Multidimensional Equality of Opportunity in the United States*

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Abstract

Is the United States still a land of opportunity? We provide new insights on this question by leveraging a novel approach that allows us to measure inequality of opportunity in the joint distribution of income and wealth. We show that inequality of opportunity in the US has increased by 58% from the cohort born in 1935 to the cohort of 1980. Increases are driven by a less opportunity-egalitarian income distribution for birth cohorts after 1950 and a less opportunity-egalitarian wealth distribution after 1960. Our findings suggest that the United States has consistently moved further away from a level playing field in recent decades.

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Keywords: Fairness, Intergenerational mobility, Time trends, Measurement

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1 INTRODUCTION

In a fair economy, people act on a level playing field to acquire monetary resources. This idea—frequently labeled as *equality of opportunity*—is widely reflected in fairness conceptions of academic philosophers and the general public (Alesina et al., 2018; Almås et al., 2020; Arneson, 2018; Cappelen et al., 2007; Cohen, 1989; Fong, 2001; Rawls, 1971; Roemer, 1998). Consequently, an active literature in economics assesses the satisfaction of the opportunity-egalitarian ideal in different countries at different points in time. We contribute to this literature by providing the first analysis of the relationship between family background characteristics and the joint distribution of income and wealth in the US.

Existing studies on inequality of opportunity and intergenerational mobility have focused either on income or, to a lesser extent, on wealth to measure monetary resources.[1] However, by excluding income or wealth from the analysis, these studies neglect essential information on individual consumption possibilities, arguably the relevant metric to assess the financial well-being of individuals. For example, unidimensional analyses will misrepresent the financial well-being of income-poor heirs who support their lifestyle by selling assets, or of asset-poor persons with high incomes. Therefore, if society cares for the financial well-being of individuals more broadly, we should move from unidimensional analyses of monetary resources to analyses of the joint distribution of income and wealth.

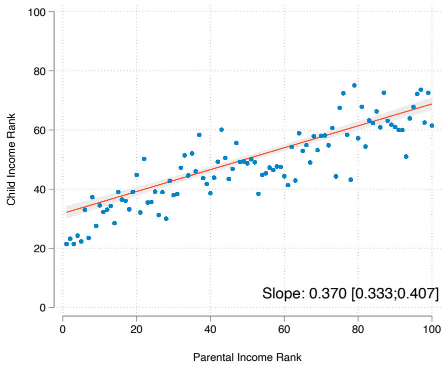
The focus on unidimensional analyses would be methodologically innocuous if income and wealth were perfect substitutes as indicators for monetary resources. There are at least two reasons why this is implausible. First, well-off parents transmit monetary resources to the next generation through bequests and inter vivo gifts (Boserup et al., 2016; Elinder et al., 2018; Wolff, 2002). In turn, expected wealth transfers distort the education and labor supply decisions of children (Kindermann et al., 2020; Kopczuk, 2013). Such behavioral responses create a wedge between the relative positions of individuals in income and wealth distributions: individuals who receive a lot of wealth from their parents are not necessarily those who earn high incomes, and vice versa. This observation is particularly relevant for analyzing time trends as inheritances have grown in many Western societies in recent decades (Piketty and Zucman, 2015). Second, changes in wealth are a function of savings and asset price changes. While the savings channel depends on income, the price channel depends on portfolio compositions. Therefore, changes in asset prices are another force that drives a wedge between the relative positions of individuals in income and wealth distributions. Again, this tendency is important for analyz-

[1] For the US, see Chetty et al. (2014a), Davis and Mazumder (forthcoming), Jácome et al. (2025), and Lee and Solon (2009) for intergenerational income mobility; Charles and Hurst (2003) and Pfeffer and Killewald (2018) for intergenerational wealth mobility; Hufe et al. (2022), Niehues and Peichl (2014), and Pistolesi (2009) for inequality of opportunity in incomes; Palomino et al. (2022) and Salas-Rojo and Rodríguez (2022) for inequality of opportunity in wealth. We discuss the conceptual similarities and differences of intergenerational mobility and equality of opportunity in section 2.

