measurement Errors. Poorly measured income, large informal sector, and lack of bookkeeping make income much harder to measure in developing countries (Deaton 1987; Browning et al. 2014).

Because income measurement is noisy, estimates of income persistence are necessarily attenuated, so that "mobility as pure movement" tends to be overestimated (Solon 1992, Zimmerman 1992, Bound et al. 1994, Fields et al. 2003). However, measurement error is an issue for measures of directional mobility as well, for it mechanically attaches higher growth rates to individuals falsely identified as having a lower baseline income and similarly lower growth rates to individuals falsely identified as having higher baseline incomes.

High Fluctuations in Income. Large and continuing fluctuations of income from year to year can artificially boost social mobility if the chosen time periods are short. Social mobility estimates can change substantially if single-year observations replace multi-year averaged income estimates. Doing so for the US, Mazumder (2005) found that persistent transitory fluctuations bias the measure of persistence (IGE) downwards in the US by approximately 30% or more.

Selection Issues. Given the scarcity of panel data, a number of studies in the inter-generational literature use the *co-residency method*. As the name indicates, the method consists of restricting the sample to households where the parents and the children reside together (Deaton 1987). Naturally, the approach suffers from selection bias by excluding parents and children who are not co-residents. Azam and Bhatt (2015) illustrated this point by showing that in India, the intergenerational mobility of education in India would be overestimated using the co-resident sample in the India Human Development Survey.

Even when panel data are available, selective attrition is a regular concern and source of bias. Moreover, the sample size in panel data tend to be small and highly selected (Solon 1999, Chetty et al. 2014a, Iversen et al. 2019).

With these caveats in mind, we turn to a brief review of the existing literature.

3.3 Educational and Occupational Mobility

Most of the intergenerational mobility literature has focused on educational or occupational outcomes, as retrospective questions regarding parental education or occupation are available in many surveys.

For adult children, it is usually straightforward to compare education with that of a parent, which is one reason why Hertz et al. (2007) could estimate 50-year trends in the intergenerational persistence of educational attainment for a sample of 42 countries. They found that a single-standard-deviation difference in parental education corresponds to a schooling difference of about 0.4 standard deviations in the next generation and that this figure has held steady for half a century. Expanding on this exercise, van der Weide et al. (2024) created the Database on Intergenerational Mobility (GDIM) with estimates for intergenerational educational mobility — both relative (the regression coefficient of the child's education on parental education) and absolute (the proportion of children that are more educated than their parents) — for the 1980 cohort in 148 countries. The estimates rely on retrospective data when possible and co-resident samples otherwise.

It appears that average relative and absolute educational mobility rates are lower in developing economies, with no sign that the gap across developed and developing countries is getting smaller. Among developing economies, East Asia and Pacific and Middle East and North Africa are the regions with the highest average mobility in education, both relative and absolute. Behrman et al. (2001) and Hertz et al. (2007) had found very high persistence (low intergenerational mobility) in Latin American countries with a correlation between parents and offspring of 0.6. However, Hertz et al. (2007) found a large decrease in persistence and an increase in absolute educational mobility across the 1950 to 1980 cohorts.

Sub-Saharan Africa and South Asia stand out as the two regions with the lowest (relative and absolute) educational mobility. On average, 36% of the children born in Sub-Saharan Africa in the 1980s have a higher level of education than their parents, asopposed to 57% for the same generation in East Asia and the Pacific. Absolute mobility for the 1980s cohort is also relatively high in Western Europe, Canada, South America, parts of the Middle East, and South Africa.

Alesina et al. (2021) study intergenerational mobility across Africa, defining upward mobility as the probability that a child born to a parent who has not completed primary school manages to do so (similar to the measure used by Card et al. 2018). Similarly, they measure downward mobility as the probability that the offspring of parents with primary education fail to complete primary school themselves. They rely on co-resident samples from census data of 26 African countries in Africa. They find substantial variation. The likelihood that children born to parents with no education complete primary schooling exceeds 70% in South Africa and Botswana; the corresponding statistic in Sudan, Ethiopia, Mozambique, Burkina Faso, and Malawi hovers below 20%. They also find variation within countries, with stronger persistence in rural Africa. While there is a gender gap in educational levels, intergenerational educational mobility is similar for boys and girls.

Educational mobility is also particularly low in South Asia. Azam and Bhatt (2015) and Emran and Shilpi (2015) study trends in relative educational mobility in India. After demonstrating selection in the co-resident sample, Azam and Bhatt (2015) use the Indian Human Development Survey (IHDS) to create a father-son matched dataset for the birth cohorts of 1940–1985. They find that the average intergenerational correlation in educational attainment in India is 0.52, which suggests significant persistence but not as strong as in Latin America at that time. This overall correlation has remained steady over time, though they find different trends at different levels of education. Mobility has increased at the lower end of the fathers' educational distribution but has decreased at the top end of that distribution. Using a co-resident sample, Emran and Shilpi (2015) found educational relative mobility to be stagnant for boys and to have increased for girls.

Asher et al. (2021) focus on the *bottom half mobility*, the expected rank of a child born to a parent in the bottom half of the parent rank distribution (similar to the AUM measure defined above), and propose an approach that takes into account the fact education data are often coarsely measured (bottom coding). They find that this measure of educational rank mobility has not improved from the 50s to the 80s birth cohorts. It seems that despite India's decades of economic growth (Chancel and Piketty 2019) and substantial improvement in the economic status of individuals in the bottom half of the socioeconomic distribution, Hnatkovska et al. (2012, 2013) for instance shows overall significant trend toward convergence in education levels, occupation distribution, wages, and consumption levels of SC/STs toward non-SC/ST levels in the National Sample Survey between 1983 and 2005, moving educational ranks remains hard. Low levels of intergenerational mobility are also found in Bangladesh and Pakistan (Grawe 2004; Asadullah 2012)

Many more estimates of educational IGE in developing countries can be found in recent reviews such as Torche (2014), Emran and Shilpi (2019), and Iversen et al. (2019).

Before turning to income mobility, note that some researchers focus on intergenerational mobility out of farming: see Bossuroy and Cogneau (2013) for Cote d'Ivoire, Guinea, Madagascar, Ghana, Uganda, and South Africa in the late 90s, Lambert et al. (2014) for Senegal in 2006/2007, Kumar et al. (2002) for India in 1996, and Wu and Treiman (2007) for China in 1996. These papers estimate a simple transition matrix and report the *odds ratio*: the odds of being in the non-farm sector given a father in the non-farm sector compared to the odds of being in the non-farm sector given a father in the farm sector. Their findings range from 4.2 in Uganda to as high as 32.4 in India (Bossuroy and Cogneau 2013). This is consistent with the findings that intergenerational occupational mobility, despite showing an increasing trend, is unquestionably low in India. The caste system has been flagged as a potential culprit (Azam 2015).

