Estimating Intergenerational Mobility via A Time-Varying Mixed Copula Method

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May 5, 2026

Abstract

This paper examines how intergenerational income mobility in the United States has evolved across birth cohorts from 1987 to 2021. We employ a time-varying mixed copula model that combines Clayton, Gumbel, and Frank copulas, with weights and dependence parameters varying smoothly over cohort years, to estimate the full joint dependence structure between parent and offspring permanent incomes. Intergenerational immobility is measured by the normalized Hellinger distance between the observed joint distribution and the independence benchmark. We find that aggregate immobility remained stable through the 1990s but increased sharply after 2000, approximately tripling by the 2010s. Decomposing this trend by copula component reveals that the deterioration is driven by upper-tail tightening: the Gumbel copula weight rises from 0.25 to 0.75, indicating increasing affluence persistence among high-income families, while the Clayton copula coefficient shows no significant trend, implying that poverty persistence did not intensify. Subgroup analyses by race and census region show declining mobility across all groups, with particularly sharp deteriorations in the Northeast and West.

Keywords: Copula; Hellinger distance; intergenerational mobility; longitudinal data; Shannon's entropy; time-varying.
JEL classification: **C43, J62, D63**

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1 Introduction

Equality of opportunity, the principle that an individual's economic success should reflect talent and effort rather than the circumstances of birth, is a cornerstone of public policy discourse in market economies. A central empirical indicator of whether this principle holds in practice is intergenerational income mobility, which measures the degree to which the incomes of offspring are statistically independent of the incomes their parents earned. In a society characterized by high mobility, parental income usually has limited predictive power over offspring outcomes, and the distribution of wealth remains fluid from one generation to the next. On the other hand, in a society with low mobility, family background effectively determines where individuals end up in the income distribution, perpetuating inequality across generations.

The United States has long been regarded as a "land of opportunity," characterized by the ideal of the "American Dream," the belief that individuals, through effort and determination, can surpass their parents' economic achievements (Samuel, 2012). However, a growing body of empirical evidence challenges this characterization. Chetty et al. (2014b) and Corak (2013) document that intergenerational income mobility in the U.S. is low relative to other developed economies, including Canada and the Nordic countries. These findings reveal persistent barriers that entrench economic disparities across generations (Chetty et al., 2014a). Chetty et al. (2017) estimate that the fraction of offspring earning more than their parents, a measure of absolute upward mobility, fell from 92% for the 1940 birth cohort to 50% for the 1984 birth cohort. This decline is attributable to slower GDP growth and an increasingly unequal distribution of economic gains. These findings raise an important question: has the dependence between parent and offspring incomes tightened uniformly across the distribution, or has the deterioration been concentrated in specific segments, for example, among affluent families at the top or among families trapped in poverty at the bottom?

The most widely used strategy for measuring intergenerational income persistence is the intergenerational income elasticity (IGE). The IGE is the slope coefficient β from a regression of offspring log permanent income on parent log permanent income:

$$y_{o,i} = \alpha + \beta y_{p,i} + \epsilon_i, \tag{1}$$

where $y_{o,i}$ and $y_{p,i}$ denote the log permanent incomes of offspring and parent in family i, respectively. The IGE has a straightforward interpretation: a value of $\beta = 0.5$ means that, on average, half of any income advantage a parent holds relative to the population mean is transmitted to the offspring. Although intuitively appealing, the IGE has a few well-documented limitations. As a single coefficient summarizing the conditional mean of offspring income given parental income, it masks *distributional* heterogeneity. In particular, it cannot distinguish whether high persistence is driven by entrenchment at the top of the income distribution, immobility at the bottom, or both. Moreover, the log-log specification is sensitive to zero-income observations, which are prevalent in short income panels, particularly among offspring in the early stages of their life cycles. Chetty et al. (2014a) highlight that the IGE is sensitive to the treatment of zero-income years for children and cannot address distributional heterogeneity, prompting their focus on rank-rank regressions instead. Mitnik et al. (2015) propose an alternative estimator that accommodates zero incomes, while Mazumder (2016) argues that sufficiently long income panels can mitigate the zero-income concern. Nevertheless, even with these methodological developments, the IGE remains a conditional-mean summary, and thus provides little information about how the parent-offspring dependence varies across different regions of the income distribution.

To address the zero-income problem, Chetty et al. (2014a) adopt the rank-rank regression, which replaces log incomes with percentile ranks and is well-defined for all non-negative income values. The rank-rank slope is scale-invariant and measures how much an offspring's position in the income distribution changes, on average, per percentile change in parental position. However, like the IGE, it is a single number that summarizes a conditional mean. It reveals limited information about whether persistence differs at the top versus the bottom of the distribution, or about the shape of the full joint distribution of parent and offspring incomes. Transition matrices, which report the probability of an offspring moving from one income quintile to another, provide richer information about mobility patterns. Yet they depend on arbitrary discrete cutoffs and do not characterize the continuous joint distribution. Absolute mobility measures, as in Chetty et al. (2017), track the proportion of offspring who surpass their parents' income and are inherently directional: they capture upward mobility but do not summarize the overall dependence structure between generations. Sibling correlations and inequality of opportunity measures offer additional perspectives but similarly focus on particular dimensions of the mobility phenomenon. For comprehensive reviews, see Solon (2018).

Methodological advances in the past decade have expanded the toolkit beyond regression-based approaches in important ways. Durlauf et al. (2023) propose entropy-based metrics based on welfare theory that measure the "distance" between the observed joint distribution of parent and offspring incomes and a counterfactual benchmark of statistical independence. Their normalized measures of Hellinger and Kullback-Leibler divergence capture nonlinearities and tail dependence that a single coefficient usually misses. They also offer a welfare-theoretic interpretation of mobility as the expected utility loss from departures from independence. Maasoumi et al. (2025) employ nonparametric kernel-based methods that accommodate higher-order moments and distributional heterogeneity across population subgroups. These methods reveal significant tail behaviors, such as stronger persistence in poverty for certain racial and regional groups, that regression-based measures fail to detect. Copula-based methods represent another direction of methodological development. By Sklar's theorem (Sklar, 1959), any bivariate joint distribution can be decomposed into its two marginal distributions and a copula function that captures all dependence between the variables, independent of the marginal shapes. Chetty et al. (2017) employ a Gaussian copula to estimate absolute mobility rates across birth cohorts. Durlauf et al. (2023) emphasize that copula models are especially effective at isolating persistent patterns of inequality, such as poverty and affluence traps, that linear regression models often miss.

Despite these advances, a gap remains in the literature. Existing distribution-wide measures of intergenerational mobility are typically estimated under the assumption that the dependence structure between parent and offspring incomes is stable over time. When time variation is considered, as in the trend analyses of Lee and Solon (2009) and Chetty et al. (2017), the focus is on tracking a single summary statistic (a regression coefficient or an absolute mobility rate) across cohorts. Such an approach cannot show whether changes in mobility are driven by tightening at the top, hardening at the bottom, or both. In other words, no existing framework combines three desirable properties simultaneously: (i) a distribution-wide measure that captures the full joint dependence structure rather than a single conditional-mean summary, (ii) allowance for the dependence structure to evolve smoothly across birth cohorts, and (iii) the ability to decompose changes in mobility into upper-tail persistence (affluence entrenchment) and lower-tail persistence (poverty traps).

Our study fills this gap by applying a time-varying mixed copula framework to the measurement of intergenerational income mobility across U.S. birth cohorts. Our strategy builds on two ideas. First, following Durlauf et al. (2023), we measure intergenerational immobility as the normalized Bhattacharyya-Hellinger-Matusita distance between the observed joint distribution of parent and offspring permanent incomes and the independence benchmark. This measure equals zero under complete mobility (statistical independence) and increases toward one as the joint distribution departs from independence. Because it depends on the copula density, it aggregates dependence across all parent-offspring quantile pairs. The resulting summary is invariant to monotone income transformations and remains comparable across cohorts even when marginal income distributions change. Second, following Yang et al. (2022), we model the copula as a time-varying convex combination of individual copulas with distinct tail-dependence properties and estimate the copula parameters as smooth functions of cohort year using kernel-weighted local likelihood. The mixed structure accommodates the nonlinear and asymmetric dependence patterns documented in the intergenerational mobility literature. It also yields a natural decomposition: the time path of each component's weight and dependence parameter reveals whether changes in overall immobility originate in the upper tail, the lower tail, or both. This approach complements, rather than replaces, directional mobility measures such as the IGE, rank-rank regression, and absolute mobility rates. It provides a distributional lens through which the evolution of intergenerational persistence can be examined.

Using data from the Panel Study of Income Dynamics (PSID) covering cohort years 1987 to 2021, we obtain three main findings. First, aggregate intergenerational immobility, as measured by the Hellinger distance index S_ρ, remained relatively stable during the late 1980s and 1990s. This stability is broadly consistent with Lee and Solon (2009), who document stable mobility for cohorts born through the mid-1970s using regression-based methods. The index then increased sharply beginning around 2000, coinciding with the collapse of the dot-com bubble. By the 2010s, it had approximately tripled relative to its 1990s level, indicating a significant deterioration for cohorts born in the 1980s and 1990s. Second, this deterioration is predominantly driven by upper-tail persistence. The weight on the Gumbel copula, which captures upper-tail dependence, rises from approximately 0.25 to 0.75 over the sample period, indicating increasing affluence persistence whereby high-income parents are increasingly likely to have high-income offspring. In contrast, the Clayton copula coefficient, which governs lower-tail dependence, shows no statistically significant trend, implying that poverty persistence did not intensify over this period. Third, subgroup analyses by race and geographic region suggest that all groups experienced declining mobility, but at different rates, with the Northeast and West exhibiting sharp deteriorations despite being economically prosperous regions.

The contribution of this study is threefold. First, we bring the time-varying mixed copula model of Yang et al. (2022) to the intergenerational mobility literature. This provides a distribution-wide measure that complements the regression-based and rank-based approaches predominant in the field, as advocated by Chetty et al. (2017) and Durlauf et al. (2023). Second, the mixed copula structure enables us to separately track upper- and lower-tail dependence over time, offering a decomposition of aggregate mobility trends that single-coefficient measures cannot provide. Third, we document new empirical facts about the evolution of intergenerational mobility in the U.S., most notably that the post-2000 deterioration is attributable to increasing affluence persistence rather than deepening poverty traps. These findings have direct implications for the design of policies aimed at promoting equality of opportunity.

The remainder of the paper is organized as follows. Section 2 presents the time-varying mixed copula framework and defines the intergenerational immobility measure. Section 3 describes the PSID data and sample construction. Section 4 reports the estimation results. We conclude in Section 5.

2 Time-Varying Intergenerational Mobility

2.1 Definition and Measure of Time-Varying Intergenerational Mobility

This section develops the immobility measure used throughout the paper. The conceptual foundation is the benchmark of complete intergenerational mobility, defined as statistical independence between parent and offspring permanent incomes. Under complete mobility, parental background provides little information about offspring outcomes, so the joint distribution of parent and offspring permanent income equals the product of their respective marginal distributions. Any departure from this independence benchmark reflects the extent to which parental income shapes offspring income, and the magnitude of that departure serves as the measure of intergenerational immobility.

Before introducing the formal notation, we clarify three aspects of the framework that bear on its economic interpretation. First, the time index t denotes the cohort year, defined as the calendar year in which offspring in a given cohort reach age 37. Each offspring contributes a single permanent-income observation, constructed as the average of annual total family income between ages 25 and 50. Time variation in the estimated parameters therefore reflects differences across birth cohorts rather than changes in individual incomes over calendar time. This cohort-based approach is conceptually related to the trend analyses in Lee and Solon (2009) and Chetty et al. (2017), and extends them by allowing the full joint dependence structure, rather than a single regression coefficient, to vary across cohorts. Second, the immobility index developed below is an undirected, distribution-wide measure of dependence. It summarizes how tightly parent and offspring incomes are linked across the entire joint distribution, but does not decompose mobility into upward versus downward movements. Third, because the strength of parent-offspring dependence can vary across different regions of the income distribution, the empirical analysis complements the aggregate index with concordance ordering tests, tail-specific copula decompositions, and quintile transition matrices.