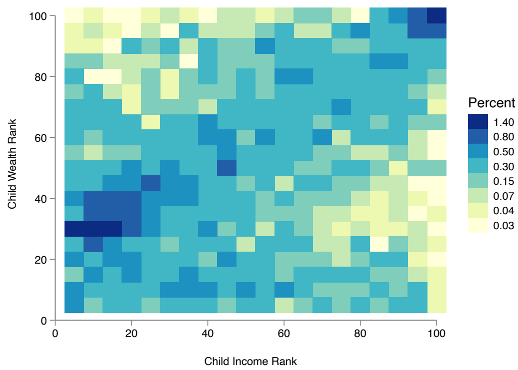
ing time trends in the US, as wealth-to-income ratios—and therefore the sensitivity of wealth to asset price fluctuations—have grown over time (Bauluz and Meyer, 2024; Kuhn et al., 2020).

In Figure 1, we provide empirical evidence to substantiate these concerns. In particular, we use data from the Panel Study of Income Dynamics (PSID) to construct a subsample that closely follows the data restrictions of Chetty et al. (2014a)—a hallmark paper in the literature on intergenerational mobility and equality of opportunity in the US. In Panel (A), we use these data to estimate the rank-rank correlation between children's incomes and the income of their parents, which is often interpreted as a measure of inequality of opportunity. We replicate the well-known finding that child incomes increase with their parents' income during childhood: an increase of parental income by ten percentile ranks is associated with an average increase of 3.7 percentile ranks in child income. This estimate is similar to the slope estimate of 0.34 in Chetty et al. (2014a). In Panel (B), we use the same data sample and construct a heatmap of income and wealth ranks in the child generation. While there is an apparent concentration around the 45-degree line, there is considerable mass in the off-diagonal elements, especially in the lower tails of the income and wealth distribution, respectively. The rank correlation of children's income and wealth is $\rho = 0.42$, indicating that income and wealth are far from perfect correlates. These

FIGURE 1. Intergenerational income transmission and the joint distribution of income and wealth in the United States



(A) Income transmission from parents to children



(B) Distribution of income and wealth among children

Data: PSID.
Note: Own calculations. Panel (A) shows a binned scatter plot of average child income ranks by the income rank of their parents. The slope is estimated using an OLS regression on the binned series. The gray shaded area around the slope indicates the 95% confidence interval. Panel (B) shows a heatmap of year-specific income and wealth ranks in the child generation. Each data point shows the share of individuals in a fixed five-percentile income (wealth) bin who belong to a particular five-percentile wealth (income) bin. Both figures are based on a PSID subsample that closely follows the data restrictions in the extended sample of Chetty et al. (2014a). We focus on birth cohorts from 1980-1989 and measure their income and wealth as the average from 2011 to 2013. Parental income ranks are calculated based on average family income from 1996 to 2005. See section 3 for detailed definitions of income and wealth. All calculations are performed using cross-sectional survey weights provided by the PSID.

patterns suggest that unidimensional analyses of equality of opportunity and intergenerational mobility may provide a distorted image of the importance of family background for individual consumption possibilities and financial well-being in the children's generation: those children with high incomes are not necessarily those with high wealth, and vice versa.

In this paper, we address these shortcomings by analyzing the relationship between family background and the joint distribution of income and wealth in the United States for the birth cohorts 1935-1980. In particular, we use the PSID to measure individuals' income and wealth.[2] Furthermore, we follow Jácome et al. (2025) and use retrospective information on childhood environments to impute family income from the US Census when children were 10-19 years old. This imputation technique allows us to analyze more cohorts and therefore a longer time trend than traditional measures based on observed parental income, since retrospective information on childhood environments is available even if parents are not part of the PSID sample. We rank family incomes relative to other families with children in the same birth cohorts and use these cohort-specific income ranks to measure family background. Then, we analyze these data by using and extending a novel index of multidimensional equality of opportunity (Kobus et al., 2024). This index satisfies fundamental properties of ex-ante measures of inequality of opportunity, e.g., Pigou-Dalton transfers between types, and multidimensional measures of inequality, e.g., sensitivity to correlation increasing transfers. Therefore, it allows us to account for both the dependence of children's outcomes on family background characteristics and the multidimensionality of monetary resources in the children's generation.