3.4 Income Mobility

Education is an important determinant of income, but it is far from being the only one. Measuring both intragenerational and intergenerational income mobility is of primary interest. However, the need for panel data for many measures of mobility has strongly limited our empirical knowledge in this area.

Several studies have estimated the Intergenerational Income Elasticity (IGE) for different countries. For example, Mohammed (2019) conducted research on India, using a two-sample instrumental approach and correcting for co-resident households. He analyzed data from the Human Development Profile of India and IHDS surveys spanning the years 1994 to 2012. His findings suggest that intergenerational income persistence in rural India is lower compared to other developing countries. The between-caste coefficient indicates that India is progressing towards cross-caste equality albeit at a relatively slow pace. Using IV to correct for measurement error, Sakri (2020) find an IGE of 0.45 in the Indonesian Family Life Survey (IFLS). Meanwhile, Leites et al. (2021) and Britto et al. (2022) estimated intergenerational mobility using administrative data in Uruguay and in Brazil respectively. It is important to note that while survey data may be susceptible to measurement errors, administrative data might miss informal earnings, which can be substantial in lower-income countries, necessitating imputation by the authors. For Uruguay, Leites et al.

(2021) find an average inter-generational ranking association (rank-rank correlation) of income of 0.29, but also that this measure of persistence increases to 0.72 for the parents in the top decile. Leites et al. (2022) find that both the inter-generational ranking association and the directional rank mobility remained mostly constant across cohorts between 1966-1983. Britto et al. (2022) find a higher rank-rank correlation of 0.55 for Brazil and estimate that a child born to below-median income parents are expected to reach the 35^{th} income percentile in adulthood.

van der Weide et al. (2024) summarize the findings from a few estimates in developing countries. As with educational mobility, persistence in income is, on average, much higher in the developing world than in high-income countries. Out of the 25 economies in the bottom third by income mobility (in the sense of low persistence), 24 are developing economies. For several developing economies – most of which are in Africa, Latin America, and the Middle East – income mobility is lower than what is expected for their levels of educational mobility (given the cross-country association between the two). South Asia and Sub-Saharan Africa are the regions in which parental background in education or income matters the most for the prospects of the offspring.

Assuming a bivariate lognormal distribution and an auto-regressive model of income allows Kraay and van der Weide (2022) to use a panel of aggregate moments to estimate bounds to the IGE using the World Inequality Database (2021) (mainly developed countries at the time) and the PovCalNet data from the World Bank for developing countries. In contrast to van der Weide et al. (2024), Kraay and van der Weide (2022) find higher intergenerational mobility among poorer countries but this may be due to the two different sources of data.

Even less is known about directional mobility. Fields et al. (2003) look at the patterns of growth of household income in Spain, Venezuela, South Africa and Indonesia in the 1990's, and found stronger growth among poorer households. In China, Fan et al. (2021) evaluate both the IGE and absolute mobility using the China Family Panel Studies (CFPS) survey. The paper shows an increase in the inter-generational income elasticity (IGE) from 0.390 for the 1970-1980 birth cohort to 0.442 for the 1981-1988 birth cohort. This increase is more pronounced among urban and coastal residents as opposed to rural and inland residents. In contrast, absolute mobility has decreased from the early cohort to the late cohort.

Since the measure of upward mobility proposed by Ray ⓡ Genicot (2023) does not require panel data, we apply it to the World Inequality Database (2021) to compute the ten-year upward mobility $\mu_{0.5}$ and associated relative measure $\rho_{0.5}$ for each year in the 1990-2018 interval for 122 countries in total. Table 1 displays the average upward mobility (in annualized percentages) as well as the associated relative measure overall and by region. In addition, we present the measures of upward mobility and relative upward mobility for each individual country in Table 3.

The average upward mobility over all countries and years was 1.43%. Overall, upward mobility was the highest in Asia (1.72%) and the lowest in Oceania, Europe, the US and Canada (1.12%). Recall that upward mobility ($\mu_{0.5}$) can be decomposed into the sum of growth and relative mobility ($\rho_{0.5}$). Looking at this decomposition reveals interesting patterns. The high level of mobility exhibited by Asia has been driven by strong growth over the 1980-2018 interval, while relative mobility has been negative in the years prior to 2010. The contrast between performance in upward mobility and relative mobility can easily be seen in the maps in Figure 1. Particularly striking is Oceania, Europe, and North America, where relatively strong growth has reinforced inequalities: relative mobility for the region was -0.34% per year over the full interval. In contrast, growth has been lower than average for Latin America and Africa, but relative mobility has been above average (0.48 for Africa and 0.19 for Latin America), indicating stronger growth among poorer individuals.

	$\mu_{\alpha=0.5}$	$\rho_{\alpha=0.5}$	$growth$
All Countries (122)			
Overall	1.43	0.12	1.28
	(1.76)	(0.95)	(1.63)
Africa (49)			
Overall	1.36	0.48	0.86
	(1.84)	(1.20)	(1.41)
1990 − 1999	0.86	0.99	-0.15
	(3.85)	(3.07)	(2.51)
2000 − 2009	1.97	0.34	1.58
	(2.90)	(1.59)	(2.50)
2010 − 2018	2.10	-0.00	1.95
	(5.99)	(1.71)	(5.87)
Latin America (8)			
Overall	1.66	0.19	1.45
	(1.26)	(0.70)	(0.86)
1990 − 1999	1.43	-0.02	1.43
	(1.83)	(0.03)	(1.83)
2000 − 2009	1.09	-0.28	1.35
	(1.72)	(1.31)	(1.32)
2010 − 2018	1.74	0.62	1.10
	(2.13)	(1.75)	(1.03)
Asia (36)			
Overall	1.72	-0.00	1.68
	(2.23)	(0.69)	(2.31)
1990 − 1999	1.16	-0.20	1.32
	(2.80)	(0.85)	(2.87)
2000 − 2009	1.85	-0.22	2.02
	(3.07)	(1.13)	(3.13)
2010 − 2018	2.02	0.54	1.40
	(3.91)	(1.28)	(3.49)
Oceania, Europe, US & CA (29)			
Overall	1.12	-0.34	1.45
	(0.85)	(0.54)	(0.82)
1990 − 1999	0.72	-0.81	1.51
	(2.43)	(1.36)	(1.69)
2000 − 2009	1.51	0.13	1.36
	(2.14)	(1.58)	(1.71)
2010 − 2018	0.99	-0.26	1.36
	(1.85)	(0.54)	(1.91)

Table 1: UPWARD MOBILITY. The table displays the average upward mobility μ and relative mobility kernel ρ (pro-poor factor $\alpha = 0.5$) and growth for the $1990 - 2018$ interval expressed in annual percentage using income deciles from the WID. Standard Deviation across countries are within parenthesis. The table also breaks down average mobility by region and decades.