Formally, let $Y_{o,t}$ and $Y_{p,t}$ denote offspring and parent permanent income for cohort year t, with joint distribution $F_t(\cdot,\cdot)$ and marginal distributions $F_{o,t}$ and $F_{p,t}$. We measure immobility by the normalized Bhattacharyya-Hellinger-Matusita distance between the observed joint distribution and the independence benchmark:

$$\begin{aligned}
S_{\rho,t} &= \frac{1}{2}E\left[1-\left(\frac{f_{o,t}(y_{o,t})f_{p,t}(y_{p,t})}{f_t(y_{o,t},y_{p,t})}\right)^{\frac{1}{2}}\right]^2 \\
&= \frac{1}{2}\iint\left[1-\left(\frac{f_{o,t}(y_{o,t})f_{p,t}(y_{p,t})}{f_t(y_{o,t},y_{p,t})}\right)^{\frac{1}{2}}\right]^2 f_t(y_{o,t},y_{p,t})dy_{o,t}dy_{p,t} \\
&= \frac{1}{2}\iint\left[f_t(y_{o,t},y_{p,t})-2\big(f_t(y_{o,t},y_{p,t})f_{o,t}(y_{o,t})f_{p,t}(y_{p,t})\big)^{\frac{1}{2}}+f_{o,t}(y_{o,t})f_{p,t}(y_{p,t})\right]dy_{o,t}dy_{p,t} \\
&= \frac{1}{2}\iint\left\{1-2\left[c_t\big(F_{o,t}(y_{o,t}),F_{p,t}(y_{p,t})\big)\right]^{\frac{1}{2}}+c_t\big(F_{o,t}(y_{o,t}),F_{p,t}(y_{p,t})\big)\right\}f_{o,t}(y_{o,t})f_{p,t}(y_{p,t})dy_{o,t}dy_{p,t} \\
&= \frac{1}{2}\iint\left\{1-\left[c_t\big(F_{o,t}(y_{o,t}),F_{p,t}(y_{p,t})\big)\right]^{\frac{1}{2}}\right\}^2 dF_{o,t}(y_{o,t})dF_{p,t}(y_{p,t}), \qquad (2)
\end{aligned}$$

where $c_t(\cdot)$ is the density of copula $C_t(\cdot)$, and $F_{o,t}(y_{o,t})$ and $F_{p,t}(y_{p,t})$ are the offspring and parent marginal distributions, respectively. Here, the fourth equality holds by Sklar's theorem (Sklar, 1959) and the fact that

$$\begin{aligned} f_t(y_{o,t}, y_{p,t}) &= \frac{\partial^2 F_t(y_{o,t}, y_{p,t})}{\partial y_{o,t} \partial y_{p,t}} = \frac{\partial^2 C_t\big(F_{o,t}(y_{o,t}), F_{p,t}(y_{p,t})\big)}{\partial y_{o,t} \partial y_{p,t}} \\ &= \frac{\partial^2 C_t\big(F_{o,t}(y_{o,t}), F_{p,t}(y_{p,t})\big)}{\partial F_{o,t}(y_{o,t}) \partial F_{p,t}(y_{p,t})} \times \frac{\partial F_{o,t}(y_{o,t}) \partial F_{p,t}(y_{p,t})}{\partial y_{o,t} \partial y_{p,t}} \\ &= c_t\big(F_{o,t}(y_{o,t}), F_{p,t}(y_{p,t})\big) f_{o,t}(y_{o,t}) f_{p,t}(y_{p,t}). \end{aligned}$$

Equation (2) gives the measure a benchmark interpretation that is economically transparent. If offspring and parent permanent incomes are independent, then the copula density equals one everywhere and $S_{\rho,t} = 0$. As the observed joint distribution moves farther from independence, $S_{\rho,t}$ rises toward one. Because the measure depends only on the copula density, it aggregates dependence across all parent-child quantile pairs rather than focusing only on a conditional mean, a rank slope, or a single transition cell. This is the sense in which $S_{\rho,t}$ provides a distribution-wide summary of intergenerational immobility.

The copula representation also clarifies why this measure is useful in the present context. $S_{\rho,t}$ is invariant to strictly increasing transformations of income, so the measured strength of dependence does not depend on whether permanent income is represented in levels, logs, or another monotone scale. That property is valuable here because permanent income is constructed from long panel averages and the marginal income distributions shift substantially across cohorts. The measure also accommodates nonlinear and asymmetric dependence and remains comparable even when the marginals change over time. At the same time, it is a scalar summary of overall dependence, not a directional measure of bottom-to-top or top-to-bottom mobility. For that reason, the empirical section supplements the aggregate index with concordance tests, tail-specific copula components, and transition-matrix evidence.

While equation (2) defines the immobility index for an arbitrary copula C_t, relying on a single standard copula family would be restrictive in this setting. In particular, it would force upper-tail and lower-tail dependence to move together, even though the intergenerational mobility literature suggests that elite persistence and poverty persistence may evolve differently (Durlauf et al., 2023). We therefore model the dependence structure as a time-varying mixed copula, that is, a convex combination of component copulas with distinct dependence shapes (Hu, 2006; Cai and Wang, 2014; Yang et al., 2022). In our empirical application, we use three widely used components with complementary tail-dependence properties. The Clayton copula concentrates dependence in the lower tail and captures poverty persistence. The Gumbel copula concentrates dependence in the upper tail and captures elite persistence. The Frank copula imposes symmetric dependence with no tail emphasis and captures baseline association. The time-varying component weights then reveal whether changes in aggregate immobility are driven by tightening at the top, hardening at the bottom, or a more symmetric shift across the entire distribution.

Formally, the time-varying mixed copula is defined as

$$C_t(u_{o,t}, u_{p,t}; \boldsymbol{\delta}_t) = \sum_{m=1}^{M} \omega_{m,t} C_{m,t}(u_{o,t}, u_{p,t}; \boldsymbol{\theta}_{m,t}), \tag{3}$$

where $\{C_{m,t}(u_{o,t}, u_{p,t}; \boldsymbol{\theta}_{m,t})\}_{m=1}^{M}$ is a set of candidate component copulas, the weights satisfy $\omega_{m,t} \geq 0$ and $\sum_{m=1}^{M} \omega_{m,t} = 1$ for each t, $\boldsymbol{\delta}_t = \left(\boldsymbol{\omega}_t^\top, \boldsymbol{\theta}_t^\top\right)^\top$ collects the weight parameters $\boldsymbol{\omega}_t = (\omega_{1,t}, \cdots, \omega_{M,t})^\top$ and dependence parameters $\boldsymbol{\theta}_t = (\boldsymbol{\theta}_{1,t}^\top, \cdots, \boldsymbol{\theta}_{M,t}^\top)^\top$, and $(u_{o,t}, u_{p,t})$ denotes the marginal quantiles of offspring and parent income. From (2) and (3), $S_{\rho,t}$ is a nonlinear function of $\boldsymbol{\delta}_t$. The index therefore inherits the tail-specific information embedded in the component copulas. For example, an increase in the Gumbel weight raises the contribution of upper-tail persistence to aggregate immobility. Compared with any single component family, the mixed copula is more flexible and can represent dependence patterns outside the class of any one component copula.[1]

To estimate $\boldsymbol{\delta}_t$, we first transform incomes within each cohort year into pseudo-uniform scores, that is, within-cohort empirical ranks. For group $g \in \{o, p\}$ and cohort year t_0, the pseudo-uniform score for individual j is

$$\widehat{u}_{g,t_0,j} = \widehat{F}_{g,t_0}(y_{g,t_0,j}) = \frac{1}{N_{g,t_0}} \sum_{i=1}^{N_{g,t_0}} I(y_{g,t_0,i} \leq y_{g,t_0,j}), \quad j = 1, \ldots, N_{g,t_0}, \tag{4}$$

where $I(\cdot)$ is the indicator function and N_{g,t_0} is the number of group-g observations at cohort year t_0. These pseudo-uniform scores remove the influence of the marginal income scales and allow the copula to capture within-cohort rank dependence alone.

[1] See Yang et al. (2022) for details on the selection of time-varying mixture copulas of the form in (3).

At a target cohort year t_0, we then estimate $\widehat{\boldsymbol{\delta}}_{t_0}$ by maximizing the following kernel-weighted local pseudo-likelihood (Tibshirani and Hastie, 1987)[2]:

$$\widehat{\boldsymbol{\delta}}_{t_0} = \arg \max_{(\boldsymbol{\omega}_{t_0}, \boldsymbol{\theta}_{t_0})} \sum_{t=1}^{T} \sum_{j=1}^{N_t} \log \left(\sum_{m=1}^{M} \omega_{m,t_0} c_{m,t_0}(\widehat{u}_{o,t,j}, \widehat{u}_{p,t,j}; \boldsymbol{\theta}_{m,t_0}) \right) K\left(\frac{t-t_0}{Th}\right), \tag{5}$$

where N_t is the number of parent-offspring pairs at cohort year t, $\widehat{u}_{o,t,j} = \widehat{F}_{o,t}(y_{o,t,j})$ and $\widehat{u}_{p,t,j} = \widehat{F}_{p,t}(y_{p,t,j})$ are the pseudo-uniform scores for pair j at cohort t, and $c_{m,t_0}(\cdot\,; \boldsymbol{\theta}_{m,t_0})$ is the density of the m-th component copula evaluated at the parameter vector corresponding to the estimation target t_0 rather than the summation index t. The bandwidth h controls the smoothness of the local estimator and, following Yang et al. (2022), is selected by leave-one-cohort-out cross-validation, choosing the bandwidth that maximizes the out-of-sample local log-likelihood over a grid of candidate values. Kernel weighting is motivated by the small within-cohort sample sizes in the PSID: with roughly 60–150 parent-offspring pairs per cohort year and a five-parameter mixed copula model, period-by-period maximum likelihood would be highly volatile. By down-weighting distant cohorts rather than discarding them, the kernel borrows information from nearby cohorts under the assumption that dependence evolves smoothly across birth cohorts. This delivers the standard nonparametric bias-variance tradeoff: a bias of order $O(h^2)$ is incurred near turning points, but estimation variance is reduced relative to the unsmoothed period-by-period estimator. The S_ρ column of Table 4 reports the corresponding unsmoothed period-by-period estimates as a benchmark. Given the estimator $\widehat{\boldsymbol{\delta}}_{t_0}$ at time t_0, we obtain the estimated copula and then compute S_{ρ,t_0} in (2) numerically using the approximation method of Davis and Rabinowitz (2007).

[2]The local likelihood in (5) requires that, within each cohort year t, the parent-offspring pairs $\{(y_{o,t,j}, y_{p,t,j})\}_{j=1}^{N_t}$ are i.i.d. draws from the copula with parameter vector $\boldsymbol{\delta}_t$. This is the standard cross-sectional independence assumption maintained throughout the intergenerational mobility literature. It does *not* impose that the copula parameters are identical across cohort years. Time variation in $\boldsymbol{\delta}_t$ is explicitly modeled through the kernel weighting in (5), which estimates $\boldsymbol{\delta}_{t_0}$ by borrowing information from cohorts near t_0 while allowing parameters to differ across cohorts. Mild cross-cohort dependence, such as that arising from shared macroeconomic conditions affecting adjacent birth cohorts, is accommodated under the weak mixing conditions in the asymptotic theory of Tibshirani and Hastie (1987) and Yang et al. (2022).

2.2 Concordance Ordering

Different mobility measures can yield conflicting trend estimates when the joint distribution of parent-offspring incomes fails to satisfy a uniform concordance ordering across cohorts (Anderson and Smith, 2024; McGee, 2025). This section introduces the concordance test of McGee (2025) and clarifies how our immobility measure $S_{\rho,t}$ should be interpreted both when concordance is established and when it is not.