Our findings can be summarized as follows. First, the playing field in the US has become more tilted in recent decades: inequality of opportunity for Americans born in 1980 is 58% higher than for Americans born in 1935. This trend is predominantly driven by a less opportunity-egalitarian income distribution for birth cohorts after 1950 and a less opportunity-egalitarian wealth distribution for birth cohorts after 1960. Second, multidimensional inequality of opportunity is consistently and substantially higher than inequality of opportunity in income. Hence, unidimensional analyses that focus on income underestimate the extent to which monetary resources are related to family background. Third, time trends are markedly different when accounting for the multidimensionality of monetary resources. For example, an exclusive focus on income suggests stability in unequal opportunities for birth cohorts after 1955. This relative stability, however, is accompanied by strong increases in the wealth dimension, leading to an overall increase in unequal opportunities that is not accounted for by unidimensional analyses focused on income. Hence, when accounting for the multidimensionality of monetary resources, it is much harder to reject the hypothesis that the opportunities for obtain-

[2] Note that Hufe et al. (2022) also use PSID data for an empirical analysis of "unfair (income) inequality" in the US. Conceptually, they extend the standard approach of measuring inequality of opportunity by adding a second philosophical principle, namely "Freedom from Poverty", and derive a new measure satisfying both principles. The analysis in the present paper differs from Hufe et al. (2022), as we use "only" the philosophical principle of "Equality of Opportunity" but extend the measurement from one dimension (income) to a multidimensional setting. There are further subtle differences in the empirical specifications but the overall trend of inequality of opportunity only (without freedom from poverty) in income (without wealth) – the only overlap between the two papers – is similar.

ing monetary resources have become more unequally distributed in recent birth cohorts in the US (Chetty et al., 2014b; Jácome et al., 2025; Lee and Solon, 2009).

We probe these findings using various robustness checks. First, we show that our conclusions for time trends are insensitive to various plausible parameterizations of our multidimensional inequality of opportunity index. Second, our conclusions are robust to various alternative data choices, including different definitions of income and wealth, measurement choices regarding parental income ranks, and sample weighting schemes. Furthermore, we show that age differences across birth cohorts and resulting lifecycle biases in measuring income and wealth will likely attenuate our estimate of an increasing trend toward more unequal opportunities.

The contribution of this paper is threefold. First, we complement recent literature that characterizes the joint distribution of income and wealth in the US (Berman and Milanovic, 2024; Kuhn et al., 2020). This literature focuses on inequalities in outcomes but remains silent on opportunities and intergenerational transmission processes. In this paper, we provide the first analysis of the joint distribution of income and wealth in the US that accounts for the relationship of these outcomes with family background characteristics. Therefore, we can assess the fairness of the distribution of monetary resources in the US through the lens of a widely-held fairness ideal, i.e., equality of opportunity.

Second, we provide a novel decomposition of multidimensional inequality of opportunity into inequality of opportunity in income, inequality of opportunity in wealth, and the association of both outcomes across family background types. Association is a distinctive feature of joint distributions that cannot be captured by unidimensional analyses. It indicates whether individuals of a given family background are more likely to fare better or worse in both dimensions simultaneously. We use a multidimensional framework to combine these three aspects and obtain an overall conclusion regarding unequal opportunities in the US.

Third, we provide novel insights regarding the evolution of equality of opportunity in the United States (Chetty et al., 2014b; Davis and Mazumder, forthcoming; Hartley et al., 2022; Jácome et al., 2025; Lee and Solon, 2009; Song et al., 2020; Ward, 2023). Consistent with existing literature, we document the relative stability of inequality of opportunity in terms of income in more recent birth cohorts (Chetty et al., 2014b; Hartley et al., 2022; Jácome et al., 2025). However, we also show that increases emerge once we account for the wealth dimension. Therefore, we provide a more comprehensive assessment of the opportunity-egalitarian ideal in the US and show that the US has consistently moved further away from a level playing field to acquire monetary resources in recent decades.

The remainder of the paper is organized as follows. In sections 2 and 3, we present our measurement approach and describe our data. Sections 4 and 5 present our baseline results and extensive sensitivity analyses, respectively. Section 6 concludes the paper.

