The Great Gatsby Curve:[*]

Upward Mobility, Persistence and Inequality

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Abstract. This paper revisits the *Great Gatsby curve* that connects inequality to mobility, using panel data spanning several countries and time periods. Existing literature observes that the intergenerational elasticity of earnings falls as inequality rises, implying that mobility (viewed as the negative of that elasticity) is negatively correlated with inequality. In sharp contrast, we show that measures of upward mobility, axiomatically aligned with progressivity in income growth rates, are robustly and *positively* associated with baseline inequality. While there is no contradiction here, our study highlights crucial differences between mobility measures based on (lower) persistence and those based on growth progressivity, and asks the reader to align their choice of measure with foundational criteria that they feel best describe "mobility". Our findings offer a re-interpretation of the Gatsby curve through the lens of shared prosperity, and have implications for the evolution of inequality within countries.

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1. Introduction

A well-known speech by Alan Krueger at the White House[2] in 2012 introduced the *Great Gatsby Curve*, which illustrates the empirical relationship between a country's baseline income inequality and its subsequent intergenerational income mobility. Figure 1 illustrates the curve. Drawing on Corak (2013), it displays a significantly positive cross-sectional relationship between income inequality and the intergenerational elasticity of earnings (IGE) measured as the regression coefficient of a child's log income on their parent's log income.[3]

Krueger translated this finding into a statement about rising inequality and its implications for socio-economic *mobility* in the United States, one that was later echoed by Janet Yellen, then Chair of the Federal Reserve:[4]

> "Higher income inequality would be less of a concern if low-income earners became high-income earners at some point in their career, or if children of low-income parents had a good chance of climbing up the income scales when they grow up. In other words, if we had a high degree of income mobility we would be less concerned about the degree of inequality in any given year. But we do not. Moreover, as inequality has increased, evidence suggests that year-to-year or generation-to-generation economic mobility has decreased."

This framing of mobility as the negative of the IGE is common in the literature, and the labels of the vertical axis in Figure 1 reinforce this notion. From the perspective of the IGE, mobility reflects the degree of economic "churning" within society; that is, the extent to which progeny incomes do not covary with parental incomes. Such a view of mobility — as the negation of "pure movement" or as the ease of positional swaps on the economic ladder — becomes even sharper when magnitudes are discarded and purely relative measures of persistence are invoked, such as the correlation between the *ordinal* positions of parent and child in the overall distribution (Dahl and DeLeire 2008), or the *rank-rank slope* espoused by Chetty et al. (2014a).

[2]Alan Krueger, "The Rise and Consequences of Inequality in the United States," 12 January 2012.

[3]This pattern has been documented both across countries (Blanden 2013; Neidhöfer et al. 2018; Amaral et al. 2019; Mogila et al. 2020; Van der Weide et al. 2024; Muñoz and Van der Weide 2025) and within countries in regional sub-units (Chetty et al. 2014a; Mogila et al. 2020; Kwon and Jeon 2020; Fan et al. 2021; Acciari et al. 2022).

[4]Janet Yellen, "Perspectives on Inequality and Opportunity from the Survey of Consumer Finances," October 17, 2014.

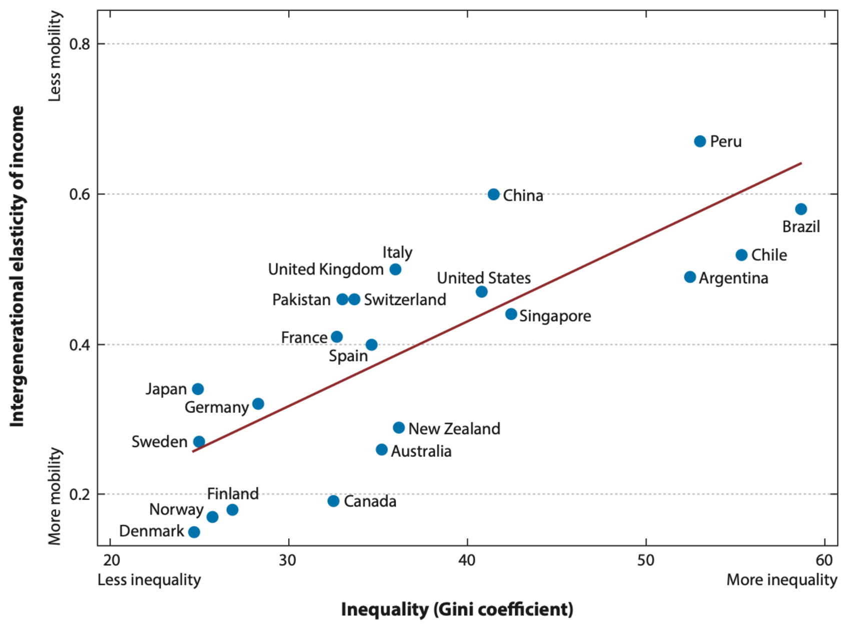


Figure 1. High inequality is correlated with low mobility. Source: Durlauf et al. (2022), based on Corak's data.

But there are other complementary views of mobility that are not simply based on the absence of persistence. These are measures that specifically emphasize absolute or relative improvements in living standards over time, either across generations or across poor and rich *in a single generation*. For instance, Chetty et al. (2014b) define "absolute mobility" by the share of children earning more than their parents, linking it to the "American Dream" of rising prosperity across generations.[5] Ray ⓡ Genicot (2023) aggregate growth experiences across individuals but with individual growth weighted by their baseline economic characteristics relative to their fellow members in society. These measures view mobility as shared prosperity (across generations, or across families in a single generation). Because the direction of economic change matters, we refer to them as measures of *upward mobility*.

One objective of our paper is to describe upward mobility from the complementary viewpoint of *growth progressivity* — faster growth accruing to the relatively poor — and to place such a concept side by side with other notions based on persistence. There is a plethora of measures in the literature (see Genicot ⓡ al. 2022 for a review),

[5]Chetty et al. (2014b) describe absolute mobility as follows: "One of the defining features of the 'American Dream' is the ideal that children have a higher standard of living than their parents... Such measures of *absolute income mobility* — the fraction of children earning or consuming more than their parents — are often the focus of policymakers when judging economic opportunity in the U.S."

and we believe there is much to be gained in viewing such measures from primitive foundations, based on desiderata that isolate the essential features of mobility. This exercise is important for several reasons:

First, "mobility" generates enormous interest among policy makers and the popular press. The word is bandied about quite loosely, and as we've seen from the references above, even academic researchers use the term in different ways. In particular, measures such as IGE place weight on the persistence of incomes within dynasties, whereas measures of upward mobility rely on comparisons of economic progress across poorer and richer dynasties. Both measures could be important, depending on the question to be addressed. As Ray ⓡ Genicot (2023) write:

> "It is certainly true that to assess the fortunes of a family over time, *that* family must be tracked... But to assess upward mobility overall, it is not an individual family that the researcher is after, but the contributions of all families to upward mobility at every point of time."

Upward mobility tracks societal fortunes as a whole, not those of individual dynasties.

Second, as we shall see, measures based on different core features have different empirical implications. The *Great Gatsby curve* implies that mobility (in the sense of low IGE) is negatively related to inequality. In striking contrast, upward mobility measures that respect growth progressivity are robustly and *positively* related to inequality. There is no paradox here; rather, the disparate empirical findings challenge the reader to align their choice of measure with the criteria that they feel best describe "mobility".

Finally, as we shall argue, the relationship between inequality and a relative version of our upward mobility measure is often interpretable as evidence for or against "inequality traps". These refer to one or more of multiple macroeconomic steady states with varying inequality, but under the same economic fundamentals. Arguments for such traps are typically made using various self-reinforcing mechanisms such as limited access to credit markets, a lack of beneficial peer effects, setup costs for entrepreneurship or human capital, or frustrated aspirations shaped by high ambient inequality (Azariadis and Drazen 1990, Banerjee and Newman 1993, Galor and Zeira 1993, Durlauf 1996, Mookherjee and Ray 2003, 2010, Genicot and Ray 2017, 2020). As we shall see, such mechanisms certainly generate traps or history dependence for individual dynasties, but whether they do so at a macroeconomic level is a more nuanced question. Our findings shed some empirical light on such questions.

2. Concepts of Upward Mobility

We begin by reviewing the IGE and its implied association to mobility via negation. We show how the IGE can be decomposed into a term that represents pure persistence in earnings, and another that tracks changes in the dispersion of log earnings. We connect this second term to a family of measures that values the progressivity of growth across different income levels, though our axiomatic development picks out not the dispersion of log incomes but a distinct (though related) subclass of measures. This conceptual part of our paper attempts to work towards a more nuanced understanding of just what "upward mobility" should mean.

2.1. The Intergenerational Elasticity of Earnings. The *intergenerational elasticity of earnings* (IGE) is derived from a regression of the logarithm of a child's income on their parent's log income.[6] Impose the log-linear specification:

$$\log y(t) = \alpha + \beta \log y(s) + u(t),$$

where y is income, s and t are start and end times, and u is an independent innovation to income. The IGE is our estimate of the coefficient β. Following familiar reasoning,

$$\text{IGE} = \hat{\beta} = \frac{\text{Cov}(\log y(s), \log y(t))}{\sigma^2(\log y(s))}. \tag{1}$$

2.1.1. Decomposition. The formula for the IGE admits a standard but useful decomposition. The correlation coefficient ρ between $\log y(s)$ and $\log y(t)$ is given by

$$\rho = \frac{\text{Cov}(\log y(t), \log y(s))}{\sigma(\log y(t))\sigma(\log y(s))}, \tag{2}$$

where σ stands for standard deviation. Combining (1) and (2), we obtain the well-known relationship (Solon 1992):

$$\text{IGE} = \underbrace{\rho}_{\text{Persistence}} \times \underbrace{\frac{\sigma(\log y(t))}{\sigma(\log y(s))}}_{\text{Change in Dispersion}}. \tag{3}$$

[6] IGEs are typically estimated using either lifetime earnings or earnings measured at a specific age for both parents and children (e.g., age 30 or 40).

In words, the IGE can be multiplicatively decomposed into two components: a *persistence* term, capturing intergenerational correlation, and a *dispersion* term, reflecting the change in the spread of log incomes over time.

2.1.2. Persistence. The first component ρ is the intergenerational correlation coefficient. It is scale-neutral and growth-rate neutral. And it is entirely immune to the widening or narrowing of economic inequality over time. On the other hand, a permutation of *who owns what* at date t, given ownership at some earlier date s, will indeed affect ρ. Therefore ρ is a measure of what is known as *exchange immobility*. It captures the extent of churning in income across time, declining as that churning climbs. It is a proxy for the "pure persistence" of incomes across time or generations.

2.1.3. Dispersion. The term $\sigma(\log y(t))/\sigma(\log y(s))$ is the change in the standard deviation of log income over time. Although it is not Lorenz-consistent,[7] it is commonly used as a measure of income dispersion. The IGE is sensitive to this metric as well as to ρ and in this sense, it goes beyond capturing pure persistence alone: it combines the degree of correlation in income ranks with changes in the overall spread of incomes.

2.1.4. Points of Departure. It is natural, then, to use the IGE for two orthogonal directions of departure. One direction ties immobility to pure persistence alone. The rank correlation between the ordinal positions occupied by parents and children in the overall income distribution (Dahl and DeLeire 2008), or the *rank-rank slope* employed by Chetty et al. (2014b), are both measures that emphasize the persistence angle, and come under the umbrella of ρ. Changes in income inequality, or indeed, even the *level* of inequality at any point of time, are of secondary import under this view. The second direction is related to the measures of upward mobility mentioned in the Introduction. These measures are sensitive to changes in income, or to changes in the distribution of income, and notions of persistence will play a secondary role. The measures come in both absolute and relative variants. We will argue that an axiomatic perspective ties down this class of measures to a specific sub-family.