For two cohorts, reference (re) and target (ta), let $C_{re}(u,v)$ and $C_{ta}(u,v)$ respectively denote the copula functions linking the marginal quantiles of parent and offspring permanent income. The reference cohort dominates the target in concordance ordering if $C_{re}(u,v) \geq C_{ta}(u,v)$ for all $(u,v) \in [0,1]^2$. When strict concordance holds, standard mobility measures, including intergenerational elasticities, rank-rank slopes, transition probabilities, and axiomatic indices, co-move and can be treated as interchangeable. On the other hand, when concordance fails, discrepancies between measures arise from the differential weights each assigns to different regions of the joint distribution, not from conflicting signals about mobility itself. Whether $S_{\rho,t}$ in (2) can be directly replaced by other standard measures therefore hinges on the presence of strict concordance.

We follow McGee (2025) and test concordance ordering for all pairwise combinations of reference and target cohorts. In empirical implementation, we replace the unknown copulas with their empirical counterparts $\widehat{C}_{re}$ and $\widehat{C}_{ta}$, and define $\Delta_{re,ta}(u,v) = \widehat{C}_{re}(u,v) - \widehat{C}_{ta}(u,v)$. Because concordance ordering can hold in either direction, we specify two one-sided null hypotheses. The first is $H_0^+ : \Delta_{re,ta}(u,v) \geq 0$ for all $(u,v) \in [0,1]^2$, and the second is $H_0^- : \Delta_{re,ta}(u,v) \leq 0$ for all $(u,v) \in [0,1]^2$. Testing both directions is necessary because a single one-sided test can verify dominance in one direction but cannot distinguish the absence of dominance from dominance in the reverse direction. The pair of tests lets us ask whether either direction can be statistically established. If neither direction is established, we treat the comparison as lacking evidence of a robust concordance ordering. The test statistics are

$$T^+ = \max_{(u,v)} \left(\frac{\max(-\Delta_{re,ta}(u,v), 0)}{\widehat{\sigma}(u,v)} \right), \quad T^- = \max_{(u,v)} \left(\frac{\max(\Delta_{re,ta}(u,v), 0)}{\widehat{\sigma}(u,v)} \right),$$

where $\widehat{\sigma}(u,v)$ is the estimated standard error of $\Delta_{re,ta}(u,v)$. Each statistic captures the maximum standardized violation of its respective null across the grid, mitigating false conclusions driven by noise at individual evaluation points.

If a concordance ordering is statistically established, the strength of intergenerational immobility is systematically higher in one cohort across all quantiles, and all standard mobility measures yield consistent conclusions. However, if strict concordance is not established, two empirically relevant scenarios arise. First, both nulls may be rejected, indicating that the dependence structure crosses over: immobility rises in some quantiles and falls in others. Second, neither null may be rejected, in which case the data do not provide enough evidence to establish dominance in either direction. This second case should be interpreted cautiously as a lack of statistically robust ordering, not as proof that no ordering exists. In both cases, the evidence does not support treating all mobility measures as interchangeable.

This is precisely the setting in which the choice of mobility measure matters most. Corollary 3 in McGee (2025) shows that, among concordance-monotone mobility measures, robustness to approximate concordance failures depends on the measure-specific weighting kernel and its Lipschitz bound. Measures that spread weight more evenly across the unit square tend to be less sensitive to localized violations. Our copula-based Hellinger distance $S_{\rho,t}$ is not identical to the Shorrocks trace measure, but it shares the relevant structural feature of integrating over the full (u, v) unit square rather than concentrating on a single transition cell, conditional mean, or tail region. We therefore interpret $S_{\rho,t}$ as a broad, distribution-wide summary of dependence, while avoiding the stronger claim that it delivers a unique global mobility ordering when strict concordance is not established.

2.3 Stochastic Dominance of Marginal Income Distributions

The copula-based immobility measure $S_{\rho,t}$ characterizes the joint dependence between parental and offspring incomes, but it does not address whether offspring are absolutely better off than their parents. To complement the mobility analysis, we examine the marginal income distributions using stochastic dominance criteria. It is important to emphasize that the stochastic dominance analysis operates on marginal distributions alone. It cannot serve as evidence for the ordering of intergenerational mobility, which is a property of the joint distribution. Alternatively, the stochastic dominance tests document changes in absolute welfare across cohorts.

We adopt a time-varying adaptation of the consistent stochastic dominance tests proposed by Barrett and Donald (2003), with the resampling procedure of Linton et al. (2005). We focus on two standard criteria: first-order stochastic dominance (FSD) and second-order stochastic dominance (SSD). Let $\{y_{g,t,i}\}_{i=1}^{N_g}$ denote income observations at time t for group $g \in \{o, p\}$, and let $\mathcal{U}_1$ be the class of all monotonically increasing utility functions. Let $\mathcal{U}_2 \subset \mathcal{U}_1$ contain those utility functions that are also concave, corresponding to nonsatiable and risk-averse individuals. Following Linton et al. (2005), offspring income $Y_{o,t}$ first-order stochastically dominates parent income $Y_{p,t}$ at time t, denoted $Y_{o,t}$ FSD $Y_{p,t}$, if and only if

(1) $E[u(Y_{o,t})] \geq E[u(Y_{p,t})]$ for all $u \in \mathcal{U}_1$ with strict inequality for some u, or equivalently,

(2) $F_{o,t}(y) \leq F_{p,t}(y)$ for all y with strict inequality for some y.

Similarly, $Y_{o,t}$ SSD $Y_{p,t}$ if and only if

(1) $E[u(Y_{o,t})] \geq E[u(Y_{p,t})]$ for all $u \in \mathcal{U}_2$ with strict inequality for some u, or equivalently,

(2) $\int_{-\infty}^{y} F_{o,t}(u)du \leq \int_{-\infty}^{y} F_{p,t}(u)du$ for all y with strict inequality for some y.

Since FSD implies SSD, rejection of SSD provides stronger evidence against welfare improvement than rejection of FSD alone.

Under the null hypothesis that $Y_{o,t}$ dominates $Y_{p,t}$ at order $j \in \{1, 2\}$, the test statistic is

$$\mathrm{SD}_{j,t} = \sqrt{\frac{N_{o,t}N_{p,t}}{N_{o,t} + N_{p,t}}} \sup_y \left(\mathcal{G}_j \left(y; F_{o,t}\right) - \mathcal{G}_j \left(y; F_{p,t}\right)\right), \quad j = 1, 2, \tag{6}$$

where $\mathcal{G}_1(x; F_{g,t}) = F_{g,t}(x)$ and $\mathcal{G}_2(x; F_{g,t}) = \int_{-\infty}^{x} F_{g,t}(v)dv$, with $F_{g,t}$ denoting the marginal distribution of group $g \in \{o, p\}$, and $N_{p,t}$ and $N_{o,t}$ are the number of parental and offspring observations at time t, respectively. The unknown marginal distributions $F_{g,t}$ are estimated using the time-varying nonparametric estimator in (4). Under the null hypothesis, $\mathrm{SD}_{j,t} \leq 0$ with probability at least $1 - \alpha$. We approximate the null distribution via bootstrap resampling.[3]

[3]We employ a family-level cluster bootstrap with 999 replications to approximate the null distribution

2.4 Inequality

The Great Gatsby Curve dubbed by Krueger (2012) introduces the relationship between inequality and intergenerational mobility. Corak (2013) observes that an increase in income inequality within a society corresponds to a stronger persistence of earnings across generations, thereby indicating lower levels of socioeconomic intergenerational mobility. This empirical finding engenders profound implications for the discourse on intergenerational distributive justice, prompting critical inquiries into the fairness of opportunity distribution between successive generations. The concept of the American dream, as expounded by Samuel (2012), is the aspiration that offspring achieve a superior standard of living compared to their parents.

The U.S., in its pursuit of the American Dream, has deliberately accepted a socioeconomic framework that is significantly different from other socioeconomic structures. This unique approach acknowledges the presence of unequal outcomes as an inherent component of the American character, with the objective of providing equitable opportunities for advancement to all members of society. The underlying rationale suggests a policy decision to prioritize equal access to opportunities over the homogenization of economic outcomes, thereby engendering a dynamic wherein inequality in results is acceptable if it increases social mobility. Chetty et al. (2014a) and Chetty et al. (2017) verify the existence of the positive slope of the Great Gatsby Curve in the U.S., which posed a great challenge to the American dream. Because the Great Gatsby Curve links equality of outcomes (measured by income inequality) to limits in opportunity (measured by intergenerational mobility), and as income inequality escalates, it reshapes the dynamics governing how family economic status interfaces with broader social determinants, consequently diminishing the propensity for intergenerational mobility (Durlauf and Seshadri, 2018; Durlauf et al., 2022).

Various methods are used to measure income inequality, including the Theil index, Atkinson index, Gini coefficients, and graphical tools such as the Lorenz curve. Among these, the Lorenz curve is a widely recognized measure of income inequality. However, it has been criticized for being overly simplistic and, at times, ambiguous in capturing

of $\mathrm{SD}_{j,t}$. For each replication, PSID family IDs are resampled with replacement, and all associated parent and offspring income observations are retained with their original cohort-year assignments. Using each bootstrap sample, the marginal empirical distributions are re-estimated as in (4) and the test statistic $\mathrm{SD}_{j,t}$ is recomputed. The reported probability $P(\mathrm{SD}_{j,t} \leq 0)$ is approximated as the empirical frequency of non-positive bootstrap statistics across the 999 replications.

inequality (Schutz, 1951). The generalized entropy family, a monotonic transformation of the Atkinson family of inequality indices, offers several advantageous welfare properties, including anonymity (invariance to permutations), continuity, scale invariance, and adherence to the Pigou-Dalton principle of transfers (aversion to inequality) (Maasoumi and Wang, 2019). A notable member of this family is the Shannon's Entropy (SE), defined as $-E\left[\log(f_{g,t}(y))\right]$ for $g \in \{o,p\}$, where $f_{g,t}(y)$ represents the income distribution. A larger SE value indicates lower levels of income inequality. SE serves as the foundational metric for Theil's inequality measure. Specifically, perfect equality is described as a scenario where all families within the same phase of their life cycles have identical annual incomes (Wertz, 1979), implying a uniform income distribution across the population. SE characterizes and quantifies the deviation from this uniform distribution, while Theil's inequality measure reflects the asymmetric Kullback-Leibler divergence of SE between population income distributions. SE is often considered a superior measure of inequality compared to the conventional Gini coefficient. It is more sensitive to inequality, especially in the tails of the income distribution, where the Gini coefficient may fail to provide meaningful insights (Atkinson et al., 1970). For instance, in evaluating poverty alleviation policies that target the extremes of income distribution, Gini coefficients often exhibit negligible changes compared to the Theil index, underscoring the limitations of the Gini coefficient in assessing such policies.

To observe the evolution of SE over time, we first need to estimate the time-varying probability density function for parent and offspring income, respectively. For any given time t_0, we employ the time-varying nonparametric kernel estimator as

$$\widehat{f}_{g,t_0}(y^*) = \frac{1}{N_g T}\sum_{i=1}^{N_g}\sum_{t=1}^{T}\frac{1}{h_{1,g}h_2}K\left(\frac{t-t_0}{Th_2}\right)K\left(\frac{y_{g,t,i}-y^*}{h_{1,g}}\right), \quad g \in \{o,p\},$$

where the bandwidths $h_{1,g}$ and h_2 are similar to that in (5). Given the estimators $\widehat{f}_{g,t_0}(y)$ at any fixed time t_0, then, for $g \in \{o,p\}$, the estimate of SE can be expressed as

$$\widehat{\mathrm{SE}}_{g,t_0} = -\int \log\left(\widehat{f}_{g,t_0}(y)\right)\widehat{f}_{g,t_0}(y)dy. \tag{7}$$

Due to the existence of logarithmic function in (7), an explicit form cannot be obtained even though the probability density function is a smooth function. To overcome this difficulty, we use the numerical approximated integral method in Davis and Rabinowitz (2007) to obtain the estimate of SE for any given time. Therefore, the formulation in (7) provides an estimate of SE across cohorts.