2 MEASUREMENT OF MULTIDIMENSIONAL EQUALITY OF OPPORTUNITY

Equality of opportunity. Consider a population $\mathcal{N} := \{1, ..., N\}$ and a set of outcomes $\mathcal{K} := \{1, \ldots, K\}$ that capture monetary resources. Individuals $i \in \mathcal{N}$ receive utility from $q \in \mathcal{K}$. We can summarize the distribution of monetary resources by outcome matrix X of dimension $N \times K$, where an element x_{iq} denotes i's outcome in dimension q. Outcomes are determined by two factors: a set Ω that captures family background characteristics and a set Θ that captures individual choices. We define $\omega_i \in \Omega$ as a comprehensive description of family background and $\theta_i \in \Theta$ as a comprehensive description of the choices made by $i \in \mathcal{N}$. For each q, there is an outcome-generating function defined as follows:

$$x_{iq} = f_q(\omega_i, \theta_i), \; \forall i \in \mathcal{N}. \tag{1}$$

In an equal-opportunity society, outcome differences are determined by individual choices θ_i but are invariant to family background ω_i (Roemer, 1998). There are different ways of translating this idea into measures. Most empirical literature relies on an *ex-ante* approach, which broadly consists of two steps. First, one partitions the population into types $T = \{t_1, ..., t_M\}$. Individuals belong to a type if they share the same family background characteristics: $i, j \in t_m \Leftrightarrow \omega_i = \omega_j$. For example, in rank-rank measures of intergenerational mobility, types are defined by parental income ranks (see Figure 1 for an example). Second, one assesses differences in average outcomes across types by regressing child outcomes on a measure of family background:

$$x_{iq} = \alpha_q + \beta_q \omega_i + \epsilon_{iq}. \tag{2}$$

There are two prominent ways of summarizing the resulting information in measures of inequality of opportunity: (i) β_q, which is the standard statistic in the literature on *intergenerational mobility* (Black and Devereux, 2011). (ii) $I(X) = I(\mathbb{E}[x_{iq}])$, where $I()$ is any inequality index applied to the expected outcomes of children conditional on family background. This is the standard statistic in the literature on *equality of opportunity* (Roemer and Trannoy, 2016). It defines inequality of opportunity as inequality between types: all within-type variation is removed, and inequality reflects only inequality arising from family background. Both measures are isomorphic and capture the opportunity-egalitarian idea: the higher β_q, the more life outcomes x_{iq} are predicted by family background ω_i, and the higher the corresponding measure of inequality of opportunity.[3]

Baseline measure. In this paper, we follow the tradition of the equality of opportunity literature and summarize outcome differences across types with an inequality index. In particular, we use the measure of Kobus et al. (2024), which allows us to account for the multidimension-

[3]One advantage of the equality of opportunity approach is that it allows for a flexible accommodation of family background characteristics other than family income or wealth.

ality of monetary resources. For simplicity and in line with our empirical application, we focus on the case of two outcome dimensions and set $K = 2$. In this case, the index is given by

$$I(X) = 1 - \left(\sum_{t=1}^{M} \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t} \frac{(\mu_1^t)^{r_1} (\mu_2^t)^{r_2}}{(\mu_1)^{r_1} (\mu_2)^{r_2}} \right)^{\frac{1}{r_1 + r_2}} \qquad \forall_t \, a_t < 0, \, r_1, r_2 < 0, \tag{3}$$

where N_t denotes the number of individuals in type t and μ_q^t (μ_q) the type (population) means in outcome q, which are assumed to be positive. The restriction to positive outcomes may be a limitation, although less so here, as positivity refers to type averages, not individual outcomes. In the following, we will describe the roles of r_q and a_t, which are weights for outcome dimension q and type t, respectively. However, before doing so, we note that if $r_q = 0$ for any of the two outcomes, I boils down to a unidimensional measure of inequality of opportunity, which is the well-known Atkinson (1970) index applied to a so-called smoothed distribution in which the outcomes of each individual are replaced with the average outcome of their type (Ferreira and Peragine, 2016). The index is bounded in the interval $[0, 1)$ and equals zero when $\mu_q^t = \mu_q$ for each type and outcome. Furthermore, as we show in Appendix B, this index can be decomposed to distinguish between the impact of each outcome and their association, which is a useful property to understand the drivers of inequality of opportunity in the US.