In what follows, we focus on the second direction of departure, as the first has already received substantial attention.

[7]It is not consistent with the majorization order and therefore with the Lorenz ordering on income distributions.

2.2. Upward Mobility. We begin by discussing some desiderata for mobility measurement. We seek a *directed* measure that tracks transitions across hierarchical categories, such as income, wealth, and social status. (This is to be contrasted with mobility across unranked categories, such as geographical locations.) To consistently emphasize this point, *we will always use the phrase* "upward mobility," rather than just "mobility."

We want to weave two commonsensical aspects of upward mobility into desiderata or axioms. The first is a relative notion: that there is a compelling case for differentially valuing similar gains to the deprived and to the affluent: the same percentage gains count for greater upward mobility if experienced by the poor rather than the rich. The second is an absolute notion: that upward mobility is enhanced when society universally climbs the ladder of ranked categories, and is reduced when society descends that ladder. There is an excellent case for netting climb against descent when computing upward mobility for society as a whole.

2.2.1. Axioms. The domain on which our axioms are to be formally placed is made out of all possible collections of income trajectories over some interval of time, one trajectory for each individual in the collection.[8] The two substantial axioms we impose are *growth progressivity* and *growth alignment*. The former states that if a collection of trajectories is morphed into another by transferring growth percentage points from the relatively rich to the relatively poor, then upward mobility — however measured — must go up. The latter axiom states that upward mobility increases if we scale up the growth *rates* of all trajectories, and it decreases if we scale those growth rates down — we mark the zero point by normalizing upward mobility to zero if every trajectory is completely flat.

Figure 2 illustrates growth progressivity. Assume that there are just two individuals A and B. Each of the three panels in the figure depict *two* data points, blue and orange, in the domain of interest, each a single collection of two log income trajectories. In the first two panels, B is poorer throughout the trajectory than A is. The growth progressivity axiom states that an x percentage-point transfer of growth from A to B enhances upward mobility for society as a whole; that is, the orange society is more upwardly mobile than the blue society for the period under consideration. (In the Figure, $x = 2$ percentage points.) The difference between the two panels underlines

[8]Births and deaths are easily incorporated into this domain; see Ray ⓡ Genicot (2023).

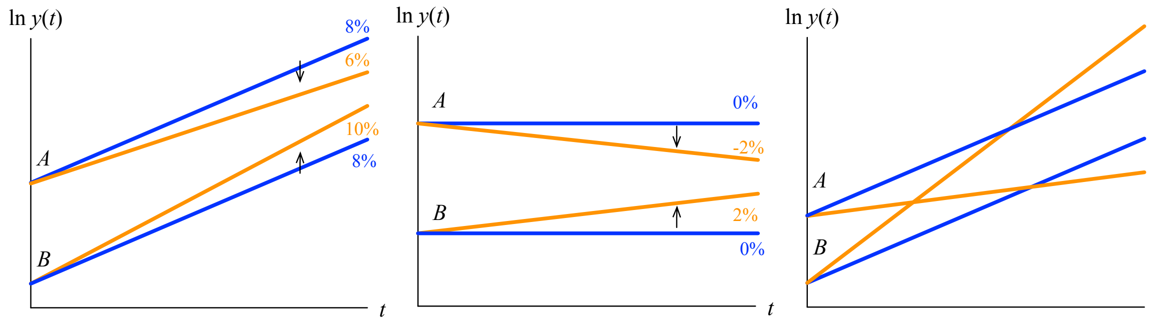


Figure 2. Illustration of the Growth Progressivity Axiom.

the purely relative nature of this axiom. In the first panel, society as a whole is growing under both blue and orange scenarios; in the second, the blue society is entirely stagnant and the orange society has overall negative growth. But the axiom nevertheless insists that because the relatively poor are outperforming the relatively rich, upward mobility is higher going from blue to orange in either setting.[9] The third panel is different. Here, the initially poorer person, B, grows faster in the orange society, but catches up and then surpasses A. Should we *still* apply growth progressivity and claim that the orange society is more mobile by virtue of the initially poorer B growing faster? The answer is no, or at least, not necessarily: the axiom is silent on what happens in Panel 3.

Our second axiom, growth alignment, is specific to absolute upward mobility. It states that if all individual trajectories exhibit faster growth than they did before, then upward mobility is necessarily higher under the new collection of trajectories than they were under the old. It places the directional nature of income or wealth at center stage: going up is more *upwardly* mobile than coming down. *Relative* upward mobility will net out these aggregate changes while still maintaining directionality; see below.

Note that growth alignment tolerates the possibility that inequality might increase in the process. Put another way, mobility measurement (even in its relativistic version)

[9]The assertion that a transfer of growth percentage *points* generates higher upward mobility may come across as too strong; after all, aggregate growth suffers as a result of this change. We have two responses to this objection. One is that we are not measuring growth, we are measuring upward mobility. The latter is far from being a sufficient statistic for social welfare as a whole, and one would have to combine several other indicators (including upward mobility) to come to a final judgment. The second is that we can readily work with the weaker axiom that a transfer of *absolute* income growth from rich to poor enhances upward mobility. As it so happens, this gives us a broader class of measures, but still indexed by the one parameter that we uncover in equation (4), though over a broader range; see Ray ⓡ Genicot (2023) for details. We prefer to defend the stronger axiom, though.

is assuredly not the same as inequality measurement, a topic which enjoys a firmer axiomatic footing than mobility does because of the widely accepted axiom of Lorenz dominance. An overall welfare judgment must take stock of mobility, inequality and other features such as growth.

2.2.2. Characterization. Let $\mathbf{y}[s,t]$ be a collection of income trajectories $\{y_i[s,t]\}$ over time interval $[s,t]$, where i ranges over a set of individuals or households. Ray ⓡ Genicot (2023) show that our core axioms[10] *necessitate* that we measure absolute upward mobility by:

$$M^\alpha(\mathbf{y}[s,t]) = \frac{1}{t-s} \ln \left[\frac{\sum_{i=1}^n y_i(t)^{-\alpha}}{\sum_{i=1}^n y_i(s)^{-\alpha}} \right]^{-\frac{1}{\alpha}}, \tag{4}$$

where $\alpha > 0$ is a weighting factor that the researcher is free to choose. As shown by Ray ⓡ Genicot (2023), this measure can be easily extended to allow for births, deaths and generally changing populations, so individual trajectories in (4) can be replaced by population shares at different income levels over $[s,t]$. Ray ⓡ Genicot (2023) argue that this absolute measure M can be converted into a relative mobility measure R via the following simple rule:

$$R^\alpha(\mathbf{y}[s,t]) = M^\alpha(\mathbf{y}[s,t]) - g(s,t), \tag{5}$$

where $g(s,t) = [\ln(\bar{y}(t)) - \ln(\bar{y}(s))]/[t-s]$ is the average rate of per-capita growth over $[s,t]$.

There is a close connection between these upward mobility measures described in (4) and (5), and the time evolution of the *Atkinson welfare function* (Atkinson 1970), given by:

$$W^\alpha(\mathbf{y}) = \left(\frac{1}{n} \sum_i y_i^{-\alpha} \right)^{-\frac{1}{\alpha}}, \text{ where } \alpha > -1. \tag{6}$$

An inspection of (4) quickly reveals that the upward mobility measure M^α is given by the instantaneous growth of Atkinson welfare over time. In Section 6, we return to this connection and in particular to a parallel link between the *relative* upward

[10]We do impose other standard restrictions. One of them is insensitivity to income scalings — upward mobility should not change whether we measure trajectories in euros or rupees. Another pair of axioms imposes some separability restrictions across replicated societies, and over time. See Ray ⓡ Genicot (2023) for details.

mobility measure R^α and Atkinson's *inequality* measure, given by

$$A^\alpha(\mathbf{y}) = 1 - [W^\alpha(\mathbf{y})/\bar{y}],$$

where $\bar{y}$ is average income under $\mathbf{y}$. This link will lead to another interpretation of our version of the Great Gatsby curve, one that permits an examination of the empirical existence of inequality traps. But we postpone that discussion for now.

2.2.3. Upward Mobility and Persistence. Our characterization of upward mobility measures stands in sharp contrast to measures based on persistence. Persistence *isn't even involved*, and as a corollary of that observation, no panel data are needed for the empirical implementation of these measures. Two cross-sections of incomes at starting and ending dates are sufficient. The Growth Progressivity axiom is largely but not entirely responsible for this outcome: the derived linearity of our measure in growth rates (a basic consequence of Progressivity) and the time additivity and scale invariance axioms jointly conspire to precipitate this feature.

This may come as a surprise to those accustomed to thinking of mobility in terms of persistence. While some may argue that mobility is a dynamic construct for dynasties or lineages and therefore requires panel data (as does the IGE), this is not the case for upward mobility in society as a whole, absolute or relative. When assessing *overall* upward mobility, it is not an individual family that you are after, but their contributions to social mobility at each point of time. And as we have argued, a family is given more social weight at any instant that it is poorer than another, but those weights are reversed as soon as their income or wealth rankings are reversed; recall, for instance, the third panel in Figure 2. As long as we restrict ourselves to upward mobility at the aggregate societal level, the need for history-dependent measurement is attenuated or eliminated, provided the domain (permanent income or wealth) proxies well for a family's expected lifetime welfare at any point of time.[11] For an extended discussion and defense of this position, see Ray ⓡ Genicot (2023).

[11]Of course, income as usually measured may not be a sufficient statistic in this sense. This is easily fixed, at least at some conceptual level: just use the appropriate unit-level variable such as wealth, or consumption, or moving income averages, as a proxy for permanent income. But the problem can run deeper. An individual's current socioeconomic position might also be driven by stigma or status for some identifiable *social group* to which that individual belongs. The fact that B is currently richer than A might not detract from the reality that B belongs to an underserved social group, demarcated by ethnicity, race, gender or religion. If such groupings are salient, our measures of upward mobility in (4) and (5) may need to incorporate this fact. In particular, Growth Progressivity must be suitably modified. For more detail, see Ray ⓡ Genicot (2023).

Finally, we should note that these measures of upward mobility can be readily applied across generations. Simply view s as pertaining to the starting generation and t as pertaining to the terminal generation. It is true that trajectories across different agents are, almost by definition, not continuous in time, there could be time overlaps as well, and populations could well change over time. Ray ⓡ Genicot (2023) discuss these issues in Sections V.E and V.F of their paper, and argue that the same measures in equations (4) and (5) continue to apply.

3. The Great Gatsby Curve for Upward Mobility

The Great Gatsby Curve in its original form employs IGE as the dependent variable, typically over a cross-section of countries. A panel specification is rarely used, owing to the absence of elasticity estimates spanning multiple generations (Amaral et al. 2019 is an exception). Even estimating a single IGE for most countries requires strong assumptions (see Muñoz and Van der Weide 2025), particularly outside the OECD, where high-quality panel or administrative data are scarce. We now reformulate the curve using relative and absolute measures of upward mobility as the outcomes of interest. That is, we replace IGE by $-M$ or $-R$ (note the obvious sign flip to facilitate comparison). Because these measures do not depend on tracking individual lineages, we have a lot more data for multiple years *and* multiple countries, and so country-level panel datasets become central to our analysis; see Section 3.2 for a description.