3 Data

The empirical data used in the analysis are drawn from the Panel Study of Income Dynamics (PSID), a nationally representative longitudinal household survey conducted by the Survey Research Center at the University of Michigan. The PSID is widely used in the study of intergenerational mobility. It began in 1968 with a large-scale survey designed to examine the dynamics of poverty in the U.S. and initially sampled thousands of households across 40 states. A key feature of the PSID is that family members retain consistent identification numbers even as family structure changes, which facilitates long-run tracking and parent-child matching. This longitudinal design yields a rich panel that is well suited to the study of intergenerational mobility. Moreover, as children form new households and are followed over time, the number of surveyed family members gradually increases.

As in Solon (1992), Bloome (2015) and An et al. (2022), we restrict the analysis to the PSID Survey Research Center (SRC) sample and exclude the Survey of Economic Opportunity (SEO) sample. This restriction mitigates concerns that low-income households would be over-represented and reduces potential complications from sampling irregularities in the SEO component. Following the standard practice in the literature, we utilize the annual total family income, measured by the summation of taxable income and transfer income, for both parents and children (Bowles and Gintis, 2002; An et al., 2022). Total family income more accurately represents the economic status of a household than individual income, and its use mitigates the zero-income problem commonly encountered in analyses reliant on administrative data, since transfer income ensures a non-negative financial position even when individual earnings are zero (Mazumder, 2018; An et al., 2022; Maasoumi et al., 2025). Moreover, sustained zero total family income over long spans of the life cycle is very rare in the PSID, so concerns regarding the sensitivity of results to years with zero income are effectively mitigated (Mazumder, 2016, 2018).

Following An et al. (2022), permanent income is defined as the average of annual total family incomes over any available years of data between the ages of 25 and 50, an approach that mitigates life-cycle bias arising from heterogeneity in lifetime earnings profiles. The income data are converted to 1968 dollars using the CPI, and the permanent income of each sample member is reported at age 37, the midpoint of the 25–50 window. We use the log of permanent income in the estimation of intergenerational mobility across cohorts. The maximum available time span in the PSID, covering the period from 1968 to 2021, is used to capture income dynamics.

We impose two sample restrictions. First, following Durlauf et al. (2017) and Durlauf et al. (2023), we require at least five annual income observations per individual. Second, to meet the sample size requirements of the time-varying nonparametric kernel estimator, we require at least 60 permanent income observations per cohort year for both offspring (observed at age 37) and parents. Because each parent may have multiple children, a larger number of offspring observations is needed to satisfy the parental threshold. These criteria yield an effective estimation period of 1987 to 2021. This period scope does not exclusively confine our data usage to these years: for example, the annual total family incomes of offspring who were 25 years old in 1968 are averaged and presented as permanent income in the estimation of intergenerational mobility for 1987 and subsequent years.

When a PSID household has multiple children, each child is included as a separate observation contributing a distinct parent-offspring permanent income pair. Because the cohort year t is defined as the year in which each offspring reaches age 37, siblings of different birth years contribute to separate cohort years and do not appear as simultaneous observations within the same cross-section. The primary source of within-family dependence is therefore cross-cohort: the same parental permanent income enters the local likelihood at multiple values of t for families with more than one child in the sample. We therefore construct bootstrap inference using a family-level cluster bootstrap that resamples entire family units with replacement.[4] These cluster-bootstrap intervals are used for the reported inference and confirm that our qualitative conclusions are robust to within-family income correlations across cohort years.

Table 1 reports summary statistics for the annual total family income of the two

[4] For each bootstrap replication, we resample PSID family IDs with replacement and retain all parent-offspring pairs associated with each selected family, preserving the original cohort-year assignments of those pairs.

matched generations in the PSID, each observed between ages 25 and 50. Members of the other generation in each matched family (their children or parents) are also tracked and surveyed at least five times between ages 25 and 50 from 1968 to 2021. Some observations in the PSID exhibit negative annual total family income. These cases indicate that total earnings received during the reference year were insufficient to cover expenditures, implying a net liability position. Because most offspring are very young in the early survey years, their data are excluded by the lower age bound of 25. Over time, more offspring reach age 25, enter the labor force, and form their own households, which increases the number of eligible offspring observations. Some offspring also age beyond 50 and are then excluded by the upper age bound. A similar pattern holds for the parental generation, as an increasing share of parents age beyond 50 over time. In addition, because 1968–2021 is a finite survey window, third-generation individuals cannot be tracked between ages 25 and 50 for the latest years, so the number of eligible parental observations declines substantially after 2017. These features do not affect the estimation of intergenerational mobility because our analysis is based on permanent total family income rather than income in a single year. Moreover, parents belong to an earlier generation than their children. Assuming each parent is at least 20 years older than the child, the parents of offspring observed at age 37 in 2021 would have been born no later than 1964.

4 Empirical Results

4.1 Full Sample Analyses

Using our matched sample data, we group all observations spanning the 1987–2021 period into five cohorts, namely the 1980s, 1990s, 2000s, 2010s, and 2020s, to conduct our concordance ordering tests. The full results of concordance tests for all reference and target cohort pairs are reported in Tables 2 and 3. Across all cohort combinations, the cluster bootstrap p-values, presented in parentheses, for both H_0^+ and H_0^- are very large, so the tests do not establish a statistically robust concordance ordering in either direction for any pair. In other words, we do not find evidence that any cohort has a joint distribution of parent-offspring incomes that uniformly dominates that of another cohort across the entire unit square. As discussed in Section 2.2, when strict concordance is not established, alternative mobility measures may assign differential weights to distinct regions of the joint distribution and therefore move in different directions. Because $S_{\rho,t}$ integrates over the full unit square rather than focusing on a particular transition cell, conditional mean, or tail region, it provides a broad summary of aggregate dependence. Changes in $S_{\rho,t}$ should therefore be interpreted as distribution-wide shifts in intergenerational dependence, not as a unique ordering that all mobility measures must share.

Using the full PSID sample and following Fan and Zhang (2000) to characterize time variation in annual data, Table 4 reports the estimated Hellinger distances (S_ρ) derived from the time-invariant mixed copula model, alongside the corresponding copula parameter estimates. The findings suggest that both the level of intergenerational mobility in the U.S. and the dependence structure between parental and offspring incomes exhibit temporal variation. To capture the intergenerational mobility across cohorts, we conduct an analysis by implementing the time-varying mixed copula model, as outlined in Section 2, starting with the full sample. To facilitate computational efficiency, the mixed model integrates Clayton, Gumbel, and Frank copulas.

Figure 1 illustrates the estimated trajectory of intergenerational immobility, proxied by S_ρ, over the period from 1987 to 2021 with the shaded region representing the 95% confidence interval.[5] As discussed in Section 2, a larger value of S_ρ corresponds to a lower level of mobility. A key observation from Figure 1 is the relative stability of S_ρ during the 1990s, followed by a pronounced increase beginning around 2000. This upward trend becomes particularly pronounced post-2005, with S_ρ reaching a value of 0.15, approximately three times higher than levels observed during the 1990s. These findings indicate a significant deterioration in intergenerational mobility for cohorts born in the 1980s and 1990s compared to those from the 1950s and 1960s.

Tables A1–A5 in Appendix report the corresponding quintile transition matrices for the five cohorts. They show top-quintile persistence rising from 0.3878 to 0.7091 and bottom-to-top mobility falling from 0.0816 to 0.0090, consistent with the increase in S_ρ. The relative stability of S_ρ during the late 1980s and 1990s is broadly consistent with Lee and Solon (2009), who document stable intergenerational income mobility for

[5]The 95% confidence intervals for $S_{\rho,t}$ are constructed via a family-level cluster bootstrap with 999 replications. For each replication, we resample PSID family IDs with replacement, retain all matched parent-child permanent-income pairs associated with each selected family, and preserve their cohort-year assignments. Using each bootstrap sample, we re-estimate the marginal empirical distributions as in (4), transform to pseudo-uniform scores, and re-maximize the kernel-weighted local log-likelihood in (5) to obtain bootstrap estimates $\widehat{\boldsymbol{\delta}}^*_{t_0}$ and the corresponding S^*_{ρ,t_0}. The 95% confidence interval at each t_0 is the interval between the 2.5th and 97.5th percentiles of the 999 bootstrap draws of S^*_{ρ,t_0}.

cohorts born through the mid-1970s using regression-based methods. The pronounced deterioration we document begins for cohorts born in the 1980s, a period beyond the window of their study, and is identified here through the distributional lens of the mixed copula rather than a single regression coefficient. This deterioration in social mobility is further supported by the sequence of stochastic dominance tests reported in Table 5, which presents the test statistics defined in (6) and the corresponding probability $P(\mathrm{SD}_{j,t} \leq 0)$ using 999 bootstrap replications for each year. The results show that the null hypotheses that offspring income first- or second-order stochastically dominates parent income are rejected at the 1% level in all years.

To evaluate the contributions of each individual candidate copula in the mixed model to the overall dependence structure, we present their respective estimated time-varying tail dependence coefficients and weights in Figures 2 and 3, respectively. Figure 2(a) shows a U-shaped pattern in the dependence coefficient of the Clayton copula. However, this time-varying trend is statistically insignificant due to the wide confidence interval. Since the Clayton copula captures lower tail dependence, this suggests that intergenerational mobility may not have meaningfully changed among the lower percentiles of the income distribution over the sample period. In contrast, Figure 2(b) reveals an upward trend in the upper tail dependence coefficient of the Gumbel copula over time, indicating an increase in intergenerational persistence among higher-income families.

Regarding the weights on the two individual copulas, panel (a) of Figure 3 reveals an upward trend in the weight of the Gumbel copula between 1987 and 2021, indicating a progressively larger contribution to the mixed copula model. Specifically, the point estimate for the Gumbel copula's weight increased threefold, from 0.25 to approximately 0.75 over this period, a rise that is statistically significant as evidenced by the 95% confidence interval. In contrast, panels (b) and (c) demonstrate that the weights associated with the Clayton and Frank copulas exhibit a declining trend during the same period. However, the 95% confidence intervals for these copulas indicate that these changes are not statistically significant with both copulas' weights stable at about 0.25. Overall, Figure 3 suggests that the Gumbel copula accounts for a progressively larger proportion in the mixed copula model, while the contributions of the Clayton and Frank copulas remain relatively stable.

Two observations about the nature of this trend merit emphasis. First, the rising weight and dependence coefficient of the Gumbel copula indicate that the increase in intergenerational immobility is concentrated at the upper tail of the joint income distribution: high-income parents are increasingly likely to have high-income offspring, reflecting stronger elite persistence over time. This is distinct from, and should not be conflated with, reduced upward mobility from the lower end of the distribution. Second, the statistically insignificant trend in the Clayton copula coefficient (Figure 2(a)) suggests that lower-tail persistence, that is, the tendency for low-income families to remain low-income, has not intensified over the same period. The aggregate rise in $S_{\rho,t}$ is therefore driven by upper-tail tightening rather than a generalized deepening of poverty traps. While affluence persistence and barriers to upward mobility from the bottom are conceptually distinct, they are connected through rank-order constraints: as high-income families cluster more tightly at the top, fewer top-rank positions become contestable by those rising from lower-income backgrounds, contributing to the overall decline in intergenerational mobility documented here.