Dimension weights r_q govern the degree of inequality aversion in outcome q. The more negative r_q, the more convex the measure in q, and the higher its sensitivity to between-type inequality in this dimension. For example, if $r_1 < r_2$, I is more sensitive to inequality in the first than in the second outcome, i.e., the former is relatively more important in the inequality assessment. r_1, r_2 are related to the inequality aversion parameter $\tilde{\epsilon}$ of the Atkinson (1970) index via $r_1 + r_2 = 1 - \tilde{\epsilon}$. As $\tilde{\epsilon}$ rises, the index becomes more sensitive to inequality at the bottom of the distribution than at the top. Note that $\tilde{\epsilon}$ is a parameter chosen by the researcher. In his seminal work, Atkinson (1970) arbitrarily set $\tilde{\epsilon}$ equal to 1, 1.5, and 2. Subsequently, empirical research has tried to infer plausible values of $\tilde{\epsilon}$ from economic policy design and tax schedules (Aristei and Perugini, 2016; Gouveia and Strauss, 1994; Young, 1990).[4] These estimates range between 1 and 2, depending on the country and period of interest. In our baseline calculations, we choose $\tilde{\epsilon} = 1.4$ ($r_1 = r_2 = -0.2$) for income and wealth. However, in section 5, we show that our conclusions on time trends do not change for a wide range of plausible choices for r_1 and r_2.

Different from Atkinson (1970), however, $\tilde{\epsilon}$ does not summarize the full degree of inequality aversion in I. Another source of inequality aversion are type weights a_t that determine how much the social planner values respective types. The higher $|a_t|$, i.e., the more negative a_t, the higher the weight attached to type t. To ensure that I measures inequality between types, a higher weight $|a_t|$ is assigned to types that have lower values of type-representative utility

[4]These estimates proceed from the idea that economic policy design in democratic societies should at least partially reflect prevailing social preferences for redistribution.

$-(\mu_1^t)^{r_1}(\mu_2^t)^{r_2}$.[5] Just as univariate measures of inequality are normalized by the population mean outcome, I is normalized by the value of representative utility at the population mean outcomes $-(\mu_1)^{r_1}(\mu_2)^{r_2}$, which represents the case of perfect ex-ante equality of opportunity.[6] In our benchmark calculations, we choose type weights that are equal to type ranks in the values of $-(\mu_1^t)^{r_1}(\mu_2^t)^{r_2}$, i.e., the higher the type utility, the lower the type rank. However, in section 5, we show that our conclusions about time trends are not altered if the type weights in these ranks are either concave or convex.

Properties. It is important to note that I is not arbitrarily chosen, but is derived from first principles by Kobus et al. (2024). In particular, it is a normative inequality index, i.e., it is derived from a welfare function as proposed by Atkinson (1970), Kolm (1977), and Sen (1973). This welfare function is *the only* welfare function that (i) is sensitive to changes in inequality between types, which is a fundamental property of ex-ante equality of opportunity (e.g., see Ramos and Van de gaer, 2016), and that (ii) has several well-known properties such as monotonicity, additivity, and ratio scale invariance. Regarding (i): to capture inequality between types in a multivariate framework, the welfare function needs to be sensitive to two types of transfers. The welfare function increases (i.e., I decreases) after *Pigou-Dalton transfers between types* that reduce the spread between types in both outcomes; the welfare function decreases (i.e., I increases) after *correlation-increasing transfers*, which increase the cross-type correlation between the outcomes of interest. In Appendix A we provide examples that illustrate those properties of the index. Regarding (ii): *Monotonicity* means that the welfare function increases with higher outcomes. *Additivity* means that the welfare function is utilitarian, i.e., the sum of individual utilities.[7] *Ratio-scale invariance* means that the ranking of distributions by the welfare function does not depend on any scale changes in the units of measurement. This requirement is sometimes considered too restrictive. Therefore, we use a weaker version requiring that the ranking of distributions by the welfare function does not depend on the same scale changes in the units of measurement across different outcomes.[8] The relation with the welfare function makes the interpretation of I intuitive. For example, a value of 0.25 (0.5) means that the existing inequality of opportunity imposes a welfare cost of 25% (50%) of each outcome's population mean. In other words, if there were perfect equality of opportunity, society would achieve the

[5]The minus in the utility expression and negative dimension weights r_1, r_2 ensure that the utility function fulfills properties described below.