3.1. Specification. A panel version of the Great Gatsby Curve would take the form:

$$\mathrm{IGE}_{js} = \beta \cdot \mathrm{Gini}_{js} + f'_j + h'_s + \varepsilon_{js},$$

where j indexes countries, s indexes birth cohorts, β is the coefficient of interest, and f'_j and h'_s are country and generation fixed effects, respectively. To match this with a specification that uses upward mobility, suppose that we have data spanning T years for a set of countries. Fix an interval Δ, which is the period of time over which upward mobility is to be assessed. That is, for every date $s \leq T - \Delta$, we will calculate a measure of upward mobility by country over the period $[s, s + \Delta]$. The baseline linear specification mirrors the structure of the IGE equation:

$$U_{js} = \gamma I_{js} + f_j + h_{rs} + \epsilon_{js}, \tag{7}$$

where j indexes country, s time and r a region that contains j, U is a measure of relative or absolute upward mobility applied over Δ periods from every s, I_{js} is a measure of inequality, f_j are country fixed-effects capturing time-invariant country characteristics, and h_{rt} are region-year fixed effects, incorporating common regional shocks across years (e.g., recessions).[12] Finally, the error term ϵ_{js} accounts for all other time-varying unobservable factors affecting mobility. Despite the similarity in right-hand-side notation, note that U is oriented towards mobility and IGE away from it, so that the same algebraic signs of β and γ have opposite interpretations.

As the reader will appreciate, an enormous number of variants are generated by the core specification (7). The equation is written for some *fixed* Δ, and all estimates are sensitive to Δ, as they are to the choice of mobility measures, not to mention different values of the inequality aversion parameter α that governs those measures. It is also possible to add time-varying controls to (7), including potential lags of the outcome variable. We will explore these alternatives at different points below.

This list excludes yet other important variations. The Gini index is naturally our baseline measure of inequality, entering as it does into the existing form of the Great Gatsby curve, and so using it maximizes comparison with that curve. But at the same time, our discussion at the end of Section 2.2.2 highlights the intimate connections between our upward mobility measures and Atkinson welfare (and inequality), which suggests a version of (7) in which the Gini is replaced by the Atkinson measure of inequality; see equation (10) for a formal definition.

This replacement will be of value when we re-interpret (7) as an equation for the dynamic evolution of inequality; see Section 6.2 for a discussion. But in turn, such a re-interpretation pushes us to go beyond linearity in (7). After all, a large literature (references below) explores the possibility of poverty or inequality traps co-existing with other non-trap steady states. Such configurations are inconsistent with the linear specification, for they ask for both multiplicity and the absence of unbounded explosive trends. That is why we also explore semi-parametric variants of the form

$$U_{js} = \Psi(I_{js}) + f_j + h_{rs} + \epsilon_{js}, \tag{8}$$

where Ψ is nonparametric or lies in some pre-assigned class of functions.

[12] We can, of course, set r equal to the entire world in which case h_{rt} reduces to time fixed effects, but we distinguish between five major politico-geographical regions; see Sections 3.2.5 and 5.3.

As a final remark before we turn to the data, note that it is crucial that inequality, however proxied, be measured at the *start* s of any interval $[s, s+\Delta]$ for all of the above specifications. Measuring inequality at the midpoint of the interval (Corak 2013) or even at the end-point $s + \Delta$ (Amaral et al. 2019) could potentially alter the sign of the coefficient and leads to stronger concerns of endogeneity.

3.2. Data. This section introduces the data and the main variables used in the analysis. Further details and a table of summary statistics can be found in Appendix A.

3.2.1. Income Distribution. Our core measures of inequality and upward mobility come from the World Inequality Database (WID). We privilege the WID because it offers the longest, most internally consistent time series and the best country coverage, allowing us to compile a balanced panel. To cross-check our results, we also employ two alternative databases: the *Poverty and Inequality Platform* (PIP) of the World Bank, which relies directly on harmonized household surveys; and the *World Income Inequality Database* (WIID, UNU-WIDER), which collates survey- and national-accounts-based series from a broad range of providers.

3.2.2. Sample. The WID provides income distribution data for a broad set of countries from 1980 to 2021. To ensure data reliability and comparability, we exclude countries for which all observations are imputed (19 countries in total), as well as very small countries with population below one million in 2021. After applying these filters, our baseline sample consists of 130 countries. In the baseline specification, we construct 10-year mobility measures and therefore the initial year s runs from 1980 to 2011.

3.2.3. Measures of Upward Mobility. The WID reports the income distribution by decile and percentile.[13] We build all mobility measures from these grouped data, because comparable micro-level income records are unavailable for most country-year observations. Absolute and relative mobility are therefore computed from (4) and (5), with i indexing either deciles or percentiles. The inequality-aversion parameter α is set equal to 0.5,[14] but our results are highly robust to the choice of α (see Section 5.4).

[13]We use pre-tax national income expressed in 2020 prices for the adult population aged 20 and over (population group 992). Income is assumed to be split equally among household members. In the raw WID files, incomes are expressed in domestic currency at 2020 constant prices. To facilitate cross-country comparison, we convert all values to U.S. dollars using the WID's PPP conversion factors.

[14]The parameter α reflects the pro-poorness of the measure. For instance, $\alpha = 0.5$ doubles the weight on the growth of someone earning \$40,000 relative to someone earning \$160,000.

Our baseline relies on annual *decile* data, which provide a more stable footing for mobility estimates by muting the outsized geometric influence of unrealistically low reported incomes. Even so, the measures remain sensitive to near-zero values. To prevent spuriously large swings, we impose a small "floor" on incomes, set at $50 in the main specification. That is, if income for any decile-year falls below the floor, the entire distribution for that country is shifted rightward by the minimum amount needed to exceed the floor. This shift is applied consistently across all years for that country, so that year-to-year comparisons remain valid and unaffected. Robustness checks using alternative floor values yield similar results (see Section 5.5). While decile data are preferred in the baseline, percentile data (with income floors imposed in the same way) are also used for robustness analysis (see Section 5.6).

3.2.4. Income Inequality Measures. We measure inequality with two indicators — the Gini coefficient and the Atkinson index — each derived from the same income-distribution data for our mobility indicators. For consistency, the Atkinson index employs the same value of α adopted in the baseline mobility calculations.

3.2.5. Additional Variables. All our specifications include country fixed effects and region-year fixed effects to account for unobserved heterogeneity across countries and for regional shocks or trends.[15] In addition, initial log income per capita is included as a baseline control. To further address potential confounding factors, we incorporate a set of time-varying control variables in several of our specifications. Given the breadth of possible covariates, we draw guidance from the growth convergence literature — particularly from Kremer et al. (2022) — to inform our selection. We include proxies for Solow fundamentals such as gross capital formation, population shares with primary and secondary education, and population growth. We can expand these to include labor force participation and political institutions (using the Polity2 score), or key aspects of fiscal and financial policy, including government spending/GDP, inflation, and the size of the financial sector, or additional demographic controls, namely the shares of the population aged below 14 and between 15 and 65, so as to capture relevant structural differences across countries and over time.[16]

[15]We consider 5 regions: Asia, the Middle East, Africa, Latin America and Neo-Europe, this last region including the European countries and the USA, Canada, Australia and New Zealand.

[16]Variables come from different sources but have all been downloaded from the World Bank database using the STATA wbopendata command, except for the education data from Barro and Lee (2013).

3.3. Stationarity. As a preliminary step, we investigate whether the main variables satisfy panel-estimation assumptions. Because our panel spans 32 annual observations — a relatively long time dimension for cross-country data — we check whether the key variables are stationary. To that end we run several panel unit-root tests; the results, reported in Appendix A.2, decisively reject the null of a unit root in every case. We therefore proceed under the assumption that all the relevant variables are stationary. Note that stationarity is compatible with nonlinearity in the underlying process. For, instance, the Gini might evolve in a locally divergent way, leading to multiple steady-state inequality levels, as long as that divergence is not global.

4. The Great Gatsby Curve, Revisited

This section presents our baseline results describing the relationship between upward mobility and baseline inequality. We begin with the specification (7) with and without controls, and go on examine its semi-parametric counterpart (8). Several variants that probe these robustness of the results are presented in Section 5 and in Appendix B.

4.1. Baseline Linear Model. Our initial approach considers the linear model in (7), which specifies a panel model for mobility. We recall that equation here for convenience:

$$U_{js} = \gamma I_{js} + f_j + h_{rs} + \epsilon_{js}, \tag{9}$$

where as already explained, U_{js} measures absolute or relative mobility for country j from year s to the horizon year $s + \Delta$ at a *given* distance Δ, I is the Gini coefficient or the Atkinson inequality measure, and f_j and h_{rs} denote country and region-year fixed effects. We augment this equation in some variations by time-varying controls, including potential lags in the outcome variable.

Table 1 presents estimates from this linear specification. Columns 1 to 4 use relative upward mobility as the dependent variable, while columns 5 and 6 use absolute upward mobility. Across all specifications, the coefficient on inequality is positive and highly significant. This indicates that, within countries, higher initial inequality is systematically associated with greater subsequent upward mobility, in sharp contrast to the Great Gatsby curve that uses IGE as the outcome variable. Using the estimates in Columns 2 and 5, a one standard deviation increase (.084) in the Gini coefficient is associated with a 1.8 percentage point rise in relative upward mobility — exceeding

Table 1. Upward Mobility and Inequality (10-Year Horizon)

	Relative Upward Mob.				Absolute Upward Mob.	
	[1]	[2]	[3]	[4]	[5]	[6]
Gini_s	21.88***	21.87***			25.08***	
	(2.756)	(2.774)			(4.670)	
Atkinson Ineq_s			22.44***	22.59***		25.41***
			(2.367)	(2.371)		(3.908)
Log income pc_s		0.016		-0.20	-7.89***	-8.14***
		(0.266)		(0.224)	(0.474)	(0.485)
R^2	0.305	0.305	0.401	0.402	0.601	0.622
Observations	4,158	4,158	4,158	4,158	4,158	4,158

Notes: This table reports estimates of the relationship between inequality (using the Gini or Atkinson indices) and upward mobility (relative or absolute, over a 10-year horizon). The sample spans 130 countries from 1980 to 2011. Robust standard errors clustered at the country level are reported in parentheses. All regressions include country and region–year fixed effects. Stars denote statistical significance at conventional levels: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***).

its standard deviation (1.51) — and a 2.1 percentage point increase in absolute upward mobility — approximately 60% of its standard deviation (3.4).[17]

Given that the difference between relative and absolute mobility reflects differences in growth, the divergence in coefficients may be interpreted as capturing the effect of inequality on subsequent growth. That said, Table B7 in the Appendix shows that while the association between growth and initial inequality is generally positive, it is never statistically significant. The effect of inequality on growth remains a topic of ongoing debate, with existing empirical evidence yielding mixed results and no consistent pattern; see, e.g., Forbes (2000) and Banerjee and Duflo (2003).

4.2. Controls in the Baseline Linear Model. To assess the robustness of these baseline results, Table 2 expands our specification (columns 2 and 5 in Table 1) by introducing a broad set of control variables commonly employed in the literature on economic growth and inequality (see Kremer et al. 2022). These include measures of democracy (Polity2), government size (government expenditure as a share of GDP), capital accumulation (gross capital formation), demographic structure (population

[17]Similarly, an increase of 1 standard deviation in Atkinson Inequality (0.084) is associated with an increase in relative upward mobility of 2.1 percentage points (1.4 standard deviations) — and an increase in absolute upward mobility of 2.13 — about 60% of its standard deviation.