Figure 4 displays the trajectory of Shannon's entropy over the sample period, suggesting a clear upward trend from the 1970s to the mid-1990s. This upward movement signifies an improvement in income equality, as higher Shannon's entropy values correspond to reduced income inequality, as discussed in Section 2.4. However, the trajectory plateaus after the mid-1990s, suggesting that progress in income equality has stagnated. This observation aligns with the findings presented in Figure 1, which indicate a decline in intergenerational mobility after the mid-1990s. Collectively, these results suggest that intergenerational mobility in the U.S. has deteriorated since the mid-1990s. Despite the improvement in income equality observed since the 1970s, its stagnation after the mid-1990s parallels the decline in overall intergenerational mobility.

4.2 Subgroup Analyses

To further investigate intergenerational mobility, we conduct subgroup analyses by splitting the full sample based on race and geographic location. Figure 5 reports the trajectories of S_ρ for White, Black, and other racial groups who do not identify as White or Black. Three key observations emerge from Figure 5. First, prior to the mid-1990s, the three racial groups exhibit comparable levels of S_ρ, with Black individuals exhibiting weaker within-group intergenerational rank persistence compared to White and other racial groups. Second, the trajectories for all three groups follow an upward trend, indicating a decline in social mobility over time. This upward trend becomes more pronounced after 2000 for White and Black individuals, whereas a notable acceleration in social immobility is observed in the mid-1990s among the other racial group. Notably, White and Black individuals display a parallel upward trajectory, whereas the divergence between White and other racial groups becomes increasingly pronounced from the mid-1990s onward, with the gap widening further after 2000. Third, among the three groups, Black individuals consistently exhibit the lowest levels of S_ρ throughout the sample period, indicating weaker within-group intergenerational rank persistence.[6] Social mobility among the other racial group experiences a marked decline over time, indicating a substantial deterioration in intergenerational mobility. Because subgroup sample sizes are necessarily smaller than those of the full sample, the confidence intervals for subgroup-specific $S_{\rho,t}$ trajectories are wider, and apparent differences in levels and trends across groups should be interpreted in light of the associated statistical uncertainty.

Figure 6 demonstrates the evolution of income inequality among the three racial groups, measured by Shannon's entropy. Among these groups, White individuals consistently exhibit the highest level of income inequality, as its trajectory is consistently lower than that of the other groups over the sample period, whereas the other two groups display comparable levels of Shannon's entropy between 1990 and 2021. However, all three groups experience a stagnation in the improvement of income equality after 1990, as evidenced by the flattening of their respective trajectories.

We extend our analysis by examining intergenerational mobility across four census regions: Northeast, North Central, South, and West. The trajectories of S_ρ in Figure 7 reveal a consistent decline in intergenerational mobility across all four regions throughout the sample period. Specifically, at the beginning of the 1990s, the North Central and West

[6] Our copula-based $S_{\rho,t}$ for each racial subsample captures *within-group* rank dependence: it measures how strongly a Black offspring's income rank among Black families is determined by their parents' income rank among Black families. It is an undirected measure of overall dependence strength and does not decompose into upward versus downward transitions, nor does it compare positions relative to the national income distribution. This stands in contrast to the directional, cross-population measures used by Mazumder (2014) and Collins and Wanamaker (2022), who document that Black families face substantially lower upward mobility and higher downward mobility relative to the full national distribution. Our finding of lower $S_{\rho,t}$ for the Black subsample, reflecting weaker within-group intergenerational rank persistence, is complementary to, rather than contradicted by, their well-established evidence. A group can simultaneously exhibit weaker within-group rank persistence (implying stronger regression to the within-group mean) and face structural barriers to upward movement in the national distribution, particularly when the group's income distribution is concentrated at lower absolute levels.

regions exhibited lower levels of S_ρ compared to the Northeast and South, indicating relatively higher mobility. However, beginning in the late 1990s, the trajectory of S_ρ in the West experienced a notable increase, surpassing all other regions by the end of the 2010s. By 2020, the Northeast and West displayed the highest levels of S_ρ, signifying the lowest intergenerational mobility in these regions.

This finding is noteworthy given that the Northeast and West are among the most economically prosperous regions in the U.S. Several factors may contribute to this pattern, though our analysis does not formally test these channels. Income inequality, which is elevated in both regions, has been linked to reduced mobility as economic disparities widen the gap between socioeconomic groups (Creamer et al., 2022). High housing costs and residential segregation may further constrain access to education and economic opportunities for lower-income households, and the concentration of high-skilled industries such as finance and technology may raise barriers for individuals lacking the necessary professional networks.

Figure 8 depicts the evolution of income inequality across the four census regions, measured by Shannon's entropy. The results indicate that all four regions follow similar trends over the sample period, with the South exhibiting the highest level of income equality, as its trajectory consistently dominates those of the other regions. Across all regions, income inequality experienced a notable improvement between 1970 and 1990. However, this progress reversed in the 1990s, with inequality levels increasing thereafter. Following the mid-1990s, all four regions resumed an upward trajectory in Shannon's entropy, signaling rising inequality. During this period, the Northeast surpassed both the North Central and West regions, ultimately displaying relatively better income equality compared to the other regions.

5 Conclusion

In this article, we employ a time-varying mixed copula model to examine how intergenerational income mobility in the United States has evolved across birth cohorts from 1987 to 2021. By allowing both the copula weights and dependence parameters to vary smoothly over time, our framework captures shifts in the full joint dependence structure between parent and offspring permanent incomes, complementing the regression-based and rank-based approaches that predominate in the existing literature.

Three findings emerge from the analysis. First, aggregate intergenerational immobility, measured by the Hellinger distance index $S_{\rho,t}$, remained stable through the 1990s but increased sharply after 2000, approximately tripling by the 2010s. Second, this deterioration is driven by upper-tail persistence rather than deepening poverty traps: the Gumbel copula weight rises from 0.25 to 0.75, indicating that high-income families are increasingly likely to transmit their economic position to their children, while the Clayton copula coefficient shows no significant trend, implying that lower-tail persistence did not intensify. Third, subgroup analyses reveal declining mobility across all racial groups and census regions, with particularly sharp deteriorations in the Northeast and West.

These findings carry implications for the ongoing debate about equality of opportunity in the United States. The post-2000 deterioration we document extends and reinforces the evidence of Chetty et al. (2017) on fading absolute mobility, and the upper-tail concentration of the decline aligns with the mechanisms underlying the Great Gatsby Curve (Corak, 2013; Krueger, 2012). Rising income inequality at the top appears to translate into stronger intergenerational persistence at the top. From a policy perspective, the results suggest that interventions focused solely on alleviating poverty traps may be insufficient to reverse the decline in mobility. Addressing elite persistence through progressive taxation, inheritance reform, or broader access to elite educational and professional networks may be equally important.

Several limitations should be noted. Our analysis documents trends in intergenerational dependence but does not identify the causal mechanisms behind them. The PSID sample, while well suited for longitudinal analysis, is modest in size, particularly for the subgroup analyses where statistical precision is limited. The kernel smoothing approach assumes that dependence parameters evolve smoothly, which may attenuate abrupt structural breaks. Finally, total family income, while avoiding the zero-income problem, aggregates diverse income sources and may mask heterogeneity in the transmission of specific income components such as labor earnings versus capital income.

The framework developed here can be extended in several directions. Following the conditional rank-rank regression of Chernozhukov et al. (2025), one could investigate how S_ρ varies with covariates such as education, wealth, or neighborhood characteristics by replacing the unconditional copula with a conditional copula, as in Liu et al. (2022). The mixed copula model could also be applied to international comparisons using harmonized panel data, or extended to three-generation analyses as longer panels become available.

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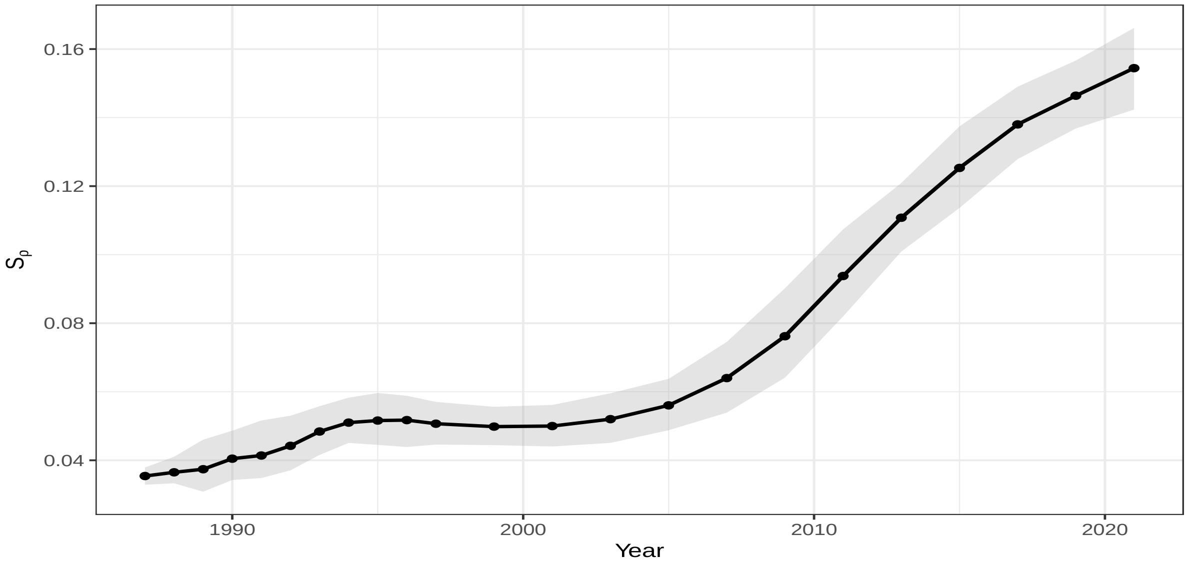
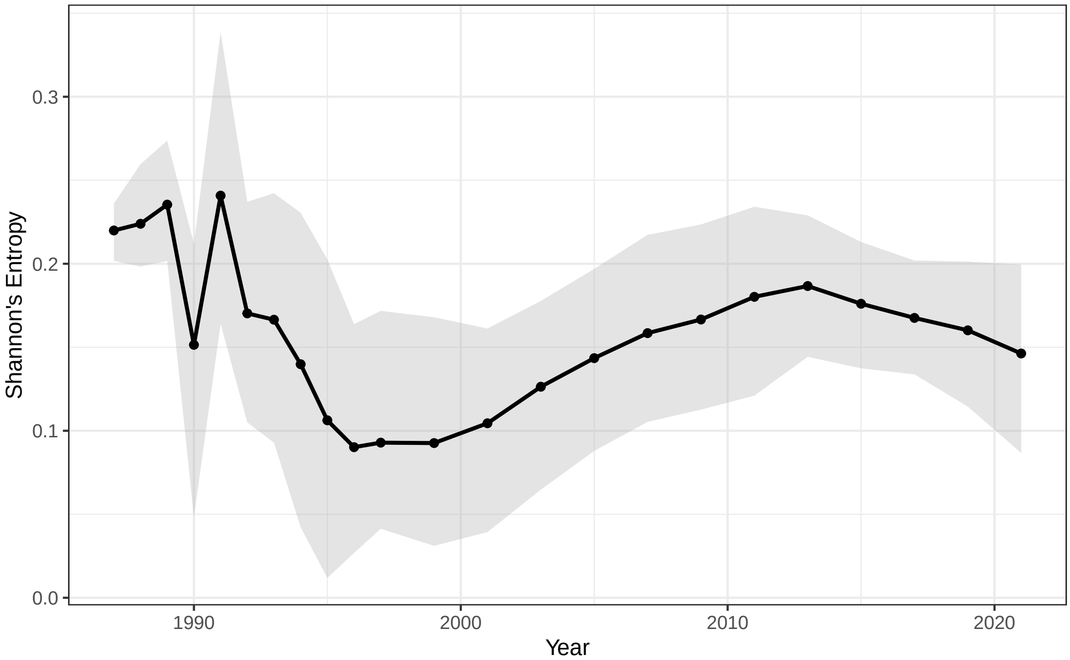
Figure 1: Dynamic intergenerational mobility