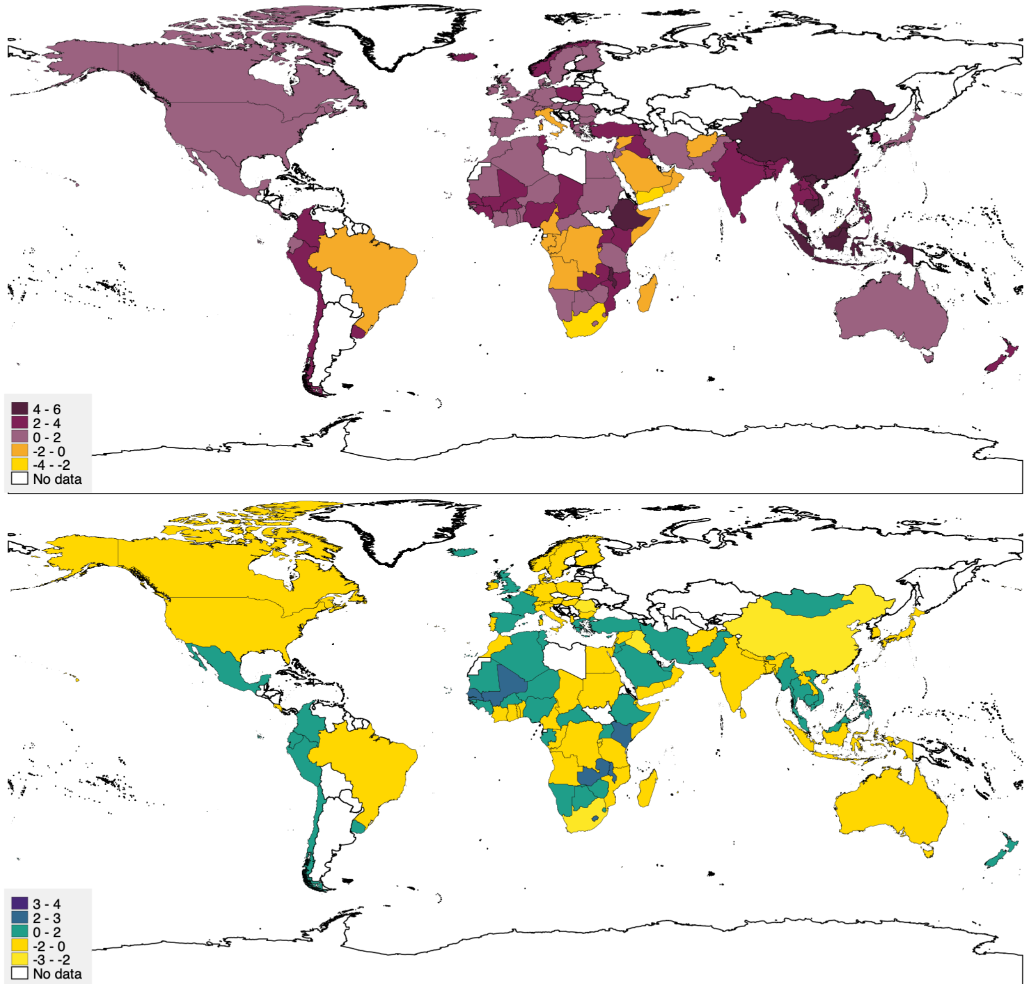

Fig. 1. MAPS of upward mobility and relative mobility (pro-poor factor $\alpha = 0.5$) over 1980-2018 (in annualized percentages) using income deciles from the World Inequality Database (2021). Source: author calculations, income deciles from the World Inequality Database (2021).

4 Correlates of Upward Mobility

The computation of mobility for different countries, and comparisons across them, is of obvious importance. But so is the understanding of how mobility co-moves with other macroeconomic variables of interest. This section visits some of the important correlates of mobility, beginning with the relationship between inequality and mobility.

4.1 The Great Gatsby Curve

Coined in a speech by Alan Krueger in 2012, "The Rise and Consequences of Inequality in the United States", the so-called "Great Gatsby curve" plots the relationship between income inequality and intergenerational income mobility. Krueger reproduced Corak (2013)'s findings that, among 13 OECD countries, there is a negative relationship between inequality in 1985 and intergenerational mobility: countries with a Gini coefficient higher by ten have, on average, a 0.2 higher persistence (IGE). That observation comes hand in hand with an irresistible prediction, which didn't escape Krueger: that because the US are even more unequal now than they were a generation ago, one should expect even less social mobility going forward.

This prediction is not obvious. On the one hand, there is a mechanical relationship between the intergenerational income elasticity and measures of inequality Berman (2199). Moreover, nonconvexities or poverty traps could result in countries with greater inequality also having lower mobility (due to stratification or credit constraints for instance). Durlauf et al. 2021 for instance, review a number of possible models of economic mechanisms underlying a negative relationship between inequality and mobility (see Durlauf et al. 2021 for a review). On the other hand, convergence, or any form of regression to the mean, would indicate that a condition of high inequality could be followed by higher mobility as the relatively poor grow faster than the relatively rich. Moreover, the original study relied on a small subset of high-income countries and may be sensitive to this selection (Mogstad and Torsvik 2021).