Table 2. Upward Mobility and Inequality: Controls

	Relative Upward Mobility						Absolute Upward Mobility					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Gini_s	21.872***	22.636***	23.297***	30.659***	31.623***	31.259***	25.081***	25.844***	29.208***	35.220***	36.948***	33.764***
	(2.774)	(3.092)	(3.345)	(3.402)	(4.334)	(4.417)	(4.670)	(4.129)	(4.589)	(4.318)	(5.216)	(5.928)
Log income p.c._s	0.016	0.392	-0.201	-0.601	-0.680	-0.704	-7.891***	-6.250***	-6.322***	-6.766***	-6.279***	-5.833***
	(0.266)	(0.361)	(0.490)	(0.441)	(0.680)	(0.701)	(0.474)	(0.819)	(0.620)	(0.679)	(1.014)	(0.996)
Polity2_s		-0.030	-0.025	-0.041**	-0.026	-0.021		-0.007	-0.010	0.007	0.029	0.027
		(0.020)	(0.019)	(0.017)	(0.021)	(0.020)		(0.021)	(0.020)	(0.025)	(0.025)	(0.028)
Gov. exp/gdp_s		0.004	0.002	0.001	-0.001	-0.000		-0.006	-0.008	-0.009**	-0.011**	-0.009*
		(0.005)	(0.004)	(0.004)	(0.005)	(0.005)		(0.007)	(0.006)	(0.005)	(0.006)	(0.005)
Gross Cap. Form. (% $\text{GDP})_s$			0.000	-0.004	0.072	0.074			-0.003	-0.020*	0.026	0.031
			(0.008)	(0.010)	(0.078)	(0.073)			(0.010)	(0.012)	(0.097)	(0.100)
Pop. Growth_s			0.028	0.014	0.018	0.010			0.020	-0.007	0.006	0.000
			(0.040)	(0.031)	(0.032)	(0.034)			(0.043)	(0.041)	(0.036)	(0.038)
% Pop. at most primary_s			0.005	-0.002	0.009	0.010			0.023	0.023	0.019	0.020
			(0.021)	(0.032)	(0.038)	(0.040)			(0.027)	(0.039)	(0.051)	(0.055)
% Pop at most secondary_s			0.007	-0.018	-0.013	-0.012			0.016	0.006	-0.002	0.005
			(0.022)	(0.024)	(0.028)	(0.028)			(0.026)	(0.032)	(0.041)	(0.043)
Labor force part._s				0.049**	0.049*	0.050*				0.034	0.084	0.089
				(0.019)	(0.026)	(0.026)				(0.051)	(0.058)	(0.058)
% Pop. below 14_s				-0.061	0.029	0.030				0.079	0.134	0.144
				(0.073)	(0.128)	(0.125)				(0.128)	(0.201)	(0.205)
% Pop. between $(15\text{-}64)_s$				0.047	0.116	0.115				0.202	0.248	0.258
				(0.058)	(0.102)	(0.098)				(0.124)	(0.169)	(0.172)
Inv/GDP_s					-0.076	-0.077					-0.041	-0.045
					(0.079)	(0.074)					(0.099)	(0.101)
Inflation $_s$					0.001***	0.001***					0.000	0.001*
					(0.000)	(0.000)					(0.000)	(0.001)
Credit by finan. sector $_s$					-0.003	-0.004					-0.009	-0.010*
					(0.004)	(0.003)					(0.006)	(0.006)
R^{α}_{js-11}						-0.006						
						(0.044)						
M^{α}_{js-11}												-0.080
												(0.060)
R^2	0.305	0.284	0.312	0.421	0.473	0.470	0.601	0.467	0.511	0.556	0.538	0.542
Obs	4158	3230	2635	1936	1430	1379	4158	3230	2635	1936	1430	1379

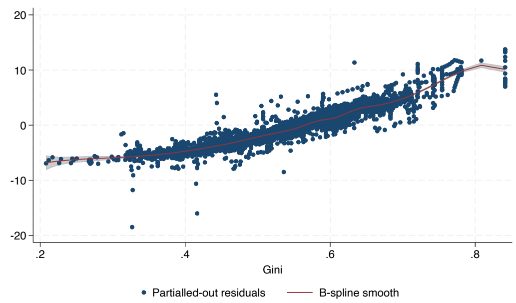
Notes: This table reports estimates of the relationship between initial relative and absolute 10-year upward mobility measures and initial inequality (measured by the Gini coeffient) progressively adding control variables. Robust standard errors clustered at the country level are reported in parentheses. All regressions include country fixed effects and region-year fixed effects.

growth and age composition), educational attainment, labor force participation, inflation, and financial development (credit to the private sector). All control variables are measured at the starting date (s), and country and region-year fixed effects continue to be included throughout.[18]

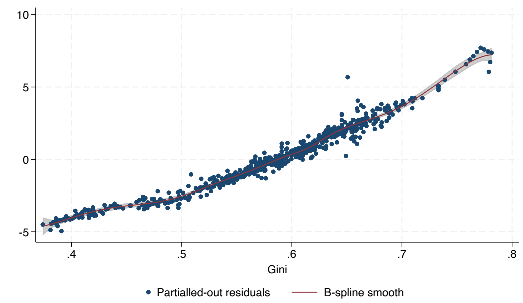
Columns [1]–[6] examine relative upward mobility, while columns [7]–[12] focus on absolute upward mobility. Across both panels, the coefficient on initial inequality (Gini_s) remains positive and highly statistically significant, and becomes larger as additional controls are sequentially introduced. This pattern strengthens the evidence for a robust and positive association between initial inequality and upward mobility.

In the last columns of each panel (columns [6] and [12]) we additionally include the lagged dependent variable that corresponds to mobility over the period $s - 11$ to

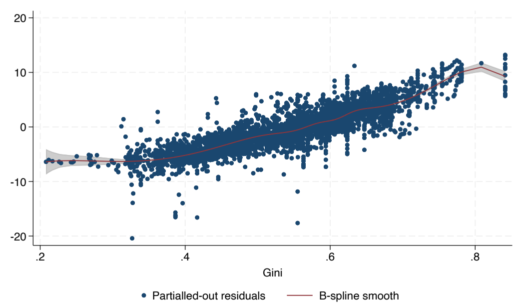
[18]Table B1 in the Appendix replicates Table 2 using Atkinson inequality in place of the Gini coefficient, obtaining very similar results.



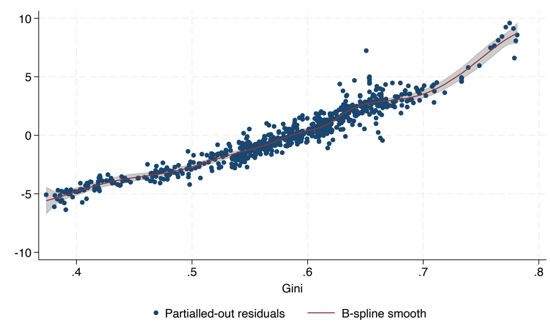
(a) Rel. mob. vs Gini_s



(b) Rel. mob. vs Gini_s, with controls



(c) Abs. mob. vs Gini_s



(d) Abs. mob. vs Gini_s, with controls

Figure 3. Upward Mobility versus Inequality: Semiparametric Estimates.
NOTES: The curve depicts the non-parametric component $\Psi(\cdot)$ estimated with the semiparametric fixed-effects series estimator of Baltagi and Li (2002). Inequality is measured by the Gini index; all other covariates enter linearly, together with country fixed effects and region–year fixed effects.

$s-1$, so as to capture any persistence in mobility dynamics. The lagged term is not significant in either case and its inclusion does not materially affect the estimated coefficient on inequality, further underscoring the stability of our core result.[19]

Taken together, these findings suggest that the relationship between inequality and upward mobility is not an artifact of omitted variable bias and that it persists even after controlling for a rich set of covariates that are known to affect growth and distributional dynamics.

4.3. A Semi-Parametric Specification. To further explore the relationship between inequality and mobility, we move beyond the linear specification and estimate a semiparametric model. This approach allows us to relax the assumption of linearity

[19]Since this is a dynamic panel, the "within transformation" used to eliminate fixed effects renders the lagged dependent variable endogenous. However, given the large time dimension, the resulting bias is likely to be small. GMM estimation of the equation yields virtually identical results.

in our key explanatory variable — inequality — while retaining a linear structure for the remaining controls. In doing so, we directly estimate the relationship hypothesised in equation (8), where the functional form of the mapping from inequality to mobility is left unspecified.

Figure 3 presents estimates of the function Ψ from equation (8) for both mobility indices using nonparametric methods. Specifically, we employ the semiparametric fixed-effects series estimator developed by Baltagi and Li (2002).[20] The method leaves unspecified the functional relationship between inequality and mobility, while the remaining covariates enter linearly. The nonparametric fit is achieved using B-splines. Panels (a) and (b) illustrate the relationship between relative upward mobility and the Gini, estimated without and with the full set of controls from Column 5 of Table 2, respectively. Panels (c) and (d) present the corresponding results using absolute upward mobility as the dependent variable.

Visual inspection of these panels reveals a monotonic relationship between mobility and inequality and little evidence of strong nonlinearity. These findings reinforce the conclusions from the previous section and suggest that the linear specification provides a reliable approximation to the underlying relationship.[21]

5. Robustness Checks

To probe the robustness of our baseline results, this section presents several checks that vary the mobility horizon, the income distribution data (from deciles to percentiles), the source of distributional information, the treatment of measurement error, the value of the inequality aversion parameter α, and other modeling specifications.

5.1. Mobility over Longer Periods of Time. The results presented thus far focus on mobility measures over relatively short horizons (10 years). We extend the analysis to longer time frames that more closely align with the approach taken in much of the intergenerational mobility literature, which typically examines mobility over approximately 30-year gaps between parents and children (see Durlauf et al., 2022 and references therein). Table 3 reports estimates using absolute and relative mobility over

[20]As a robustness check, we also estimated specifications similar to those in Section 4, including quadratic and cubic terms of inequality. The results closely match those from the nonparametric specification, providing no evidence of meaningful nonlinearities.

[21]Figure B1 in the Appendix substitutes the Gini coefficient with Atkinson inequality.

20- and 30-year periods as the dependent variable. Inequality is measured using the Gini index at the beginning of each period. Specifications with and without controls are considered. The estimated effect of inequality remains positive and significant.

Table 3. UPWARD MOBILITY AND INEQUALITY: 20- AND 30-YEAR HORIZONS

	RELATIVE UPWARD MOBILITY				ABSOLUTE UPWARD MOBILITY			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$\text{Gini}_s, \Delta = 20$	17.805***	19.741***			20.474***	23.825***		
	(1.684)	(1.529)			(1.897)	(2.086)		
$\text{Gini}_s, \Delta = 30$			9.090***	10.779***			11.151***	10.068***
			(1.157)	(0.620)			(1.551)	(2.715)
Log Income $\text{p.c.}_s, \Delta = 20$	0.074	0.327			-5.352***	-3.488***		
	(0.130)	(0.307)			(0.237)	(0.575)		
Log Income $\text{p.c.}_s, \Delta = 30$			0.098	-0.027			-3.525***	-3.028***
			(0.148)	(0.135)			(0.224)	(0.375)
CONTROLS	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.482	0.746	0.227	0.916	0.780	0.660	0.566	0.889
Obs	2858	693	1558	105	2858	693	1558	105

NOTES: This table reports estimates of the relationship between initial inequality (measured by the Gini coefficient) and upward mobility (both relative and absolute, over 20- and 30-year horizons). Control variables include Polity2, government expenditure, capital formation, population growth and structure, education levels, labor force participation, inflation, and credit to the financial sector. Robust standard errors clustered at the country level. All regressions include country fixed effects and region–year fixed effects.

5.2. Measurement Error in WID Data. Our baseline estimates rely on the World Inequality Database (WID). Although the WID offers unparalleled country-year coverage, its series are partly constructed by interpolating survey and administrative data — an approach that can introduce noise.[22] To verify that our main results do not hinge on such measurement issues, we pursue three complementary strategies: (i) we replicate the analysis with two alternative sources, the World Bank's Poverty and Inequality Platform (PIP) and the World Income Inequality Database (WIID); (ii) we smooth the raw income distributions in all datasets by averaging over adjacent years, thereby attenuating transitory shocks and glitches in reporting or measurement; and (iii) We rerun the core regressions, dropping observations from WID that are based on interpolated data.