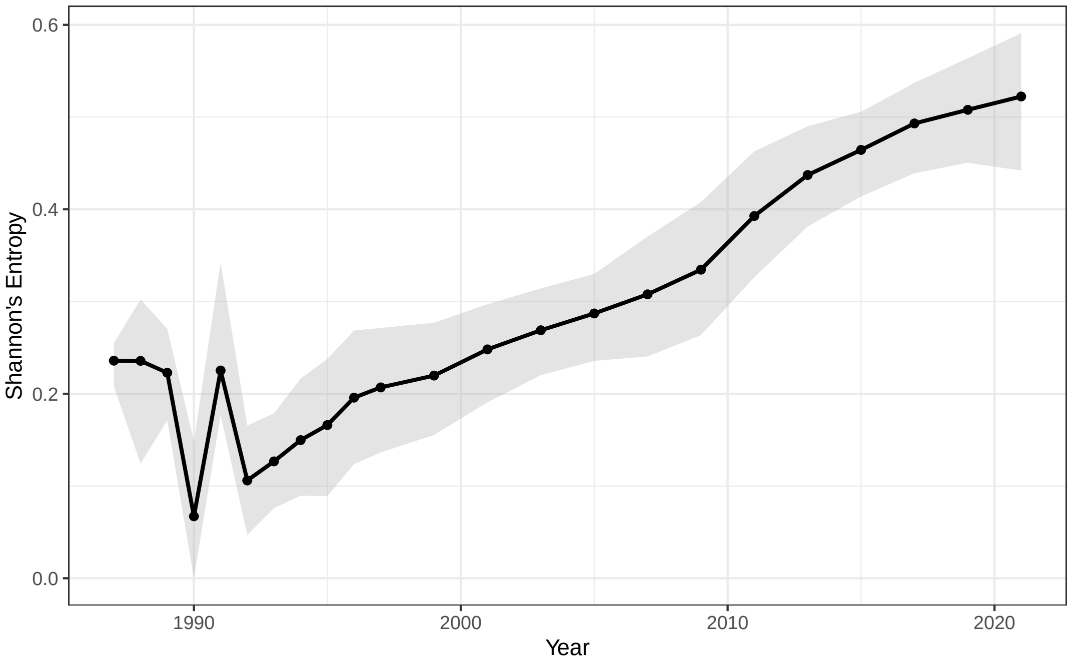


Notes. This figure shows estimated trajectory of entropy S_ρ in different years. A larger S_ρ value indicates lower levels of intergenerational mobility. The shaded area represents the 95% confidence interval.

Figure 2: Time series of estimated tail dependence coefficients



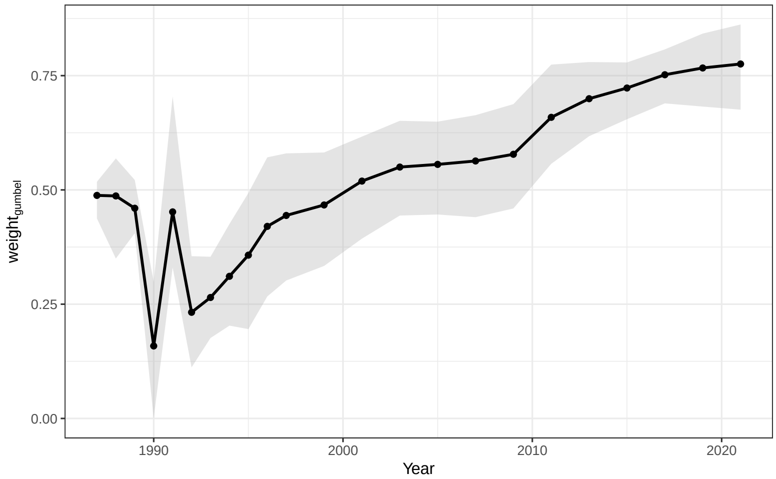
(a) Lower Tail Dependence



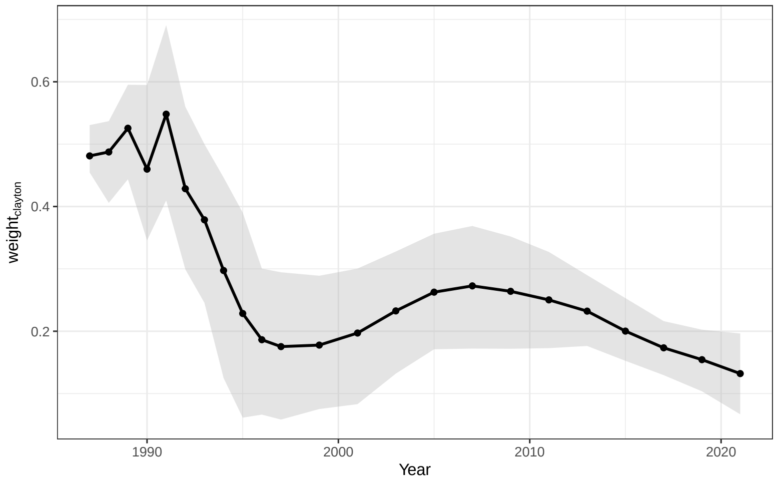
(b) Upper Tail Dependence

Notes. These figures show the estimated trajectories of tail dependence coefficients for different years obtained from a time-varying mixed copula model. The shaded area represents the 95% confidence interval.

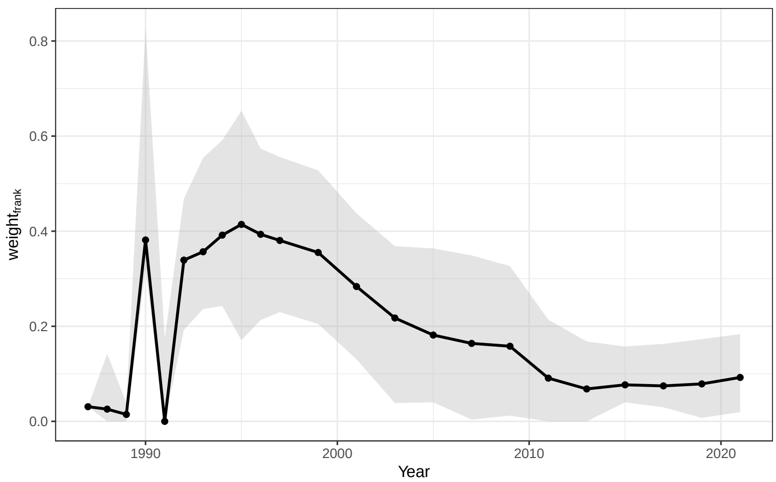
Figure 3: Time series of estimated copula weights



(a) Gumbel copula



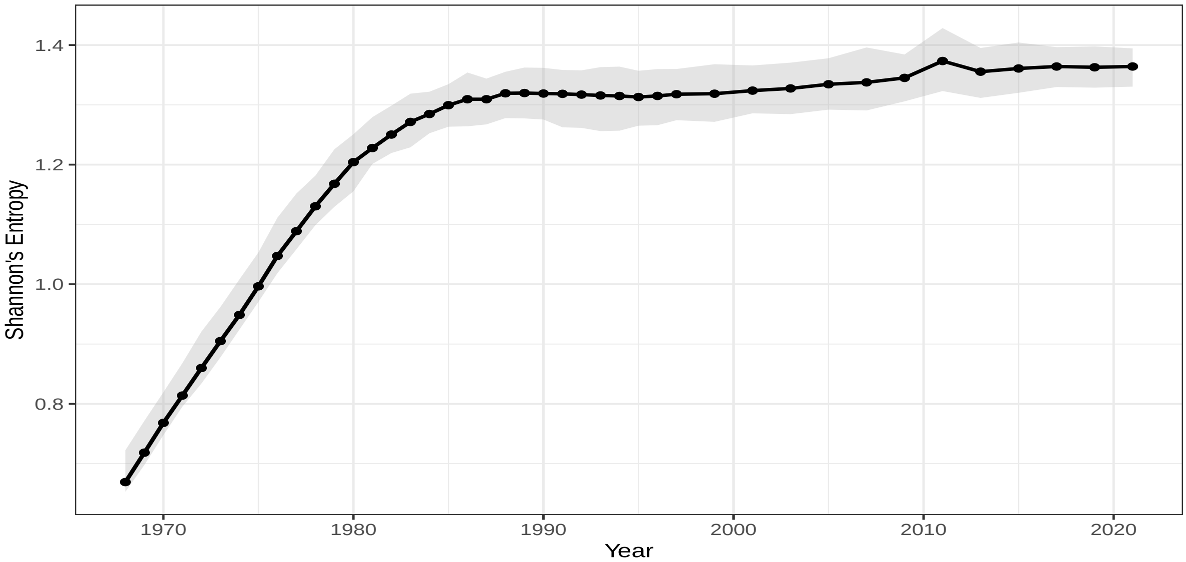
(b) Clayton copula



(c) Frank copula

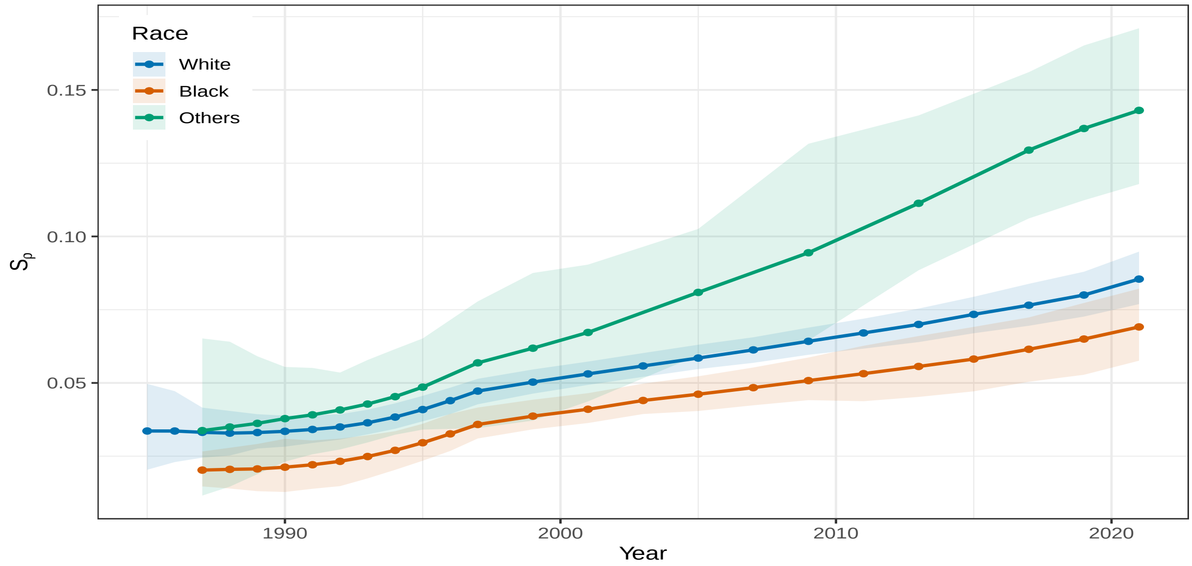
Notes. These figures show the estimated trajectories of the weights corresponding to each individual copula in the mixed copula model for different years. The shaded area represents the 95% confidence interval.