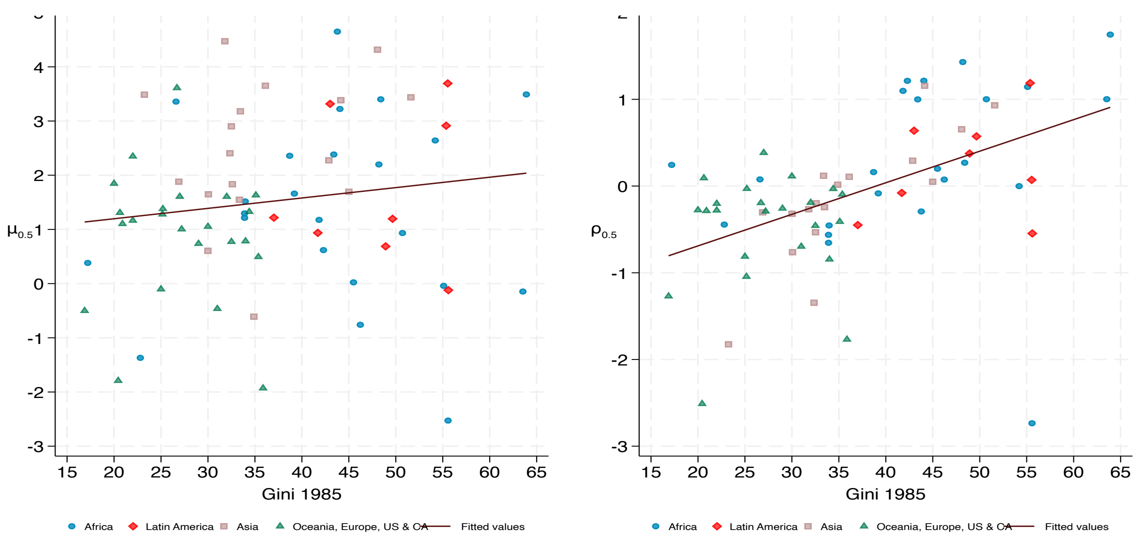

Fig. 2. GREAT GATSBY CURVE. Following Krueger (2012), these panels plot mobility on the vertical axis and the Gini coefficient of inequality in the base year on the horizontal axis. The left panel displays upward mobility $\mu_{0.5}$ and the right panel relative mobility $\rho_{0.5}$ over the 1985-2015 intervals expressed as annualized percentages, along with linear fits for all the countries. Source: Ray ⓡ Genicot (2023).

Using the World Inequality Database (2021) data, Ray ⓡ Genicot (2023) look at the relationship between the 30-year measures of upward mobility $\mu_{0.5}$ and $\rho_{0.5}$ and inequality for a set of 71 countries. They show that 30-year upward mobility and inequality are also inversely correlated for the countries considered by Krueger Corak (2013). Gini coefficients that are ten units higher tend to be 0.7 p.p. less upward mobile. However, the relationship between upward mobility and inequality almost disappears among an expanded set of high-income countries. Moreover, they find a positive relationship between upward inequality and upward mobility among developing countries, in particular among African and Asian countries. The relationship is especially true for the measure of relative upward mobility.

This means that the conjectured relationship does not stand up to close scrutiny among a wider set of countries. More work is needed to conclusively settle this question. In particular, it would be important to study changes within countries. At this point, evidence is scarce. Support of a positive correlation between intergenerational mobility and inequality has been found within handful of relatively high income countries: in China by Fan et al. (2021), in Italy by Güell et al. 2015 and in Sweden Branden 2019). While the relationship is less clear in the US (Chetty et al. 2014a). No evidence is available for poorer countries. Moreover, there is reason to expect that the initial baseline variable that could retard mobility is not high inequality but high *polarization*, in the sense of Esteban and Ray (1994) or Foster and Wolfson (2010). But such an analysis is beyond the scope of this survey.

5 Other Correlates

Many recent papers find that social mobility differs across geographical areas and try took for correlates of mobility (see Table 5). Though not a causal exercise, the idea is that identifying correlates of mobility could help identify key determinants of mobility (but see Mogstad and Torsvik 2021 for a critical review of this literature). The previous section discussed in detail the relationship between mobility and inequality. This section briefly discusses a few other correlates that have been highlighted in the literature.

One expects education to be important for intergenerational mobility. Government expenditures on education (van der Weide et al. 2024) and parental education (Alesina et al. 2021, Munoz 2021) have been found to be positively correlated with educational mobility in developing countries. In the US, Card et al. (2018) and Chetty and Hendren (2018a,b) find that education is correlated with absolute measures of mobility. A priori, it is less clear how education correlates with intragenerational mobility, and there could be non-linear effects.

Because directional absolute measures of mobility reward growth, theories of convergence would predict a negative relationship between directional mobility and initial income per capita, while it is a priori not clear whether one would expect relative measures of mobility to be higher or lower as income increase. In terms of educational mobility, greater mobility has been found to be associated with higher levels of GDP though the effect is non-linear (van der Weide et al. 2024).

The literature has also found urbanization to matter for mobility, whether it is because cities provide better opportunities for its residents or because migration to cities is an important source of upward mobility (Chetty et al. 2014a, Alesina et al. 2021 in terms of educational mobility).

Segregation is negatively correlated with mobility in the US (Chetty et al. 2014a, Chetty and Hendren 2018a,b). More widely, ethnic fragmentation has been found to have both positive and negative effects on growth (see Alesina and Ferrara 2005 for a review), with some negative effects on public good provision and a possible association with conflict.

Authors	Country	Measure	Variable	Findings
Andersen (2001)	LA & the Caribbean	Schooling gaps	Education	Gap in years of missing education (-) Urbanization (+) GDP (+) Educational attainment old generation (+) Income inequality (?)
Hertz (2006)	US	Upward mobility	Income	Education (+) Black race (-) Health (+) Better state of residence (+)
Corak (2013)	Various countries	Great Gatsby Curve	Income	Income inequality (-)
Chetty et al. (2014a)	US	IGE, rank-rank income, AUM and Q1 to Q5 proba	Income	Segregation (-) Income inequality (-) K-12 quality (+) Social capital (+) Family stability (+)
Mitnik et al. (2015)	US	Upward mobility	Income	Income inequality (-)
Card et al. (2018)	US	Upward mobility	9th grade completion	Education(+)
Chetty and Hendren (2018a)	US	Rank-rank slope	Earnings, education, fertility & marriage	Segregation (-)
Chetty and Hendren (2018b)	US	Children's rank	Income	Poverty (-) Income inequality (-) K-12 quality (+) Crime (-) Family stability (+)
Güell et al. (2018)	Italy	Upward mobility	Income	Economic activity (+) Education(+) Social capital (+)