First, we turn to the World Bank's PIP platform, which has data that draw directly from household surveys.[23] Table B2 in Appendix B reports the relationship between 10-year

[22]See https://wid.world/wid-world/ for the specifics of interpolation.
[23]https://pip.worldbank.org

upward mobility — both relative and absolute — and initial inequality, measured by the Gini and Atkinson indices. The coefficients on baseline inequality remain positive, sizeable, and statistically significant, mirroring the WID-based results. Each panel shows specifications with and without the full control set.

We then repeat the exercise using the WIID. The results, shown in Table B3 (Appendix B), are again virtually unchanged. The consistency across WID, PIP, and WIID underscores that our key finding — a strong positive link between initial inequality and subsequent upward mobility — is not an artifact of any particular data source.

To continue to address concerns about potential measurement error in the income data, we smooth year-to-year fluctuations and replace each annual observation with a three-year centered rolling average of the income distribution.[24] This approach is conservative and aims to mitigate the influence of transitory shocks or reporting inconsistencies that may distort the measurement of upward mobility. Table 4 reports the results from this specification. The estimates remain very similar to those presented in the main analysis, suggesting that mean-reverting measurement error is unlikely to be driving our core findings.

Finally, one of the key strengths of the WID is its integration of multiple data sources, which yields a well-balanced panel dataset. Because the compilation process also relies on several interpolations — within countries and, in some cases, across countries — measurement error may be introduced. To ensure that our results are not driven by these interpolated observations, we re-estimate our core regressions after excluding them. The results, reported in Table B4 in Appendix B, are in line with those presented in the main text.[25]

5.3. Regional Heterogeneity. We next examine whether the inequality-mobility relationship varies across major world regions. Specifically, we interact the Gini coefficient with dummies for Asia, Latin America, the Middle East, and Africa, using "Neo-Europe" — Europe, the United States, Canada, Australia, and New Zealand — as the reference category. This specification allows the coefficient on inequality to differ by region. The results are reported in Table 5.

[24]Similar results are found if 5 year windows are considered instead.

[25]We exclude observations that are interpolated, identified based on patterns in the raw decile series. Specifically, we drop years in which relative mobility changes by less than a small pre-specified threshold, as these are likely not based on underlying microdata. See Appendix B and Table B4 for details.

Table 4. Upward Mobility and Inequality: Averaged Income Data

	Relative Upward Mobility		Absolute Upward Mobility	
	[1]	[2]	[3]	[4]
Gini_s	22.315***	31.701***	25.885***	37.348***
	(2.782)	(4.609)	(4.938)	(5.482)
Log income pc_s	-0.040	-0.817	-8.152***	-5.965***
	(0.251)	(0.715)	(0.510)	(1.066)
Controls	No	Yes	No	Yes
R^2	0.338	0.473	0.635	0.535
Obs	3898	1430	3898	1430

Notes: Income variables at time τ are constructed by averaging the income distribution over three years ($\tau-1$, τ, and $\tau+1$ for $\tau = 2, \ldots, T-1$). Robust standard errors clustered at the country level. All regressions include country and region-year fixed effects and even columns also include control variables (similar to those in Column 5, Table 2.

Table 5 shows that the positive association between initial inequality and upward mobility found in the baseline regressions is remarkably consistent across regions once regional heterogeneity is taken into account. The stand-alone Gini coefficient now captures the effect for the omitted region (Neo-Europe), while each interaction term measures the incremental effect for the other regions.

For *relative* upward mobility, the Gini retains a large and highly significant coefficient for Neo-Europe in both specifications. None of the regional interactions is statistically different from zero in the parsimonious regression, indicating that Africa, Asia, Latin America, and the Middle East do not depart detectably from the Neo-European benchmark at that stage. After the full set of covariates is added, only the Middle-East interaction becomes (marginally) significant and positive, raising the total inequality–mobility gradient in that region by roughly one half compared with Neo-Europe. Hence, conditional on observable country characteristics, inequality appears to foster relative mobility somewhat more strongly in the Middle East than elsewhere, but the magnitude of the difference is modest.

For *absolute* upward mobility, Neo-Europe again exhibits a robust positive effect of inequality. The sole significant interaction in the specification without controls is the Middle-East term, which is large and negative, essentially offsetting the baseline and driving the net effect for that region close to zero. Once macroeconomic and institutional controls are introduced, however, this interaction shrinks and loses significance, showing that the initial divergence is fully explained by observable factors such as demographic structure, fiscal stance, or inflation. All other regional interactions remain statistically indistinguishable from zero throughout.

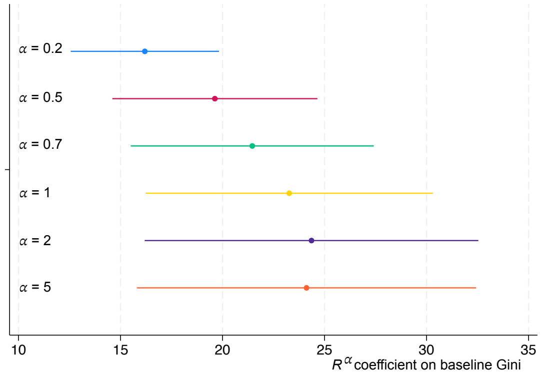
Taken together, these findings underscore that the inequality–mobility relationship is globally stable: departures from the Neo-European pattern are limited to the Middle East and are either modest (for relative mobility) or disappear after standard controls (for absolute mobility).

Table 5. Upward Mobility and Inequality: Regional Heterogeneity

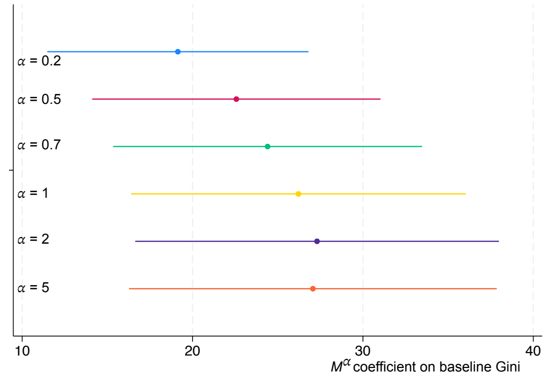
	Relative Upward Mobility		Absolute Upward Mobility	
	[1]	[2]	[3]	[4]
$Gini_s$	22.161***	25.104***	26.350***	29.309***
	(4.253)	(3.231)	(8.037)	(6.936)
$Gini_s$×Africa	3.228	9.315	2.305	10.126
	(5.635)	(7.045)	(9.054)	(10.354)
$Gini_s$×Asia	-8.599	-10.748	-5.049	-2.975
	(5.865)	(6.987)	(11.984)	(11.014)
$Gini_s$×Latin Am.	-10.158	15.837	-4.673	20.648
	(15.355)	(11.450)	(17.429)	(14.290)
$Gini_s$×Middle East	-3.672	12.355*	-31.505**	2.824
	(6.064)	(6.801)	(15.905)	(11.807)
Log income p.c.$_s$	0.090	-0.263	-7.830***	-5.969***
	(0.261)	(0.650)	(0.496)	(1.045)
Controls	No	Yes	No	Yes
R^2	0.313	0.498	0.605	0.544
Obs	4158	1430	4158	1430

Notes: This table reports estimates of the relationship between initial inequality (Gini coefficient) and upward mobility (relative and absolute) allowing for regional heterogeneity. The omitted region is *"Neo-Europe."* Controls include: Polity2, government expenditure, capital formation, population growth and structure, education levels, labor force participation, inflation, and credit to the financial sector. Robust standard errors clustered at the country level are reported in parentheses. All regressions include country fixed effects and region-year fixed effects.

5.4. Sensitivity to the Inequality-Aversion Parameter α. Figure 4 plots the estimated relationship between initial inequality and upward mobility for several values of the pro-poor parameter $\alpha \in \{0.2, 0.5, 0.7, 1, 5\}$. Panel (a) displays results for relative upward mobility (Column 2, Table 1), while Panel (b) shows the same for absolute upward mobility (Column 5, Table 1). The results are robust to different values of α. Indeed, the estimated positive relationship between inequality and mobility strengthens as α increases, that is as the mobility measure becomes more pro-poor.



(a) Relative Upward Mobility



(b) Absolute Upward Mobility

Figure 4. Upward Mobility and Inequality: Sensitivity to the Inequality-Aversion Parameter α. Notes: Panels (a) and (b) plot the estimated coefficient on baseline inequality (Gini_s) with 95% confidence intervals when the dependent variable is, respectively, relative and absolute upward mobility. Mobility indices are recalculated for $\alpha \in \{0.2, 0.5, 0.7, 1, 2, 5\}$; estimates for smaller α appear higher in each panel. All regressions replicate the specifications reported in columns 2 and 5 of Table 1 for Panels (a) and (b), respectively.

5.5. Alternative Floor Values. As noted earlier, our upward-mobility measures are highly sensitive to near-zero incomes. To ensure this does not drive our results, we apply a "floor" adjustment that guarantees strictly positive income values in every country-year. In our baseline we adopt a conservative global floor of USD 50 per person per year ($\approx$ USD 0.14/day in 2020 PPP). To examine the robustness of our findings, we re-estimate all models using a higher benchmark of USD 183 per person per year ($\approx$ USD 0.50/day), following Kraay et al. (2023).

Appendix Table B5 shows that the key coefficients on initial inequality remain virtually unchanged—inequality continues to predict higher upward mobility with the same magnitude and statistical significance. We have also tested lower floors (e.g. USD 10), and our conclusions hold across these alternative specifications.

5.6. Income Distribution by Percentiles. As noted in Section 3.2.3, our baseline specification uses decile data from the World Inequality Database to compute mobility and inequality measures. Table B6 in Appendix B demonstrates that our findings remain robust when using percentiles instead of deciles.

6. The Great Gatsby Curve, Upward Mobility and Inequality Traps

The core specification (8), generated by our measure of relative upward mobility, can also be viewed as a dynamic equation for the evolution of inequality. In particular, it can be used to assess the existence of "inequality traps." Such traps generalize the notion of poverty traps to possibly growing economies. They can arise from nonconvexities in investment or imperfect access to credit markets, just as poverty traps do, especially when those nonconvexities or lack of access are recast in relativistic terms; see, e.g., Dasgupta and Ray (1986), Banerjee and Newman (1993), Galor and Zeira (1993), Dasgupta (1997), Mookherjee and Ray (2003), Rigolini (2004), Matsuyama (2007, 2011), Ghatak (2015), Ghatak and Newman (2025). They can also stem from psychological features such as self-control or aspiration failures; see Ray (2006a), Banerjee and Mullainathan (2008), Bernheim et al. (2015), Dalton et al. (2015) and Genicot and Ray (2017). In what follows, we provide an overview of the conceptual issues involved, and then reinterpret our version of the Great Gatsby curve.

6.1. Inequality Traps. All poverty and inequality traps emerge from some form of history dependence; that is, from the experience of a condition that leads to the perpetuation of that condition. But we must be careful to distinguish between "micro" and "macro" history dependence. The former refers to persistent outcomes at the level of the individual or the family: relatively small units in an environment with many such interactive units. The latter refers to history dependence for *all* of society — namely, several macroeconomic configurations, each self-perpetuating, with some of them presumably interpretable as traps given their unpalatable features. Macro history dependence implies micro history dependence, but not the other way around.

Classical views of convergence, such as Solow (1956), Becker and Tomes (1979, 1986) and Loury (1981) exhibit neither micro nor macro history dependence. In these settings, each individual unit follows a Markov process with a unique ergodic distribution, and the macroeconomic outcome simply mirrors that ergodic behavior over its cross-section of units. In contrast, traps are typically (though not always) built from a model with *interactive* agents, as in Banerjee and Newman (1993). However, whether those traps typically appear at the micro level alone or also at the macro level, is a more subtle question, as we now explain.