[6]An alternative normalization would be based on mean utility across types rather than utility at mean outcomes. The two normalizations are the same if social welfare is maximized and the mean outcomes in each type are equal to the population mean. However, normalization by mean utility across types has some additional problems when it comes to the axioms of inequality measurement—see Bourguignon (1999) for a discussion.

[7]Kapera et al. (2023) show that additivity can be relaxed for some of the results in Kobus et al. (2024), but not for the derivation of measures of inequality of opportunity. If a weaker axiom than additivity is used (e.g., subgroup decomposability, see Tsui, 1995), symmetry must be imposed everywhere, and this would be inconsistent with the inequality of opportunity framework, where types are not symmetric. Therefore, if symmetry is relaxed, the aggregation axiom must be stronger to derive the measure.

[8]This relaxation allows measures of the form we propose below in Equations (4) and (5).

same level of welfare using only 75% (50%) of the available monetary resources in income and wealth.

Interpretation. A slightly different representation of the measure further simplifies its interpretation:

$$I(X) = 1 - \left(\sum_{t=1}^{M} \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t} \left(\frac{(\mu_1^t)^\alpha (\mu_2^t)^{1-\alpha}}{(\mu_1)^\alpha (\mu_2)^{1-\alpha}} \right)^{\epsilon} \right)^{\frac{1}{\epsilon}}, \quad \alpha \in (0,1),\, a_t < 0,\, \epsilon < 0, \tag{4}$$

where we rewrite (3) using $\alpha := \frac{r_1}{r_1+r_2}, 1-\alpha := \frac{r_2}{r_1+r_2}$, so that $\alpha, 1-\alpha$ are normalized outcome weights and $\epsilon := r_1 + r_2$. This representation highlights that I can be viewed as a two-stage aggregation function, which is a popular approach to measuring multidimensional welfare and inequality.[9] In the first stage, individual outcomes of a type are aggregated into a single individual score via the Cobb-Douglas function ($u^t = (\mu_1^t)^\alpha (\mu_2^t)^{1-\alpha}$). In the second stage, the distribution of these individual scores is aggregated as in Atkinson (1970), $(\sum_{t=1}^{M} \omega_t (u^t)^\epsilon)^{\frac{1}{\epsilon}}$, with appropriate weights $\omega_t = \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t}$ and $\epsilon = 1 - \tilde{\epsilon}$. We use the word "score" to indicate that, within the framework of equality of opportunity, the first-stage Cobb-Douglas function does not necessitate a utility interpretation, but can be viewed as an individual advantage.[10] However, in the following, we use the utility interpretation, which is more in line with the traditional social choice literature. Thus, the individual aggregation function represents preferences over income and wealth; however, they do not have to coincide with the preferences of any individual in the population. Instead, the utility function should be interpreted as the utility function used by a policy maker to convert individual outcomes into an interpersonally comparable measure of well-being (Gajdos and Weymark, 2012).

Extension. Given the two-stage representation, a natural extension of I emerges. If the first stage aggregation function is interpreted as a utility function, then the measure of Kobus et al. (2024) has a fixed unit elasticity of substitution between outcomes q. In the context of this paper, this implies a degree of complementarity between income and wealth that may be too high. However, this constraint can be relaxed by allowing the first-stage function to be a constant elasticity of substitution (CES) function. Therefore, in Appendix A, we derive the following extended inequality of opportunity measure:

$$\tilde{I}(X) = 1 - \left[\sum_{t=1}^{M} \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t} \left(\frac{\alpha(\mu_1^t)^\beta + (1-\alpha)(\mu_2^t)^\beta}{\alpha(\mu_1)^\beta + (1-\alpha)(\mu_2)^\beta} \right)^{\frac{\epsilon}{\beta}} \right]^{\frac{1}{\epsilon}}, \tag{5}$$

[9] This approach originates from Maasoumi (1986) and is reviewed in Aaberge and Brandolini (2015).