Figure 4: Dynamic income inequality



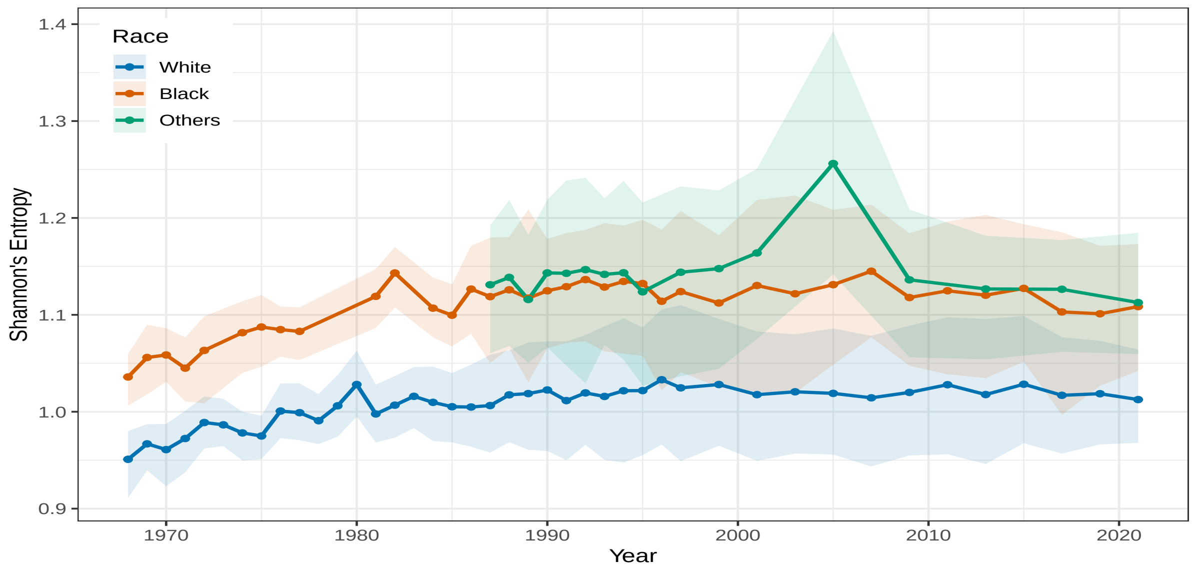
Notes. This figure shows estimated trajectory of Shannon's entropy in different years. A larger Shannon's entropy value indicates lower levels of income inequality. The shaded area represents the 95% confidence interval.

Figure 5: Dynamic intergenerational mobility of different races



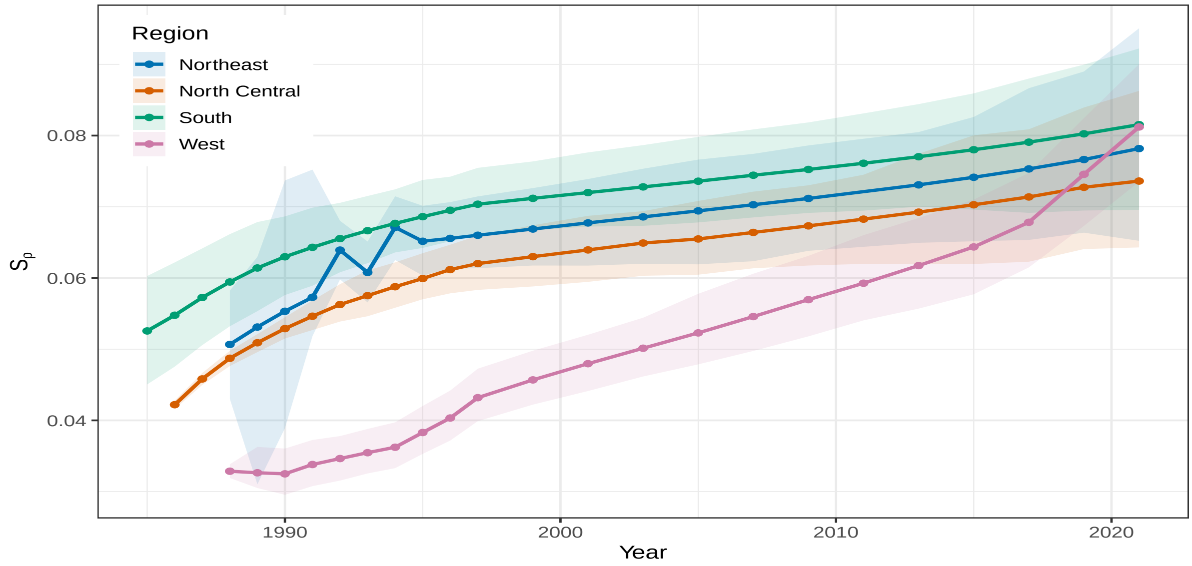
Notes. This figure shows estimated trajectory of entropy S_ρ for different races in different years. A larger S_ρ value indicates lower levels of intergenerational mobility. The shaded area represents the 95% confidence interval.

Figure 6: Dynamic income inequality of different races



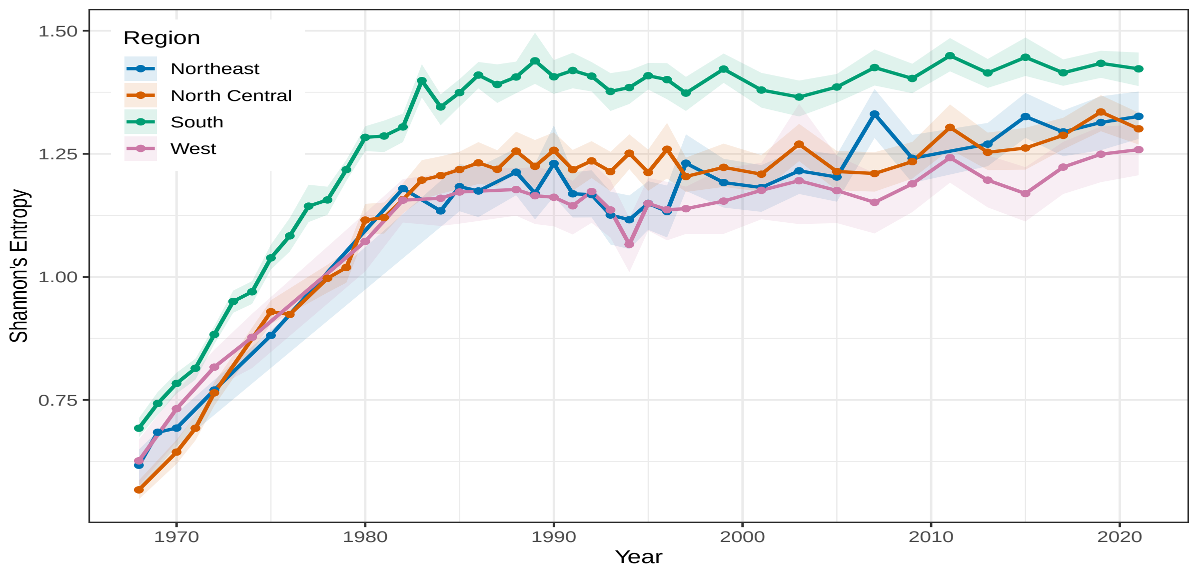
Notes. This figure shows estimated trajectory of Shannon's entropy for different races in different years. A larger Shannon's entropy value indicates lower levels of income inequality. The shaded area represents the 95% confidence interval.

Figure 7: Dynamic intergenerational mobility of different regions



Notes. This figure shows estimated trajectory of entropy S_ρ for different regions in different years. A larger S_ρ value indicates lower levels of intergenerational mobility. The shaded area represents the 95% confidence interval.

Figure 8: Dynamic income inequality of different regions



Notes. This figure shows estimated trajectory of Shannon's entropy for different regions in different years. A larger Shannon's entropy value indicates lower levels of income inequality. The shaded area represents the 95% confidence interval.

Table 1: Summary statistics

	Offspring						Parent					
Year	Obs.	Mean	SD	Min	Median	Max	Obs.	Mean	SD	Min	Median	Max
1968	1	10925.00	-	10925.00	10925.00	10925.00	3019	9133.94	5965.01	200.00	8065.00	65400.00
1969	2	7016.42	3526.43	4522.85	7016.42	9509.98	3124	9872.34	6904.41	1055.17	8633.23	78140.31
1970	5	6197.14	2226.86	4224.33	5275.86	8732.46	3243	10314.85	6772.21	0.91	9050.83	83376.81
1971	8	6943.95	4054.89	1262.83	5963.04	14990.74	3350	10342.944	6533.89	257.72	9277.93	85905.93
1972	25	7936.29	3020.81	1812.60	7825.49	15489.50	3495	10669.04	6825.20	0.82	9623.26	82390.13
1973	54	8565.46	4648.13	1455.81	7866.58	23931.18	3486	11286.19	6994.84	0.80	10215.02	65651.20
1974	102	9403.48	4828.02	1149.75	8198.58	29617.07	3472	11970.07	7905.78	375.74	10572.48	75146.60
1975	162	8725.91	5867.68	1112.48	7432.78	57586.47	3460	11674.98	7657.63	0.68	10330.38	67668.50
1976	244	8317.62	5046.03	557.94	7612.18	47304.15	3430	11355.59	7490.54	0.62	9906.56	61992.90
1977	350	8975.49	4862.89	969.59	8458.97	32358.62	3442	12068.92	7910.81	0.59	10525.93	58620.10
1978	444	9150.03	5157.21	110.11	8478.59	34492.44	3391	12177.57	7419.92	0.55	10901.04	55055.22
1979	596	9551.28	5424.75	153.41	8897.73	36818.18	3302	12312.22	7293.95	0.51	11045.45	51135.85
1980	743	9415.49	5500.04	91.95	8734.98	41435.05	3255	12243.62	7709.81	0.46	10803.79	95073.32
1981	897	9134.14	5996.88	0.40	8193.33	56479.23	3144	11845.24	9261.79	0.40	10430.24	214175.71
1982	1029	8841.47	5736.19	0.37	7932.52	54988.27	3076	11169.86	7191.02	0.37	9989.03	78701.44
1983	1161	8859.83	5935.91	0.35	7952.54	51095.43	3033	10927.92	7764.41	0.35	9468.37	105803.39
1984	1318	9302.21	6556.04	0.33	8342.32	66987.74	2896	11429.10	7823.90	0.33	10269.22	86849.61
1985	1495	9613.39	6843.95	0.32	8510.71	67974.52	2789	12077.67	9466.26	0.32	10662.47	127676.64
1986	1649	9782.14	7365.30	0.31	8684.37	81571.05	2677	12048.12	8607.62	0.31	10638.35	93111.96
1987	1799	9931.97	7297.27	0.30	8674.16	95446.19	2596	12676.57	10111.43	0.30	10956.83	138573.50
1988	1940	10196.06	7520.71	0.29	8825.47	89007.77	2476	12662.50	10004.33	0.29	11245.10	140639.03
1989	2057	10588.71	8087.06	0.28	9064.33	98450.69	2343	13101.26	11729.87	0.28	11454.55	158304.08
1990	2195	10613.05	8264.62	0.27	9279.58	128347.67	2228	13310.50	12534.76	0.27	11572.56	180585.75
1991	2314	10651.70	8936.53	0.26	9192.26	131755.67	2135	13230.81	11221.61	0.26	11600.12	127670.23
1992	2449	10462.20	8587.65	0.24	8886.05	134824.21	2017	13501.12	13874.36	0.24	11174.93	238832.85
1993	2528	10761.37	8678.82	0.24	9126.38	127393.01	1983	13271.73	10986.25	0.24	11676.50	135762.24
1994	2659	14430.66	89752.45	-1323.31	9006.56	2309433.73	2013	17926.88	103020.64	-5173.59	11320.61	2309433.73
1995	2692	13774.88	75642.58	-1800.30	9264.74	2250661.73	1875	15187.99	53289.03	-3691.31	11640.42	2250661.73
1996	2743	11654.27	13294.31	-3283.98	9413.84	317377.79	1769	14253.45	14292.59	-1678.45	11668.99	226930.44
1997	2211	11768.48	10651.02	0.21	9584.57	164103.29	1665	13968.00	10971.29	0.21	11486.17	110607.54
1999	2396	12624.22	11017.08	-15042.13	10167.97	159221.51	1359	15787.61	17989.89	-557.28	12545.35	407467.90
2001	2578	13381.30	13428.93	-11614.59	10655.95	264577.43	1075	15881.37	15221.48	-8642.94	12980.88	264577.43
2003	2731	13166.50	15216.96	-880.83	10414.54	392288.74	835	14799.06	13066.21	222.57	12242.41	142463.05
2005	2939	13222.82	22407.39	-6888.71	10227.08	971484.65	543	13967.01	13302.00	-6888.71	11657.82	220402.84
2007	3042	12712.77	13549.33	-3256.94	9942.93	353083.29	337	13601.70	12062.10	99.30	11088.16	141268.07
2009	3261	12612.53	14057.06	0.77	9910.45	321681.18	191	12496.59	10562.51	72.83	10771.83	81845.86
2011	3155	11619.17	11617.88	22.95	9310.05	237685.50	95	11296.56	8820.97	241.74	10863.00	62733.98
2013	2886	12045.11	16153.04	-4068.76	9447.96	481857.73	28	8330.67	5190.39	1667.03	7029.37	23380.85
2015	2569	12402.80	11057.00	0.28	9865.45	142055.22	7	7659.56	4338.61	2029.29	9089.53	12397.27
2017	2354	13385.95	13094.72	1.39	10713.61	287735.08	1	15707.56	-	15707.56	15707.56	15707.56
2019	2105	14446.10	14789.18	-35592.83	11160.13	282337.88	0	-	-	-	-	-
2021	1829	15202.46	20587.51	-52851.97	11485.63	549402.65	0	-	-	-	-	-

Notes. This table reports the summary statistics of the annual total family income of two generations (aged between 25 and 50) in PSID, with their offspring or parents have been matched. Additionally, the another generation within the sample (their children or parents), are also tracked and surveyed at least five times between the ages of 25 and 50 from 1968 to 2021, and their annual total family incomes are converted to 1968 U.S. dollars using the Consumer Price Index.