				Income inequality (-)
Narayan et al. (2018)	Various countries	IGE	Education	GDP (+) Government expenditure on education (+) Inequality in opportunities (-)
Vu and Lo Bue (2019)	Vietnam	Upward mobility	Education	Literacy of the old generation (0)
Li et al. (2019)	India	Mobility close to the poverty line	Consumption	Cast (-) Urbanization (+)
Costas-Fernández et al. (2020)	England & Wales	Upward/downward mobility	Occupation	Transport infrastructure (+)
Fontep and Sen (2020)	Cameroon	mother-daughter or father-son correlation	Education and occupation	Gender bias (-)
Corak (2020)	Canada	Upward mobility	Income	Inequality (-) Migration (+) Employment in manufacture (0)
Funjika and Gisselquist (2020)	US & India	IGE	Income	Inequality between groups (-)
Acciari et al. (2022)	Italy	Rank-rank slope, IGE, AUM and Q1 to Q5 proba	Income	Labor force participation (+) Youth unemployment (-) Highly-skilled employment rate (+) Educational attainment old generation (+) Family instability (-) Crime (-) Economic openness (+) Social capital (+) School quality (+)
Alesina et al. (2021)	Africa	Upward mobility	Education	Literacy of the older generation (+) Colonial investment in transportation (+) Missionary activities (+) Closeness to the capital (+) Malaria (-) Levels of development at independence (+) Urbanization (+)

				Employment in services and manufacture (+)
Bingley et al. (2021)	Denmark	Intergenerational correlation	Education	Parents' assortative mating (+)
Compaore et al. (2021)	Africa	Upward mobility	Education	Foreign aid (+)
Emran et al. (2021)	India	Absolute and relative mobility	Education	Urbanization (+) Gender bias (-) Educational attainment old generation (+)
Neidhöfer et al. (2021)	Latin Amer.	Various upward mobility measures	Education	GDP per capital (+) Luminosity (+) Poverty (-) Employment (+) Formality (+) Literacy (+) Houses with access to water (+) Houses with access to electricity (+) Child mortality (-)
Munoz (2021)	LA & the Caribbean	Upward mobility	Education	Primary completion of the previous generation (+) Distance to the capital (-) Employment in agriculture and industry (+)
Mogstad and Torsvik (2021)	Various countries	Various measures	Income	Neighborhoods (?)
Agte et al. (2022)	India	Various upward mobility measures	Education	Credit constraint (-) Literacy of the old generation (+)
Blanden et al. (2022)	Various countries	Educational Great Gatsby Curve	Education	Income inequality (-)
Britto et al. (2022)	Brazil	Various mobility measures	Income	Parents' assortative mating (+) Gender bias (-) White race (+) North region (-)

Table 5 lists a number of recent findings. It is clear that most of our knowledge concerns education mobility or developed countries. Further work is needed to identify the main determinants of income mobility in developing countries.

6 Conclusion

We review the literature on directional mobility in developing countries. The empirical literature on mobility, in particular on intergenerational mobility, has grown considerably in the past years, but they largely pertain to developed countries in which panel data are available. The literature in developing countries has remained far more limited, in large part because of the scarcity of panel surveys.

Recent developments in the literature offer solutions and promises that could open the door to new avenues of research. A first line of work suggests ways of approximating the relevant information of the copulas that underlies panel-dependent measures of mobility. This is an approach based on empirical regularities. A second line of work proposes new measures of absolute and relative upward mobility that are panel-free. This is an approach grounded on theoretical conceptualization.

These are exciting developments, but studying upward mobility in developing countries has a large unfinished agenda.

First, more work is needed to understand, empirically, the relative advantages of the two approaches and how much they differ. The measures are conceptually different and therefore have the potential to differ. In particular, upward mobility captures shared prosperity and is not affected by pure exchange mobility. Understanding if these conceptual disparities translate into differing mobility comparisons across countries or periods remains a pertinent question.

Second, many questions also remain unanswered regarding the determinants of mobility. Notably, the analysis presented here suggests a predominantly positive relationship between inequality and upward mobility in Africa and Asia, diverging from the negative relationship—termed the 'Great Gatsby curve'—observed in OECD countries. Unraveling the true drivers behind these patterns holds significant implications for policy.

Third, the 'pro-poor weight' in measures of upward mobility is not constrained by theory. It would be insightful to survey policymakers to gauge their preferred weight or estimate it from existing policies.

Finally, further thought is needed to integrate *social groups* to the analysis of upward mobility. Clearly, an individual's current socioeconomic position might also be driven by stigma or status for some identifiable social group to which that individual belongs. An individual's current socioeconomic status can often be shaped by stigma or status associated with their identifiable social group. Ray ⓡ Genicot (2023) proposes an extended measure that tracks group income and inequality, requiring panel information only on groups. Implementing this measure in countries with pronounced ethnic or caste divisions would be pivotal in understanding whether acknowledging these social divisions alters assessments of a country's upward mobility.

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Appendices

A. Asymptotic Variance

In this section, we follow Cowell and Flachaire 2015's approach (Section 6.4.3.1) to derive the asymptotic variance for the measures of upward mobility of Ray ⓡ Genicot (2023).[5]

Absolute Mobility

Consider the following moment: $\nu = E(y^{-\alpha})$.

The estimator of upward mobility can be written as a nonlinear function of two consistently estimated moments:

$$\mu_\alpha\left(\mathbf{y}[s,t]\right) = \psi(\nu_t, \nu_s) = -\frac{1}{\alpha(t-s)}\left[ln(\nu_t) - ln(\nu_s\right],$$

From the Central Limit Theorem, this estimator is also consistent and asymptotically Normal, with asymptotic variance that can be calculated by the delta method:

$$Var(\mu_\alpha) = \frac{1}{n}\left[\frac{\partial\psi}{\partial\nu_t}\,\frac{\partial\psi}{\partial\nu_s}\right]\begin{bmatrix}\sigma^2_{y_t^{-\alpha}} & \sigma_{y_t^{-\alpha}y_s^{-\alpha}} \\ \sigma_{y_t^{-\alpha}y_s^{-\alpha}} & \sigma^2_{y_s^{-\alpha}}\end{bmatrix}\left[\frac{\partial\psi}{\partial\nu_t}\,\frac{\partial\psi}{\partial\nu_s}\right]^T, \tag{3}$$

$$= \frac{1}{n}\left[\left(\frac{\partial\psi}{\partial\nu_t}\right)^2\sigma^2_{y_t^{-\alpha}} + 2\left(\frac{\partial\psi}{\partial\nu_t}\,\frac{\partial\psi}{\partial\nu_s}\right)\sigma_{y_t^{-\alpha}y_s^{-\alpha}} + \left(\frac{\partial\psi}{\partial\nu_s}\right)^2\sigma^2_{y_s^{-\alpha}}\right], \tag{4}$$

where $\sigma^2_{y_j^{-\alpha}} = Var(\nu_j) = \frac{1}{n}\sigma^2_{y_j^{-\alpha}}$ $j = s,t$ and $\sigma_{y_t^{-\alpha}y_s^{-\alpha}} = Cov(\nu_s,\nu_s) = \frac{1}{n}\sigma_{y_s^{-\alpha},y_t^{-\alpha}}$.