[10] For example, in the terminology of Cohen (1989), background conditions facilitate "access to advantage."

where a new parameter β governs the elasticity of substitution $\sigma = \frac{1}{1-\beta}$. If $\beta = 0$, this measure corresponds to the index in Equation (4) since $\sigma = 1$. If $\beta = 1$, this measure captures the case of perfect substitutes since $\sigma = \infty$. As $\beta \to -\infty$, outcomes q become more complementary. We analyze the sensitivity of our results to different choices of β in section 5.

3 DATA

Data source. We aim to assess the evolution of equal opportunities in the US while accounting for the multidimensionality of monetary resources. Therefore, we require a dataset with information on income, wealth, and measures of family background for a long period. In the US, the Panel Study of Income Dynamics (PSID) is the only publicly available data source that satisfies these criteria. For example, while the Survey of Consumer Finances (SCF) offers a long time series on household income and wealth, it contains limited information on the family background of its respondents, making it unsuitable for our analysis.

The PSID collects rich income and family background information for a nationally representative sample of US households from 1968 onwards. From 1984 until 1999, it collected household wealth information every five years. Since then, survey items on wealth have become a regular part of every PSID wave. Children who leave the parental household become independent sampling units in the PSID. Therefore, it is possible to link data across generations. In its most recent waves, the PSID comprises more than 9,000 households. We use the PSID waves 1970-2017 for our analysis.[11]

We now turn to a description of the most relevant variables for our analysis.

Monetary resources. We consider two dimensions of monetary resources: income and wealth. We measure income as annual disposable household income. It comprises total household income from labor, asset flows, windfall gains, private transfers, public transfers, private retirement income, and social security pensions net of total household taxes. We measure wealth as household net worth. It comprises the sum of home equity, other real estate, private businesses, vehicles, transaction accounts, corporate equities, annuities/IRAs, and other savings net of any debt. We deflate all income and wealth figures to 2015 USD and trim income and wealth distributions each year at the 0.5 and 99.5 percentiles to account for misreporting in the extreme tails of the distributions (Brewer et al., 2017). However, in Figure S.1, we show that our results are not sensitive to either winsorizing (instead of trimming) income and wealth at the same thresholds or using the raw outcome data.

[11] We drop the 1968/69 waves since these waves miss important information on family background characteristics, e.g., parental occupation.

We measure income and wealth at the household level to account for resource sharing among household members. For our baseline estimates, we follow the recent literature and measure household income and wealth without adjustments for household size (e.g., Chetty et al., 2014a; Fagereng et al., 2021; Jácome et al., 2025). However, robustness analyses in section 5 show that our results remain unaffected when deflating household income and wealth by the modified OECD equivalence scale.

Wealth and income data in the PSID are often considered inferior to their analogs in the SCF. First, the SCF is designed to assess the financial situation of households. Therefore, it elicits income and wealth information with greater detail than the PSID. Second, the SCF oversamples wealthy households and provides a dedicated weighting scheme to correct the underrepresentation of wealthy families in survey data. Thus, it is likely to better represent the upper tails of income and wealth distribution than the PSID.[12]

In Figure S.2, we compare PSID and SCF concerning time trends in disposable household income and household net worth from 1984 to 2017. As expected, the SCF consistently assigns higher income and wealth shares to the top 10% of the distribution. This trend is mainly driven by the upper tails, as indicated by the substantial divergence of the 95th percentiles of the income and wealth distributions in SCF and PSID, respectively. On the contrary, the middle and lower tails are very similar in both data sources, as indicated by the overlap of the 50th and 5th percentiles of the income and wealth distributions. This substantial overlap is also reflected in the similarity of inequality measures in both data sets. Notably, despite the under-coverage of top income and wealth in the PSID, household income and wealth inequality trends are very similar in both data sources.