Consider the simplest model of binary occupational choice, as described in Ljungqvist (1993), Freeman (1996) and Ray (2006b). Assume there are just two occupations, skilled and unskilled. Both occupations enter as inputs into a production function satisfying the Inada conditions. Now suppose that each parent in a single-parent single-child dynasty funds an occupational choice for her child. Can all of them make the same choices? The answer is no. If all parents choose to leave their descendants unskilled, then the return to skilled labor will become enormously high, encouraging some fraction of the population to educate their children. Similarly, it is not possible for all parents to educate their children, if unskilled labor is also necessary in production. *Even if all agents have identical wealth and preferences to start with*, they must sort into distinct occupations. This is of little import for parents with equal wealth who must be indifferent across the choices, but if capital markets are imperfect, their choices will have long-lasting effects on the economic lives of their descendants. This is micro history dependence, in that the symmetry-breaking accidents of the past can harden into more persistent long-run outcomes for individual dynasties.

Can such micro history dependence be translated into corresponding traps at the macro level? The answer is yes. Society could converge to two different aggregate outcomes, one with a "high" share of skilled labor, and the other a trap with a "low" share of skilled labor. Both types of history dependence co-exist. But the case for macro history dependence begins to fade as the number of occupations expands. As Mookherjee and Ray (2002, 2003, 2010) have argued, the resulting richness of the occupational space completely pins down the wage function across occupations, eliminating macro history dependence while preserving micro history dependence. That unique outcome can display a high degree of economic inequality. Moreover, unlike the convergence models, that inequality is not experienced in an ergodic fashion by every dynasty. There is still history dependence at the level of the dynasty, but there is no *macro* history dependence. Society displays an equilibrium level of inequality that serves as a steady state, no matter what the initial levels of societal inequality.

Figure 5 depicts the relationship between baseline inequality and the growth rate of that inequality under different dynamic processes governing inequality. In the first panel, changes in inequality are self-reinforcing both above and below an "unstable" critical threshold I^*, giving rise to macro history dependence. There is a virtuous circle of low inequality at I_ℓ, and a trap at I_h. In contrast, the second panel depicts a scenario where inequality converges to a *stable* level I^*, regardless of initial conditions.

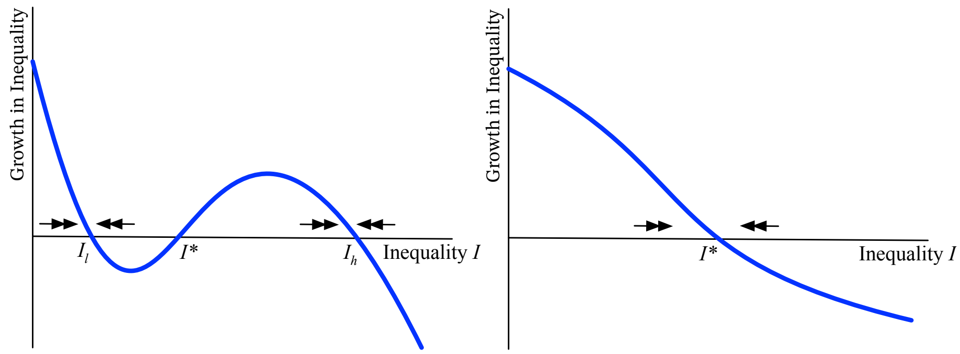


Figure 5. Inequality and Growth in Inequality. This figure displays the relationship between baseline inequality and the growth of that inequality under different processes guiding the evolution of inequality.

6.2. The Inequality Trap Interpretation for the Great Gatsby Curve. Our empirical results speak to the relative importance of these phenomena. The formulation (8) can be used to connect the discussion above — especially the dynamic evolution equation for inequality depicted in Figure 5 — to our version of the Great Gatsby curve for relative upward mobility. For any given income distribution $\mathbf{y}$ with mean $\bar{y}$, recall from (6) that the Atkinson welfare function is given by:

$$W^{\alpha}(\mathbf{y}) = \left(\frac{1}{n}\sum_i y_i^{-\alpha}\right)^{-\frac{1}{\alpha}}, \text{ where } \alpha > -1,$$

with the associated *Atkinson inequality measure* given by

$$A^{\alpha}(\mathbf{y}) = 1 - [W^{\alpha}(\mathbf{y})/\bar{y}] \equiv 1 - \text{ Atkinson equality.} \tag{10}$$

With minimal manipulation, we can use (4), (5) and (10) to conclude that $R^{\alpha}(\mathbf{y}[s,\, s+\Delta])$ is just the growth of Atkinson equality $W^{\alpha}(\mathbf{y})/\bar{y}$ over the interval $[s,\, s+\Delta]$, so that the Great Gatsby specification (8) can be equivalently reinterpreted as

$$\text{Growth in Atkinson Equality in } j \text{ over } [s,\, s+\Delta] = \Psi(A^{\alpha}(\mathbf{y}(s))) + f_j + h_{rs} + \epsilon_{js}.$$

This reinterpretation corresponds to the conceptual within-country specification:

$$\text{Growth in Atkinson Equality} = \Phi\Big(\text{Atkinson Inequality at Baseline}\Big), \tag{11}$$

for some function Φ defined on A. That is, viewed in this way, the Great Gatsby specification (using Atkinson inequality) turns into an equation for the dynamic evolution of inequality. Whenever the left-hand side of (11) is positive (resp. negative), inequality falls (resp. rises), and moreover, steady state levels of inequality are given by the zeroes of (11). In short, the specification (11) maps directly into a mirror image of the evolution equation depicted in Figure 5, the only difference being that it is expressed in terms of growth in *equality* rather than inequality.

In particular, if the relative upward mobility equation is "upward-sloping" with a unique zero, Atkinson inequality must have a unique steady state, which is additionally the unique stable attractor as long as Φ is an increasing function, leading to the corresponding decreasing function shown in the second panel of Figure 5.

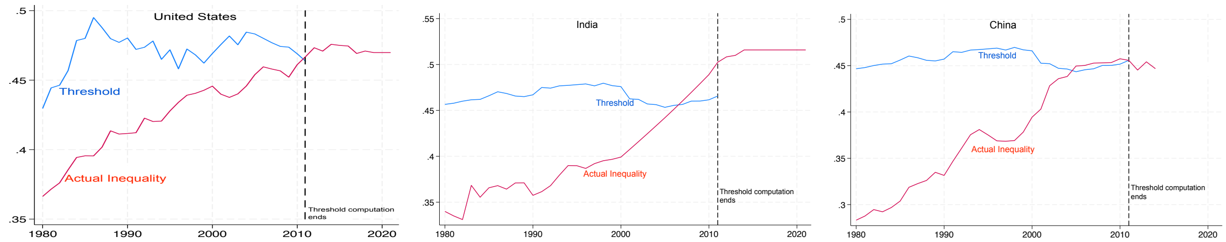
And — as we discuss next — that is precisely what the data say.

6.3. Convergence to Steady State Inequality. Our empirical findings state unequivocally that a higher level of inequality results in a higher degree of relative upward mobility. This is true no matter whether we use the Gini coefficient or the Atkinson index of inequality at baseline. Given the interpretation just developed in Section 6.2, our results therefore suggest that there is a unique (though possibly country-specific and possibly time-varying) degree of economic inequality that serves as a global attractor from all initial conditions. That is, the second panel of Figure 5 (and not the first) appears to be the relevant picture.

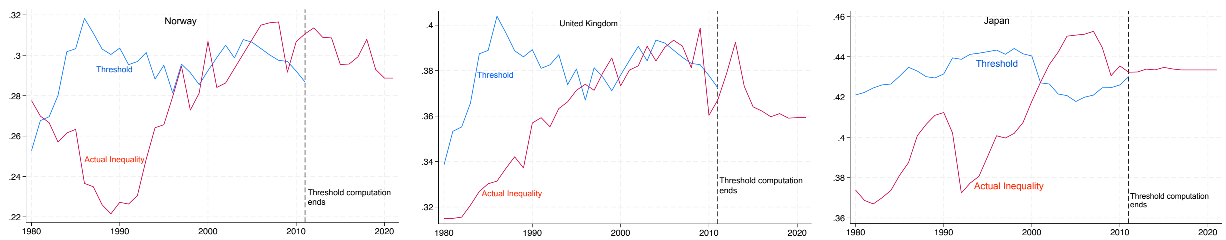
Something about the phrases "unique steady state inequality" or "global attractor" appears to suggest that they are somehow incompatible with divergent trends in inequality — the sort of alarming movement over decades that have caught our attention of late. We would like to explicitly kill that idea. A country-specific steady state level inequality could be located well above that country's *current* level of inequality, causing sustained degradation in inequality. Our econometric specification allows us to compute the implicit steady-state level of inequality, denoted by $\bar{I}_{js}$, for each country j and time period s. This represents the value of inequality for which the conditional expection of relative mobility is zero. Assuming that relative mobility is given by equation (9) and that ε_{js} is exogeneous, the steady state level of inequality can be obtained as

$$\bar{I}_{js} \equiv -\frac{\text{country } j \text{ fixed effect + region-time fixed effect at } s}{\gamma}. \tag{12}$$

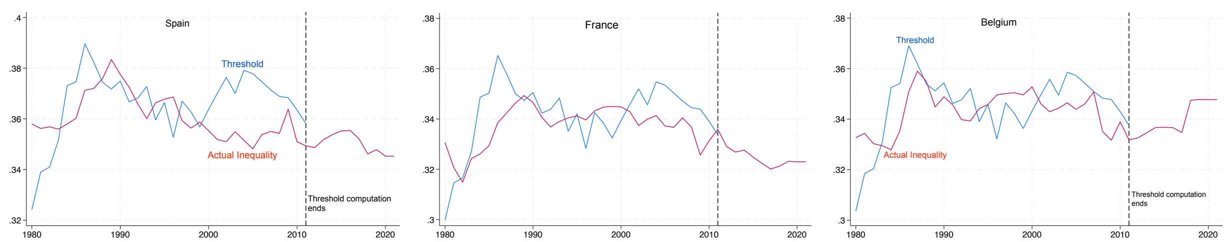
Our estimated coefficient suggests the following dynamic patterns: (a) $I_{js} < \bar{I}_{js} \Rightarrow I_j$ rises; and (b) $I_{js} > \bar{I}_{js} \Rightarrow I_j$ falls. Figure 6 displays some of these steady state levels, along with the paths of actual inequality levels of the countries in question.



(a) Rising Inequality Throughout



(b) Initially Rising Inequality



(c) Inequality Crisscrossing with Steady States

Figure 6. Inequality and Estimated Steady State Inequality for Selected Countries.
NOTES: Each panel displays country- and time-specific steady state Gini coefficients (in blue), estimated using the formula (12), and actual Ginis over time (in red).

The top row of the figure shows the United States, India and China, three leading examples of countries that have shown a dramatic widening in inequality. These countries are also estimated to have a high steady state level of inequality, towards which their actual inequality appears to be climbing. The middle row shows countries with a similar initial widening of inequality (during a period in which inequality falls short of steady state levels), followed by some intertwining with their estimated steady states, with one alternately higher than the other. Norway stands out as an exemplar of this pattern, but see also the UK and Japan. The bottom row shows alternation throughout: we display Spain, France and Belgium as interesting examples.