Using $\frac{\partial\psi}{\partial\nu_j} = -\frac{1}{\alpha(t-s)\nu j}$, we get

$$var(\mu_\alpha) = \frac{1}{n\alpha^2(t-s)^2}\left[\frac{var(\nu_t)}{(\nu_t)^2} + 2\frac{covar(\nu_t\nu_s)}{(\nu_t\nu_s)} + \frac{var(\nu_s)}{(\nu_s)^2}\right]. \tag{5}$$

The estimate the asymptotic variance of the upward mobility is then obtained by using into (**??**) the sample estimates,

$$\hat{\nu}_j = \frac{1}{n}\sum_{i=1}^n y_i^{-\alpha}(j),\;\; Var\hat{(}\nu_j) = \frac{1}{n}\sum_{i=1}^n\left(y_i^{-\alpha}(j) - \hat{\nu}(\mathbf{y}(j))\right)^2 \;\;\&\;\; \widehat{Covar}(\nu_t,\nu_s) = \frac{1}{n}\sum_{i=1}^n\left(y_i^{-\alpha}(s) - \hat{\nu}(\mathbf{y}(s))\right)\left(y_i^{-\alpha}(t) - \hat{\nu}(\mathbf{y}(t))\right).$$

Relative Mobility

The approach is similar for the measure of relative upward mobility. In addition to ν, consider the moment $\gamma = E(y)$ with sample estimate $\hat{\gamma}(\mathbf{y}) = \frac{1}{n}\sum_{i=1}^n y_i$.

The estimator of relative upward mobility is a nonlinear function of four consistently estimated moments:

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[5] We are grateful to Emmanuel Flachaire for his guidance.

$$\rho_{\alpha}\left(\mathbf{y}[s,t]\right) = \psi(\nu_t,\gamma_t,\nu_s,\gamma_s) = \frac{1}{(t-s)}\left[-\frac{1}{\alpha}ln(\nu_t) - ln\gamma_t + \frac{1}{\alpha}ln(\nu_s) + ln\gamma_s\right].$$

The delta method to derive the asymptotic variance gives:

$$Var(\rho_{\alpha}) = \frac{1}{n}\left[\frac{\partial\psi}{\partial\nu_t}\,\frac{\partial\psi}{\partial\nu_s}\,\frac{\partial\psi}{\partial\gamma_t}\,\frac{\partial\psi}{\partial\gamma_s}\right]\begin{bmatrix}\sigma^2_{y_t^{-\alpha}} & \sigma_{y_t^{-\alpha}y_s^{-\alpha}} & \sigma_{y_t^{-\alpha}y_t} & \sigma_{y_t^{-\alpha}y_s}\\ \sigma_{y_t^{-\alpha}y_s^{-\alpha}} & \sigma^2_{y_s^{-\alpha}} & \sigma_{y_t y_s^{-\alpha}} & \sigma_{y_s^{-\alpha}y_s^{-\alpha}}\\ \sigma_{y_t^{-\alpha}y_t} & \sigma_{y_s^{-\alpha}y_t} & \sigma^2_{y_t} & \sigma_{y_t y_s}\\ \sigma_{y_t^{-\alpha}y_s} & \sigma_{y_s^{-\alpha}y_s} & \sigma_{y_t y_s} & \sigma^2_{y_s}\end{bmatrix}\left[\frac{\partial\psi}{\partial\nu_t}\,\frac{\partial\psi}{\partial\nu_s}\,\frac{\partial\psi}{\partial\gamma_t}\,\frac{\partial\psi}{\partial\gamma_s}\right]^T \quad (6)$$

where $\sigma^2_c = var(c)$ and $\sigma_{cd} = cov(c,d)$.

As above, we can then use $\frac{\partial\psi}{\partial\nu_j} = -\frac{1}{\alpha(t-s)\nu_j}$ and $\frac{\partial\psi}{\partial\gamma_j} = -\frac{1}{(t-s)\gamma_j}$, together with the sample estimates of the moments into (6) to obtain the estimate of the asymptotic variance of the relative upward mobility.

B. The data

To compute the mobility measures, we use decile data from the World Inequality Database 2021. The dataset combines fiscal, survey, and national accounts data. In countries with small informal sectors and high-quality tax microdata, that tax data is the main source. Income surveys and imputation methods are used to make minor adjustments to account for non-filers and certain tax-exempt incomes. In contrast, income surveys are the main sources for most emerging economies, and tax datasets are only used to correct the top of the income distribution. Income surveys come mainly from the World Bank (via PovcalNet). The income data are pre-tax total incomes, computed using the equal-split assumption (that is, if the tax unit has more than one income-contributing individual contributing, the assumption is that everyone contributes in equal part to the total income of that tax unit). All incomes are expressed in PPP and in real terms, with a base year of 2021. A detailed description of the methodology is available on the WID website.

In terms of inequality, we use the GINI coefficients from the World Bank (WB) supplemented with data from the World Income Inequality Database (WIID) when missing. For each country-year observation missing in the World Bank database, we select from the WIID the Gini values that 1. have been estimated either by the World Bank or alternatively the OECD; 2. are of average or high quality; and 3. are similar to our primary source. We use Ginis in gross/net income and that cover urban or all areas in the computation. Finally, we interpolate the Gini coefficients for the country and years (between 1980 and 2020) that are still missing after excluding any country that does not have data available before 1995. Lowering this threshold to 1990 would not change the interpolation mean and standard deviation, but using 1995 allows us to keep substantially more countries (32 countries more).

Countries are considered high-income countries if they were classified as such in 1987 (or the closest year before 1995) according to the World Bank.

C. Mobility

Table 2 presents, for each country, the average ten-year upward mobility $\mu_{0.5}$ and its relative counterpart $\rho_{0.5}$ expressed in annual percentage.