Table 2: Test statistics T^+ for concordance ordering across cohorts

	Reference cohort				
	1980s	1990s	2000s	2010s	2020s
Target cohort					
1990s	3.318 (0.917)				
2000s	3.111 (0.983)	3.806 (0.923)			
2010s	6.197 (0.803)	9.142 (0.787)	7.409 (0.840)		
2020s	7.151 (0.603)	9.113 (0.820)	9.141 (0.770)	4.165 (0.940)	

Notes. This table reports the bootstrap-based test statistic T^+, constructed following the procedure in McGee (2025), for the null hypothesis (H_0^+: $\Delta_{re,ta}(u,v) \geq 0$) that the copula of the target cohort is not stronger in concordance than that of the reference cohort. P-values are in parentheses.

Table 3: Test statistics T^- for concordance ordering across cohorts

	Reference cohort				
	1980s	1990s	2000s	2010s	2020s
Target cohort					
1990s	2.723 (0.990)				
2000s	2.471 (0.997)	2.471 (0.993)			
2010s	2.431 (0.727)	2.246 (0.76)	2.746 (0.42)		
2020s	1.681 (0.993)	1.267 (0.997)	1.307 (0.999)	2.368 (0.997)	

Notes. This table reports the bootstrap-based test statistic T^-, constructed following the procedure in McGee (2025), for the null hypothesis (H_0^-: $\Delta_{re,ta}(u,v) \leq 0$) that the copula of the reference cohort is not stronger in concordance than that of the target cohort. P-values are in parentheses.

Table 4: Annual estimates

Year	S_ρ	Tail dependence		Weight		
		Lower tail	Upper tail	Gumbel	Frank	Clayton
1987	0.0377	0.3865	0.0609	0.1335	0.0000	0.8665
1988	0.0554	0.1661	0.3509	0.6736	0.0000	0.3264
1989	0.0441	0.2089	0.2996	0.5074	0.0829	0.4096
1990	0.0233	0.0004	0.0004	0.4679	0.5321	0.0000
1991	0.0551	0.1455	0.0366	0.0763	0.6198	0.3039
1992	0.0398	0.2296	0.0003	0.0000	0.4304	0.5696
1993	0.0505	0.2421	0.1790	0.3269	0.1423	0.5309
1994	0.0442	0.1510	0.2812	0.4428	0.3384	0.2188
1995	0.0642	0.2891	0.0828	0.2176	0.2674	0.5150
1996	0.0762	0.0056	0.1198	0.1970	0.8030	0.0000
1997	0.0429	0.0018	0.1533	0.3846	0.6154	0.0000
1999	0.0550	0.0969	0.2402	0.5896	0.2992	0.1112
2001	0.0497	0.1229	0.3107	0.6379	0.1158	0.2463
2003	0.0392	0.3032	0.0814	0.2081	0.2735	0.5184
2005	0.0503	0.0428	0.2600	0.4876	0.4102	0.1022
2007	0.0853	0.1830	0.4300	0.7489	0.0000	0.2511
2009	0.0712	0.1562	0.2138	0.3082	0.4321	0.2597
2011	0.0752	0.1526	0.4243	0.6295	0.0000	0.3705
2013	0.1064	0.2028	0.3691	0.6455	0.1165	0.2380
2015	0.1373	0.1137	0.4545	0.6777	0.2234	0.0989
2017	0.1434	0.1867	0.5450	0.8191	0.0000	0.1801
2019	0.1867	0.0795	0.5920	0.7912	0.1700	0.0398
2021	0.1566	0.1097	0.4366	0.6668	0.2319	0.1013

Notes. This table reports the estimated values of S_ρ, copula weights, and tail-dependence coefficients for each year obtained using the annual calculation method adopted by Fan and Zhang (2000).

Table 5: Stochastic-dominance tests

Year	FSD	$P(\text{SD}_1 \leq 0)$	SSD	$P(\text{SD}_2 \leq 0)$
1987	0.0766	(0.000)	229.58	(0.000)
1988	0.1203	(0.000)	858.92	(0.000)
1989	0.2035	(0.000)	1050.50	(0.000)
1990	0.2789	(0.000)	639.87	(0.000)
1991	0.3846	(0.000)	755.76	(0.000)
1992	0.4500	(0.000)	842.82	(0.000)
1993	0.4957	(0.000)	834.63	(0.000)
1994	0.4145	(0.000)	1759.80	(0.000)
1995	0.5366	(0.000)	1070.12	(0.000)
1996	0.6751	(0.000)	1347.92	(0.000)
1997	1.1356	(0.000)	3389.99	(0.000)
1999	0.9339	(0.000)	3610.85	(0.000)
2001	1.5358	(0.000)	3459.49	(0.000)
2003	0.8555	(0.000)	2653.20	(0.000)
2005	1.1972	(0.000)	3237.92	(0.000)
2007	0.6095	(0.000)	1036.41	(0.000)
2009	0.8523	(0.000)	2259.08	(0.000)
2011	0.4020	(0.000)	2329.06	(0.000)
2013	0.6818	(0.000)	3647.65	(0.000)
2015	0.3566	(0.000)	839.00	(0.000)
2017	0.5715	(0.000)	1528.21	(0.000)
2019	0.2645	(0.000)	7497.44	(0.000)
2021	0.3289	(0.000)	4109.66	(0.000)

Notes. This table reports the test statistics and the probability $P(\text{SD}_{j,t} \leq 0)$ of the stochastic-dominance test by bootstrap technique with 999 replications.

Appendix: Transition Matrices

Table A1: Intergenerational income transition matrix for the 1980-cohort

		Offspring				
		Q1	Q2	Q3	Q4	Q5
Parent	Q1	0.4898	0.2041	0.1429	0.0816	0.0816
	Q2	0.3333	0.2708	0.1667	0.1250	0.1042
	Q3	0.0800	0.2600	0.2400	0.2400	0.1800
	Q4	0.0213	0.1702	0.2340	0.3191	0.2553
	Q5	0.0816	0.0816	0.2245	0.2245	0.3878

Notes. This table presents the transition matrix, estimated using the full sample of offspring who were aged 37 between 1987 and 1989. Each cell entry represents the conditional probability that, conditional on parents being in a particular quintile, their child transitions to a specific quintile. Quantile Q1 denotes the bottom 1st income quintile, representing the poorest 20 percent of households in the income distribution. Quantile Q5 denotes the top 5th income quintile, representing the richest 20 percent of households in the income distribution.

Table A2: Intergenerational income transition matrix for the 1990s-cohort

		Offspring				
		Q1	Q2	Q3	Q4	Q5
Parent	Q1	0.5063	0.2358	0.1195	0.1132	0.0252
	Q2	0.2461	0.2713	0.2618	0.1546	0.0662
	Q3	0.1424	0.2532	0.2785	0.1899	0.1361
	Q4	0.0669	0.1433	0.1911	0.2707	0.3280
	Q5	0.0380	0.0949	0.1487	0.2722	0.4462

Notes. This table presents the transition matrix, estimated using the full sample of offspring who were aged 37 between 1990 and 1999. Each cell entry represents the conditional probability that, conditional on parents being in a particular quintile, their child transitions to a specific quintile. Quantile Q1 denotes the bottom 1st income quintile, representing the poorest 20 percent of households in the income distribution. Quantile Q5 denotes the top 5th income quintile, representing the richest 20 percent of households in the income distribution.

Table A3: Intergenerational income transition matrix for the 2000s-cohort

		Offspring				
		Q1	Q2	Q3	Q4	Q5
	Q1	0.5102	0.2585	0.1395	0.0748	0.0170
	Q2	0.2509	0.2680	0.2680	0.1340	0.0790
Parent	Q3	0.1301	0.2397	0.1986	0.2568	0.1747
	Q4	0.0788	0.1473	0.2363	0.2911	0.2466
	Q5	0.0307	0.0853	0.1570	0.2423	0.4846

Notes. This table presents the transition matrix, estimated using the full sample of offspring who were aged 37 between 2000 and 2009. Each cell entry represents the conditional probability that, conditional on parents being in a particular quintile, their child transitions to a specific quintile. Quantile Q1 denotes the bottom 1st income quintile, representing the poorest 20 percent of households in the income distribution. Quantile Q5 denotes the top 5th income quintile, representing the richest 20 percent of households in the income distribution.

Table A4: Intergenerational income transition matrix for the 2010s-cohort

		Offspring				
		Q1	Q2	Q3	Q4	Q5
	Q1	0.6299	0.2740	0.0819	0.0071	0.0071
	Q2	0.2278	0.3416	0.3167	0.1032	0.0107
Parent	Q3	0.0857	0.2214	0.3071	0.3107	0.0750
	Q4	0.0464	0.1000	0.2107	0.3750	0.2679
	Q5	0.0107	0.0605	0.0854	0.2028	0.6406

Notes. This table presents the transition matrix, estimated using the full sample of offspring who were aged 37 between 2010 and 2019. Each cell entry represents the conditional probability that, conditional on parents being in a particular quintile, their child transitions to a specific quintile. Quantile Q1 denotes the bottom 1st income quintile, representing the poorest 20 percent of households in the income distribution. Quantile Q5 denotes the top 5th income quintile, representing the richest 20 percent of households in the income distribution.

Table A5: Intergenerational income transition matrix for the 2020s-cohort

		Offspring				
		Q1	Q2	Q3	Q4	Q5
	Q1	0.6396	0.2252	0.1081	0.0180	0.0090
	Q2	0.2883	0.4595	0.1802	0.0541	0.0180
Parent	Q3	0.0541	0.2162	0.4505	0.1982	0.0811
	Q4	0.0179	0.0714	0.2232	0.5000	0.1875
	Q5	0.0000	0.0273	0.0364	0.2273	0.7091

Notes. This table presents the transition matrix, estimated using the full sample of offspring who were aged 37 between 2020 and 2021. Each cell entry represents the conditional probability that, conditional on parents being in a particular quintile, their child transitions to a specific quintile. Quantile Q1 denotes the bottom 1st income quintile, representing the poorest 20 percent of households in the income distribution. Quantile Q5 denotes the top 5th income quintile, representing the richest 20 percent of households in the income distribution.