As already discussed, this finding is compatible with a simple Solow-like model of convergence augmented by stochastic shocks. It is also compatible with a more nuanced story that accommodates micro history dependence and rejects the idea that each dynasty moves all over the cross-sectional wealth distribution, while at the same time it also rejects history dependence at the macroeconomic level (Mookherjee and Ray 2002, 2003, 2010). Given the widespread empirical evidence for poverty traps (see, e.g., Carter and Barrett 2007; Haushofer and Shapiro 2020; Balboni et al. 2023), we are entirely comfortable with the latter interpretation, and we would conjecture that a state of micro but not macro history dependence best describes the situation at hand. In contrast, the stochastic optimal growth model with convergence forces upon us the absurd viewpoint that every dynasty equally passes through all wealth levels and classes of occupational choices separated by distinct setup costs. That said, our paper does not provide a formal test separating these two hypotheses. To do so, we would likely need panel data at the dynastic level.

We end by noting that the version of the Great Gatsby curve that regresses *absolute* upward mobility on baseline inequality has a more complex interpretation. Recall that absolute upward mobility is the sum of per-capita growth rates and relative upward mobility. As already noted, then, the relationship between upward absolute mobility and baseline inequality will be driven by both the dynamic process governing the evolution of inequality, as also the relationship between inequality and growth. The latter relationship has been extensively debated (see, e.g., Persson and Tabellini 1994; Bénabou 1996; Aghion et al. 1999; Forbes 2000; Banerjee and Duflo 2003; Galor and Moav 2004; Berg and Ostry 2011; Oechslin and Zweimüller 2014). We do not address this distinct question in the present paper. Nevertheless, it is of interest to note that no matter the form of this relationship, it appears to be dwarfed by the relative upward mobility relation, so that even absolute upward mobility is significantly and positively related to baseline inequality.

7. Epilogue: Reconciling Two Great Gatsby Curves

Our findings challenge the conventional wisdom embedded in the Corak-Krueger version of the Great Gatsby Curve, which posits a negative relationship between inequality and social mobility, typically measured by the intergenerational elasticity (IGE) of income. By contrast, we document a robust positive relationship between inequality and upward mobility within countries, both in relative and absolute terms. How might these findings be reconciled?

As discussed in Section 2, the IGE can be viewed as the product of a persistence index ρ and the ratio of standard deviations of log income across generations. In contrast, our measures of upward mobility (that correspond to changes in Atkinson welfare) are conceptually and empirically linked to changes in income distribution and growth, rather than persistence. In particular, relative upward mobility is tied to reductions in Atkinson inequality, which, while not conceptually equivalent to the standard deviation of log income, is highly correlated with it.[26] This framing implies that if inequality increases upward mobility, while at the same time the IGE also rises with inequality, then it is persistence *alone* that drives the traditional form of the Great Gatsby curve. That is the core insight from our decomposition: inequality fosters upward mobility on average, while tightening persistence.

Why might inequality increase *both* upward mobility and persistence? As we've argued in Section 6, the first of these two effects is closely related to the idea that there is some country-time-specific value of "steady state inequality." If inequality exceeds that value, it self-corrects, raising relative upward mobility in the process. And if inequality falls short of that value, it climbs. The underlying mechanism reflects political, institutional, or behavioral responses to inequality and is strong enough to generate gains in absolute upward mobility as well, empirically dominating any negative effects on overall growth.

In contrast, an increase in inequality appears to tie future incomes more tightly to current incomes, thereby heightening persistence. This effect in turn is strong enough so that the *product* of persistence and relative upward mobility supports the Corak-Krueger version of the Great Gatsby curve. How we subjectively evaluate this product effect depends on which aspects of mobility are more salient to us from an intuitive perspective. If our argument is convincing, we should not be "evaluating" the product of persistence and relative upward mobility. We should be looking at these objects separately, especially given the sharp divergence in their empirical behaviors. Indeed, such questions and findings open avenues for future research, not just to conceptualize how we view mobility, but to further explore the underlying mechanisms at play.

Importantly, these findings should not be interpreted as suggesting that higher inequality is *desirable* from a policy perspective. The average positive association we document does not imply that inequality is beneficial, nor does it suggest that

[26]For instance in our baseline dataset (WID), the correlation between relative mobility and the ratio of standard deviations is -0.67 and -0.55, for $\Delta = \{30, 10\}$, respectively.

increasing inequality is a viable tool for promoting mobility. (That would be like throwing someone down a ladder for the pleasure of watching him come back up again.) Our results describe an empirical pattern, one that coexists with substantial heterogeneity across countries.

From a policy perspective, the results underscore the nuanced relationship between inequality and social mobility. Rather than reinforcing a binary view that "inequality is bad for mobility," our findings suggest that different components of mobility are affected in different ways. One central implication is that if there is truly some steady state level of inequality by country, our task should lie in ameliorating that steady state inequality by identifying and resetting the parameters that influence it. We should add that this is quite different from a view of interventions based on multiple steady states, and more work is needed to settle such questions.

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Appendix

A. Summary Statistics and Preliminary Analysis

A.1. Summary Statistics. Table A1 provides summary statistics of the main variables employed in the empirical analysis (based on the WID data).

Table A1. SUMMARY STATISTICS

	Summary Statistics				
	Obs.	**Mean**	**Std. Dev.**	**Min**	**Max**
$R^{\alpha}(\mathbf{y}[s,s+10])$	4253	-0.049	1.509	-18.206	12.071
$R^{\alpha}(\mathbf{y}[s,s+20])$	2923	-0.043	1.060	-5.021	6.932
$R^{\alpha}(\mathbf{y}[s,s+30])$	1593	-0.047	0.838	-3.143	3.760
$M^{\alpha}(\mathbf{y}[s,s+10])$	4253	1.032	3.404	-23.666	18.745
$M^{\alpha}(\mathbf{y}[s,s+20])$	2923	1.228	2.198	-10.924	10.230
$M^{\alpha}(\mathbf{y}[s,s+30])$	1593	1.052	1.648	-9.870	6.334
Gini	4253	0.448	0.084	0.198	0.668
Atkinson Inequality	4253	0.682	0.085	0.362	0.912
Log Income p.c.	4253	9.437	1.046	5.486	11.632

NOTES: This table reports descriptive statistics for the main variables used in the empirical analysis. All income-related measures are constructed using data from the World Inequality Database (WID). Upward mobility is computed using decile level data with $\alpha = 0.5$ and reported over 10-, 20-, and 30-year intervals.

A.2. Panel Unit Root Tests. This section assesses the stationarity of the key variables in the empirical analysis, which is critical to ensuring that the panel estimators employed in the main text are consistent and have well-behaved limit distributions. Given the relatively short length of the series (for instance, the 10-year mobility measures are available for only 32 years), univariate unit root tests are unlikely to have sufficient power. For this reason, we use panel unit root techniques.

First, we employ the Levin et al. (2002) test to detect the presence of a unit root. The null hypothesis posits that the panels contain a unit root, while the alternative assumes that all panels are stationary, under the assumption of a common autoregressive parameter. The test accounts for the presence of a time trend and considers different lag lengths to correct for autocorrelation in the residuals.[27] For robustness, we also compute Fisher tests, which combine the p-values from unit root tests conducted on each univariate process to produce an overall test statistic.

Table A2 presents the results of the panel unit root tests described in the main text. Two tests are employed: the Levin et al. (2002) test and the Fisher test, see Choi (2001) . Year effects and time trends are included, and the results remain robust when these terms are omitted. Short-term correlation is addressed by including lags of the dependent variable, selected using the AIC. The maximum number of lags allowed in the tests is 4, but the results are robust to alternative lag specifications.

In all cases, the null hypothesis that all panels contain a unit root is decisively rejected.

Table A2. Panel Unit Root Tests

	Panel Unit Root Tests			
	(Adjusted) LLC [1]	**LLC p-value** [2]	**Fisher Stat.** [3]	**Fisher p-value** [4]
Relative Upward Mobility	-5.79	0.00	846.51	0.00
Absolute Upward Mobility	-4.30	0.00	730.27	0.00
Atkinson Inequality	-5.13	0.00	730.27	0.00
Gini	-7.16	0.00	746.92	0.00
Log Income	-4.78	0.00	691.50	0.00

Notes: All variables are constructed from the World Inequality Database (WID). Mobility measures are based on decile-level data with $\alpha = 0.5$. The table reports results from the panel unit root test of Levin et al. (2002), and Fisher-type tests based on inverse chi-squared statistics following Choi (2001).

B. Additional Results

This appendix reports additional robustness checks. First, we re-estimate the models in Section 4 using the Atkinson inequality index instead of the Gini coefficient (Table B1 and Figure B1). Second, we use alternative income distribution datasets — the World Bank's PIP and the UN's WIID — with results shown in Tables B2 and B3. Third,

[27]This test relies on two restrictive assumptions: namely, that each variable exhibits the same degree of persistence across all countries and that year fixed effects fully capture any cross-sectional dependence. Levin et al. (2002) recommend using their test with panels of "moderate" size, defined as between 10 and 250 panels with 25 to 250 observations per panel. This framework is well-suited to our data, which contain 130 countries with a maximum of 50 time periods, depending on the variable.

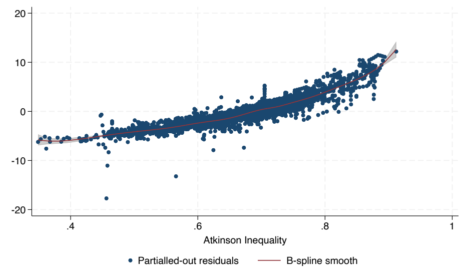
Table B4 drops observations from the WID that appear to be interpolated. Fourth, Table B5 presents results using higher consumption-floor values. Fifth, Table B6 uses mobility and inequality measures based on percentile data rather than deciles. In all cases, the positive and statistically significant relationship between baseline inequality and subsequent upward mobility remains unchanged. Finally, Table B7 further investigates the relationship between inequality and income growth.

Table B1. Upward Mobility and Inequality: Controls

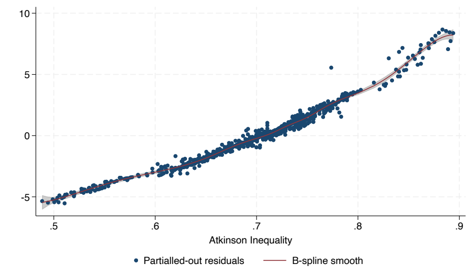
	Relative Upward Mobility						Absolute Upward Mobility					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Atk. Ineq$_s$	22.593***	24.043***	23.538***	30.460***	29.545***	30.495***	25.410***	26.197***	28.264***	35.885***	34.828***	32.726***
	(2.371)	(2.845)	(2.879)	(2.666)	(3.314)	(3.251)	(3.908)	(3.660)	(4.435)	(4.142)	(4.507)	(5.065)
Log Income p.c.$_s$	-0.205	0.035	-0.315	-0.796	-1.032	-1.128	-8.136***	-6.619***	-6.421***	-7.021***	-6.705***	-6.453***
	(0.224)	(0.332)	(0.518)	(0.496)	(0.748)	(0.761)	(0.485)	(0.920)	(0.604)	(0.636)	(0.960)	(0.961)
Polity2$_s$		-0.021	-0.020	-0.029*	-0.023	-0.016		0.002	-0.004	0.022	0.033	0.032
		(0.019)	(0.019)	(0.017)	(0.021)	(0.020)		(0.019)	(0.020)	(0.022)	(0.024)	(0.027)
Gov. exp/gdp $_s$		0.003	0.001	0.000	-0.001	-0.000		-0.007	-0.010*	-0.010*	-0.012*	-0.010
		(0.004)	(0.005)	(0.005)	(0.006)	(0.005)		(0.007)	(0.006)	(0.005)	(0.007)	(0.006)
Gross Cap. Formation (% GDP)$_s$			0.001	-0.002	0.055	0.060			-0.002	-0.018	0.006	0.015
			(0.009)	(0.010)	(0.080)	(0.070)			(0.010)	(0.012)	(0.093)	(0.092)
Pop. Growth $_s$			0.037	0.022	0.022	0.016			0.029	0.002	0.012	0.007
			(0.038)	(0.025)	(0.028)	(0.028)			(0.045)	(0.034)	(0.034)	(0.035)
% Pop at most primary $_s$			0.005	0.002	0.006	0.007			0.022	0.028	0.017	0.018
			(0.021)	(0.030)	(0.037)	(0.038)			(0.027)	(0.037)	(0.050)	(0.054)
% Pop at most secondary $_s$			0.003	-0.020	-0.017	-0.017			0.010	0.004	-0.007	0.000
			(0.023)	(0.024)	(0.028)	(0.027)			(0.027)	(0.033)	(0.041)	(0.042)
Labor force part. $_s$				0.054***	0.055**	0.057***				0.041	0.091*	0.096*
				(0.019)	(0.024)	(0.022)				(0.049)	(0.052)	(0.052)
% Pop. below 14 $_s$				-0.049	0.037	0.038				0.098	0.146	0.148
				(0.073)	(0.123)	(0.117)				(0.120)	(0.185)	(0.188)
% Pop. between (15-64) $_s$				0.050	0.120	0.120				0.210*	0.256*	0.256
				(0.057)	(0.100)	(0.096)				(0.112)	(0.152)	(0.155)
Inv/GDP$_s$					-0.057	-0.060					-0.018	-0.026
					(0.081)	(0.071)					(0.095)	(0.094)
Inflation $_s$					0.001**	0.002***					0.000	0.002**
					(0.000)	(0.000)					(0.000)	(0.001)
Credit by finan. sector $_s$					-0.002	-0.003					-0.008	-0.009*
					(0.003)	(0.003)					(0.005)	(0.005)
R_{s-1}						0.040						
						(0.045)						
M_{s-1}												-0.056
												(0.061)
R^2	0.402	0.384	0.393	0.530	0.499	0.501	0.622	0.498	0.547	0.625	0.557	0.562
Obs	4158	3230	2635	1936	1430	1379	4158	3230	2635	1936	1430	1379