Area	$\mu_{0.5}$	$\rho_{0.5}$	growth	Area	$\mu_{0.5}$	$\rho_{0.5}$	growth	Countries	$\mu_{0.5}$	$\rho_{0.5}$	growth
Africa				**Africa**				**Africa**			
AO	-0.75	-1.19	0.44	LR	-0.87	0.02	-0.89	TZ	1.47	-0.63	2.09
	(0.05)	(0.14)	(0.04)		(0.04)	(0.12)	(0.13)		(0.04)	(0.13)	(0.11)
BF	3.66	1.30	2.31	LS	0.77	1.86	-1.07	UG	3.09	0.13	2.91
	(0.04)	(0.13)	(0.12)		(0.04)	(0.15)	(0.06)		(0.04)	(0.14)	(0.13)
BI	-1.99	-0.48	-1.53	MA	1.47	-0.02	1.48	ZA	-2.67	-2.93	0.27
	(0.03)	(0.12)	(0.22)		(0.05)	(0.13)	(0.05)		(0.05)	(0.14)	(0.03)
BJ	0.33	-0.82	1.15	MG	-0.88	-0.08	-0.81	ZM	3.39	1.52	1.83
	(0.04)	(0.14)	(0.07)		(0.04)	(0.13)	(0.11)		(0.04)	(0.17)	(0.07)
BW	1.46	0.67	0.78	ML	3.61	1.87	1.69	ZW	0.47	0.86	-0.39
	(0.05)	(0.16)	(0.03)		(0.04)	(0.13)	(0.10)		(0.04)	(0.15)	(0.06)
CD	-1.82	-0.01	-1.82	MR	1.50	1.52	-0.02	**Asia**			
	(0.04)	(0.13)	(0.13)		(0.05)	(0.13)	(0.05)	AE	-1.90	0.71	-2.63
CF	0.41	1.08	-0.67	MU	3.61	-0.19	3.73		(0.12)	(0.14)	(0.03)
	(0.04)	(0.17)	(0.14)		(0.06)	(0.12)	(0.03)	AF	-1.25	0.14	-1.39
CG	-0.87	-0.25	-0.62	MW	4.46	2.86	1.55		(0.04)	(0.11)	(0.08)
	(0.04)	(0.14)	(0.06)		(0.03)	(0.16)	(0.18)	BD	2.63	-0.30	2.89
CI	0.52	-0.14	0.66	MZ	3.14	-0.12	3.21		(0.04)	(0.11)	(0.10)
	(0.05)	(0.13)	(0.05)		(0.03)	(0.16)	(0.19)	BN	-1.21	0.06	-1.27
CM	-0.21	-0.42	0.21	NA	1.58	0.45	1.12		(0.14)	(0.11)	(0.02)
	(0.04)	(0.14)	(0.06)		(0.04)	(0.17)	(0.04)	BT	3.77	0.64	3.07
CV	4.71	1.18	3.43	NE	0.82	0.26	0.56		(0.05)	(0.13)	(0.05)
	(0.04)	(0.14)	(0.06)		(0.04)	(0.12)	(0.15)	CN	4.53	-1.68	6.12
DJ	2.44	-0.15	2.56	NG	2.71	0.87	1.80		(0.05)	(0.11)	(0.05)
	(0.04)	(0.13)	(0.08)		(0.05)	(0.13)	(0.05)	HK	1.51	-0.81	2.31
DZ	0.98	1.15	-0.17	RW	1.25	-0.85	2.10		(0.09)	(0.12)	(0.02)
	(0.06)	(0.12)	(0.03)		(0.04)	(0.13)	(0.13)	ID	4.14	-0.51	4.57
EG	1.16	-0.50	1.65	SC	1.24	-0.04	1.28		(0.05)	(0.13)	(0.05)
	(0.06)	(0.12)	(0.03)		(0.07)	(0.14)	(0.03)	IL	1.55	-0.15	1.68
ET	4.45	0.50	3.85	SD	1.88	0.07	1.80		(0.08)	(0.13)	(0.02)
	(0.04)	(0.13)	(0.16)		(0.04)	(0.12)	(0.07)	IN	2.58	-1.51	4.06
GA	-0.25	0.45	-0.70	SL	5.64	4.95	0.65		(0.04)	(0.12)	(0.08)
	(0.07)	(0.13)	(0.03)		(0.04)	(0.15)	(0.12)	IQ	0.54	0.29	0.25
GH	1.43	-0.65	2.07	SN	2.53	1.75	0.77		(0.06)	(0.14)	(0.03)
	(0.04)	(0.13)	(0.06)		(0.04)	(0.14)	(0.07)	IR	0.40	0.25	0.15
GM	1.34	1.40	-0.06	SO	-1.53	-0.01	-1.53		(0.06)	(0.13)	(0.03)
	(0.04)	(0.14)	(0.09)		(0.03)	(0.12)	(0.48)	JO	0.11	0.40	-0.30
GN	2.79	1.53	1.23	SZ	1.30	0.83	0.46		(0.06)	(0.13)	(0.03)
	(0.04)	(0.13)	(0.11)		(0.05)	(0.16)	(0.04)	JP	0.37	-0.08	0.45
GW	0.72	1.07	-0.35	TD	1.75	-0.19	1.93		(0.09)	(0.12)	(0.02)
	(0.04)	(0.16)	(0.09)		(0.04)	(0.14)	(0.13)	KH	3.60	1.44	2.11
KE	2.12	2.14	-0.03	TG	0.11	-0.09	0.20		(0.04)	(0.14)	(0.09)
	(0.04)	(0.15)	(0.05)		(0.04)	(0.13)	(0.13)	KR	2.18	-0.99	3.15
KM	-0.23	0.23	-0.46	TN	2.33	0.76	1.54		(0.08)	(0.11)	(0.02)
	(0.04)	(0.14)	(0.07)		(0.05)	(0.12)	(0.04)	LA	3.36	-0.38	3.69

Countries	$\mu_{0.5}$	$\rho_{0.5}$	growth	Area			growth	Area	$\mu_{0.5}$	$\rho_{0.5}$	growth
Asia				**Oceania, Europe, US & CA**				**Oceania, Europe, US & CA**			
	(0.04)	(0.13)	(0.06)	AU	0.79	-0.42	1.20	PL	2.16	-1.07	3.20
LB	0.79	-0.52	1.31		(0.10)	(0.11)	(0.02)		(0.08)	(0.10)	(0.03)
	(0.06)	(0.14)	(0.03)	BE	1.06	-0.01	1.07	PT	0.55	-0.23	0.78
LK	3.23	-0.54	3.72		(0.11)	(0.10)	(0.02)		(0.08)	(0.11)	(0.02)
	(0.05)	(0.12)	(0.04)	BG	0.31	-1.45	1.77	RO	0.10	-1.89	2.02
MM	7.79	0.53	6.98		(0.07)	(0.10)	(0.03)		(0.07)	(0.11)	(0.03)
	(0.04)	(0.13)	(0.14)	CA	0.31	-0.67	0.99	SE	1.78	-0.28	2.05
MN	2.63	0.29	2.31		(0.10)	(0.11)	(0.02)		(0.11)	(0.10)	(0.02)
	(0.05)	(0.13)	(0.04)	CH	0.43	-0.08	0.50	US	0.86	-0.59	1.45
MV	1.77	1.52	0.25		(0.12)	(0.10)	(0.02)		(0.09)	(0.13)	(0.02)
	(0.06)	(0.13)	(0.03)	CY	1.43	0.25	1.17	**Latin America**			
MY	4.14	0.62	3.44		(0.09)	(0.11)	(0.02)	BR	-0.86	-1.06	0.21
	(0.07)	(0.12)	(0.03)	DE	0.13	-0.46	0.59		(0.06)	(0.12)	(0.03)
NP	2.06	-0.19	2.23		(0.11)	(0.11)	(0.02)	CL	3.09	0.29	2.75
	(0.04)	(0.11)	(0.09)	DK	1.28	-0.35	1.63		(0.06)	(0.12)	(0.03)
OM	-1.64	-0.01	-1.64		(0.12)	(0.10)	(0.02)	CO	2.52	1.02	1.48
	(0.06)	(0.16)	(0.03)	ES	1.32	0.31	1.00		(0.05)	(0.18)	(0.03)
PH	2.30	0.50	1.77		(0.09)	(0.11)	(0.02)	CR	0.99	-0.60	1.58
	(0.05)	(0.13)	(0.04)	FI	1.01	-0.29	1.30		(0.06)	(0.13)	(0.03)
PK	1.49	0.22	1.26		(0.10)	(0.10)	(0.02)	EC	1.54	0.72	0.82
	(0.04)	(0.12)	(0.07)	FR	0.99	0.30	0.69		(0.06)	(0.10)	(0.04)
PS	2.35	0.02	2.30		(0.11)	(0.10)	(0.02)	MX	1.21	0.59	0.61
	(0.05)	(0.13)	(0.05)	GB	1.74	0.15	1.57		(0.06)	(0.12)	(0.03)
SA	-0.63	0.31	-0.95		(0.09)	(0.11)	(0.02)	PE	1.98	0.03	1.93
	(0.10)	(0.14)	(0.03)	GR	-0.28	-0.14	-0.14		(0.05)	(0.16)	(0.04)
SG	1.59	-0.61	2.19		(0.08)	(0.13)	(0.02)	UY	2.78	0.52	2.22
	(0.12)	(0.11)	(0.02)	HU	0.05	-1.10	1.16		(0.08)	(0.08)	(0.03)
SY	-2.13	-0.42	-1.73		(0.09)	(0.09)	(0.02)				
	(0.04)	(0.14)	(0.05)	IE	1.63	-0.30	1.91				
TH	2.96	1.08	1.85		(0.10)	(0.10)	(0.02)				
	(0.05)	(0.14)	(0.04)	IS	2.30	0.35	1.93				
TR	2.19	0.16	2.00		(0.12)	(0.10)	(0.02)				
	(0.06)	(0.14)	(0.03)	IT	-0.49	-0.56	0.07				
TW	2.79	-0.43	3.17		(0.10)	(0.10)	(0.02)				
	(0.10)	(0.10)	(0.02)	LU	2.25	-0.22	2.44				
VN	4.17	0.08	4.00		(0.14)	(0.11)	(0.02)				
	(0.04)	(0.13)	(0.08)	MT	2.13	-0.31	2.42				
YE	-2.93	-0.20	-2.78		(0.09)	(0.10)	(0.02)				
	(0.04)	(0.15)	(0.06)	NL	0.98	-0.38	1.35				
Oceania, Europe, US & CA					(0.12)	(0.10)	(0.02)				
AL	2.32	-0.35	2.64	NO	2.63	-0.55	3.15				
	(0.05)	(0.11)	(0.05)		(0.12)	(0.09)	(0.02)				
AT	1.00	-0.08	1.07	NZ	1.82	0.66	1.15				
	(0.11)	(0.10)	(0.02)		(0.09)	(0.11)	(0.02)				

Table 2. UPWARD MOBILITY BY COUNTRY. The table displays the average upward mobility μ, relative mobility kernel ρ (pro-poor factor $\alpha = 0.5$) and growth for the $1990 - 2018$ interval expressed in annual percentage. Asymptotic standard errors (see Appendix 6) are within parenthesis. Source: author calculations, income deciles from the World Inequality Database (2021).

D. Income and educational mobility

Since education is an important determinant of income, we would expect upward mobility and educational absolute mobility to be positively correlated. To check this, we look at the 30-year upward mobility $\mu_{0.5}$ (pro-poor factor $\alpha = 0.5$) and the measure of absolute inter-generational educational mobility from van der Weide et al. (2024). Figure 3 shows an overall positive correlation despite many outliers.

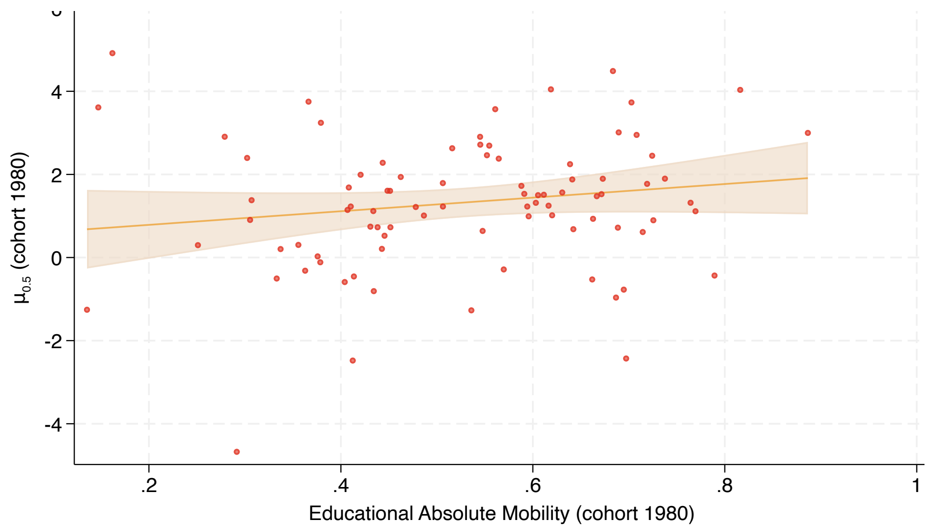

Fig. 3. UPWARD MOBILITY AND ABSOLUTE ECONOMIC MOBILITY. The figure plots the 30-year upward mobility $\mu_{0.5}$ (pro-poor factor $\alpha = 0.5$, income deciles from the World Inequality Database 2021) on the vertical axis and the absolute inter-generational educational mobility from van der Weide et al. (2024) on the horizontal axis, both for the 1980 cohort.