Notes: This table reports estimates of the relationship between inequality and upward mobility (relative or absolute) over a 10-year horizon, progressively adding control variables. Robust standard errors clustered at the country level are reported in parentheses. All regressions include country fixed effects and region-year fixed effects.

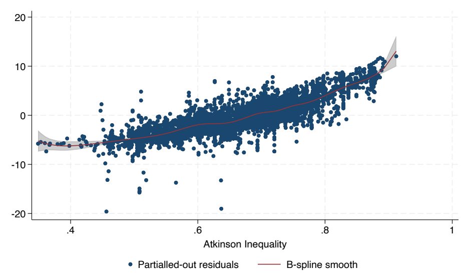
Semiparametric Estimation



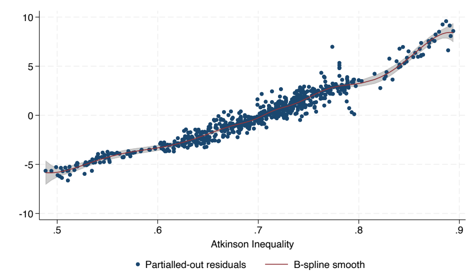
(a) Relative Mobility and Atkinson Inequality



(b) Relative Mobility and Atkinson Inequality, with controls



(c) Absolute Mobility and Atkinson Inequality,



(d) Absolute Mobility and Atkinson Inequality, with controls

Figure B1. Upward Mobility and Atkinson Inequality: Semiparametric Estimates. The nonparametric component $\Psi(\cdot)$ is estimated using the semiparametric fixed-effects series estimator (Baltagi and Li 2002). All other covariates enter linearly, with country and region-year fixed effects included throughout.

Table B2. Upward Mobility and Inequality: PIP Dataset

	Relative Upward Mobility					Absolute Upward Mobility				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Gini_s	19.934***	19.716***	24.686***				28.297***	27.908***		
	(2.224)	(2.158)	(3.503)				(5.031)	(6.622)		
Atk. Ineq_s				15.186***	15.176***	16.589***			21.378***	18.208***
				(1.515)	(1.537)	(1.549)			(2.701)	(2.828)
Log income p.c._s		-0.011	-0.368		0.039	0.341	-8.907***	-10.003***	-8.827***	-9.187***
		(0.304)	(0.743)		(0.240)	(0.387)	(0.607)	(1.085)	(0.486)	(0.774)
Controls	No	No	Yes	No	No	Yes	No	Yes	No	Yes
R^2	0.547	0.540	0.777	0.698	0.698	0.871	0.661	0.819	0.714	0.855
Observations	1238	872	442	872	872	442	872	442	872	442

Notes: This table reports estimates of the relationship between inequality (Gini or Atkinson) and ten-year upward mobility (relative or absolute), with measures computed from PIP data. The sample includes 105 countries over 1979-2013. Robust standard errors, clustered at the country level, are reported in parentheses. All regressions include country and region-year fixed effects.

Table B3. Upward Mobility and Inequality: WIID Dataset

	Relative Upward Mobility					Absolute Upward Mobility				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
$Gini_s$	19.557***	20.646***	31.623***				30.091***	43.303***		
	(3.376)	(4.228)	(6.665)				(5.681)	(9.605)		
Atk. $Ineq_s$				16.893***	17.047***	21.546***			22.992***	28.330***
				(2.841)	(2.837)	(2.988)			(3.278)	(4.159)
Log income $p.c._s$		0.871**	-0.327		0.825**	0.172	-5.839***	-7.388**	-5.940***	-6.751**
		(0.370)	(1.327)		(0.356)	(1.262)	(0.973)	(2.925)	(1.004)	(2.845)
Controls	No	No	Yes	No	No	Yes	No	Yes	No	Yes
R^2	0.457	0.503	0.687	0.617	0.625	0.794	0.610	0.668	0.648	0.709
Observations	1373	868	353	868	868	353	868	353	868	353

Notes: This table reports estimates of the relationship between inequality (Gini or Atkinson) and ten-year upward mobility (relative or absolute), with all measures computed from WIID data. The sample covers the years 1979-2013 and includes 136 countries. Robust standard errors, clustered at the country level, are reported in parentheses. All regressions include country and region-year fixed effects.

Table B4. Upward Mobility and Inequality: Dropping Interpolated Observations

	Relative Upward Mobility				Absolute Upward Mobility			
	$\tau = 0.001$		$\tau = 0.01$		$\tau = 0.001$		$\tau = 0.01$	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$Gini_s$	22.661***	31.745***	22.864***	31.790***	27.214***	37.456***	27.993***	37.407***
	(2.812)	(4.280)	(2.808)	(4.305)	(4.470)	(5.118)	(4.219)	(5.211)
Log income pc_s	0.053	-0.652	0.048	-0.637	-7.593***	-6.103***	-7.544***	-6.174***
	(0.300)	(0.754)	(0.299)	(0.771)	(0.535)	(1.058)	(0.525)	(1.121)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.321	0.488	0.322	0.485	0.584	0.548	0.583	0.544
Obs	3790	1382	3655	1347	3790	1382	3655	1347

Notes: This table replicates our core regressions after excluding observations likely based on interpolated income distributions. The WID dataset flags countries for which the entire series is imputed; these are excluded from the full sample. For countries with partially observed distributions, we identify likely interpolated years by examining decile growth patterns. Specifically, we drop year s whenever $\left|R^{\alpha}_{s+1} - R^{\alpha}_{s}\right| < \eta$, with $\eta \in \{0.01, 0.001\}$, where R^{α}_{s} denotes relative mobility in year s. In these cases, all deciles exhibit identical growth rates—an implausible pattern suggesting interpolation from aggregates rather than genuine microdata. This procedure flags 530 and 373 observations, respectively. Although near-zero changes in mobility may arise for other reasons, such instances are rare in practice.

Table B5. Upward Mobility and Inequality: Other Floor Values

	Relative Upward Mobility				Absolute Upward Mobility	
	[1]	[2]	[3]	[4]	[5]	[6]
$Gini_s$	16.731***	16.530***			19.580***	
	(1.900)	(1.970)			(3.676)	
Atkinson $Ineq_s$			18.525***	18.812***		22.998***
			(1.681)	(1.782)		(3.250)
Log income pc_s		0.775***		-0.149	-7.120***	-8.253***
		(0.279)		(0.237)	(0.419)	(0.411)
R^2	0.288	0.307	0.401	0.401	0.612	0.639
Observations	4158	4158	4158	4158	4158	4158

Notes: This table reports estimates of the relationship between inequality (Gini or Atkinson) and ten-year upward mobility (relative or absolute). A floor value equal to USD 183 has been used (Kraay et al. 2023). All regressions include country and region-year fixed effects. Standard errors, clustered at the country level, are reported in parentheses.

Table B6. Upward Mobility and Inequality: Percentile-Based Income Measures

	Relative Upward Mobility				Absolute Upward Mobility			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$Gini_s$	10.783***	19.499***			14.382***	24.259***		
	(1.905)	(3.293)			(2.658)	(3.711)		
Atkinson $Ineq_s$			21.455***	31.051***			26.908***	38.939***
			(3.907)	(5.251)			(4.884)	(7.163)
Log Income $p.c._s$	2.511***	1.184	0.769**	-0.504	-5.519***	-4.667***	-7.692***	-6.792***
	(0.205)	(0.774)	(0.389)	(0.957)	(0.404)	(0.698)	(0.548)	(0.918)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.409	0.460	0.424	0.483	0.591	0.517	0.595	0.543
Observations	4158	1430	4158	1430	4158	1430	4158	1430

Notes: This table presents estimates of the relationship between upward mobility and initial inequality (Gini or Atkinson index). All income-based measures are constructed from percentile data in the World Inequality Database. A uniform income floor of USD 50 per person per year ensures strictly positive values. All regressions include country and region-year fixed effects. Robust standard errors clustered at the country level are in parentheses.

Table B7. Growth and Inequality

	[1]	[2]	[3]	[4]	[5]	[6]
Gini_s	-0.043	0.321	0.321	0.591	0.456	0.533
	(0.532)	(0.366)	(0.362)	(0.456)	(0.286)	(0.325)
Log Income p.c._s		-0.791***	-0.664***	-0.612***	-0.617***	-0.560***
		(0.053)	(0.095)	(0.064)	(0.061)	(0.092)
Polity2_s			0.002	0.002	0.005**	0.006**
			(0.002)	(0.002)	(0.002)	(0.003)
Gov. Exp./GDP_s			-0.001*	-0.001**	-0.001***	-0.001***
			(0.001)	(0.000)	(0.000)	(0.000)
Gross Capital Formation_s				-0.000	-0.002	-0.005
				(0.001)	(0.001)	(0.005)
Population Growth_s				-0.001	-0.002	-0.001
				(0.004)	(0.002)	(0.002)
% Pop. at Most Primary_s				0.002	0.002	0.001
				(0.002)	(0.002)	(0.003)
% Pop. at Most Secondary_s				0.001	0.002	0.001
				(0.002)	(0.002)	(0.003)
Labor Force Participation_s					-0.001	0.003
					(0.004)	(0.005)
% Pop. Below Age 14_s					0.014	0.011
					(0.011)	(0.016)
% Pop. Age $15\text{–}64_s$					0.016	0.013
					(0.011)	(0.015)
Investment/GDP_s						0.004
						(0.005)
Inflation_s						-0.000
						(0.000)
Credit by Financial Sector_s						-0.001
						(0.000)
R^2	0.256	0.618	0.509	0.576	0.641	0.561
Observations	4158	4158	3230	2635	1936	1430

Notes: This table reports the estimated relationship between initial inequality (Gini coefficient) and subsequent growth, measured as the change in log income per capita over a 10-year horizon. All regressions include country and region-year fixed effects. Robust standard errors, clustered at the country level, appear in parentheses.