Family background and types. The measurement of family background is the foremost data challenge in the literature on intergenerational mobility and equality of opportunity. Modern data sets in the US, including the PSID, provide data links across generations that allow researchers to directly assess the financial situation of parental households during childhood (e.g., Chetty et al., 2014a; Davis and Mazumder, forthcoming; Lee and Solon, 2009). However, these data links often only cover a limited number of birth cohorts, curtailing their suitability for assessing time trends. Alternatively, many researchers have resorted to imputation-based data-linking techniques in the US Census to assess intergenerational transmission processes (e.g., Song et al., 2020; Ward, 2023). However, these linking techniques have drawbacks concerning the imputation accuracy and the representativeness of the resulting samples. In this paper, we follow recent literature and evaluate family backgrounds with an imputation procedure that combines retrospective information on childhood environments from the PSID with income information from the US Census (Jácome et al., 2025). We will provide a detailed outline of this imputation procedure in the following.

[12] See also Pfeffer et al. (2016) for a detailed comparison of wealth definitions in PSID and SCF.

First, we compile retrospective information on childhood environments likely correlated with parental income in the PSID. In particular, we consider the following information: maternal/paternal education (no education, 1-8 years of schooling, 9-11 years of schooling, high school degree, some college, college degree or more), maternal/paternal occupation (1-digit 1970 Census codes plus unemployment as a separate category), maternal/paternal migration status (US-born, foreign-born), race (non-Hispanic white, other), Census region of upbringing (Northeast, Midwest, South, West), and household composition during childhood (single, two-parent households).

Second, we compile corresponding information in US Census data from 1950-1990. In particular, we use the 1% samples of the 1950-1970 US Censuses and the 5% samples of the 1980/90 Censuses (Ruggles et al., 2024). We restrict the Census samples to working-age individuals (30-59) living in households with any biological children up to age 18. We then calculate the average pre-tax family income separately for men and women in each *education* $\times$ *occupation* $\times$ *migration status* $\times$ *race* $\times$ *Census region* $\times$ *household composition* cell.

Third, we match the cell-specific average family incomes from the US Census to the PSID using respondents' retrospective information on their mothers and fathers. In particular, we match PSID respondents with information from the decennial US Census that was conducted when they were between 10 and 19 years of age. The choice of this age range is consistent with prior work on intergenerational income mobility and recent evidence emphasizing the importance of parental income during adolescence for child outcomes (Carneiro et al., 2021; Chetty et al., 2014a; Eshaghnia et al., 2025). We approximate family income by calculating the average imputed family income of mothers and fathers.[13] In Figure S.3, we address potential concerns about noisy imputations due to small cell sizes in the US Census. The average imputed family income in our core estimation sample is derived from 8,253 data points in the US Census, and close to 50% of all imputed family incomes are derived from cells with at least 2,000 data points. Furthermore, we show that our results are insensitive to excluding observations whose family income was derived from small cells in the US Census.

Lastly, we calculate income ranks during childhood for each birth cohort. In particular, we assign individuals to birth cohorts based on 5-year intervals. For example, birth cohort 1935 includes individuals born between 1933 and 1937; birth cohort 1940 includes those born between 1938 and 1942, etc. Then, we partition each birth cohort into 50 parental income ranks based on the distribution of imputed parental income. Alternative type partitions are possible, e.g., based on 25 or 100 income ranks. We discuss the (dis)advantages of finer and coarser type partitions in section 5. In this section, we also show that our main conclusions are not affected by the chosen granularity of the partition.

[13] Note that this measure accounts for single-parent households. We calculate average incomes in the US Census while accounting for household composition, and also match data to the PSID based on the household composition criterion.

Our imputation procedure has important advantages over using direct data links between individuals and their parents in the PSID. First, it allows us to construct a longer time series. The PSID started its data collection in 1968. Therefore, linked parental income during childhood (10-19) is unavailable for birth cohorts before 1950. On the contrary, retrospective information on childhood environments is collected from all respondents irrespective of their birth date, allowing us to assess the development of inequality of opportunity since the 1935 cohort. Second, it is well-known that PSID subsamples with intergenerational links are positively selected on their socioeconomic status (Ward, 2023). In Table S.1, we show that the PSID subsample with intergenerational links is likelier to be non-Hispanic white and to come from families with higher imputed parental income. This composition bias is particularly pronounced for earlier birth cohorts. Therefore, our imputation based on retrospective information allows for a broader representation of the US population.

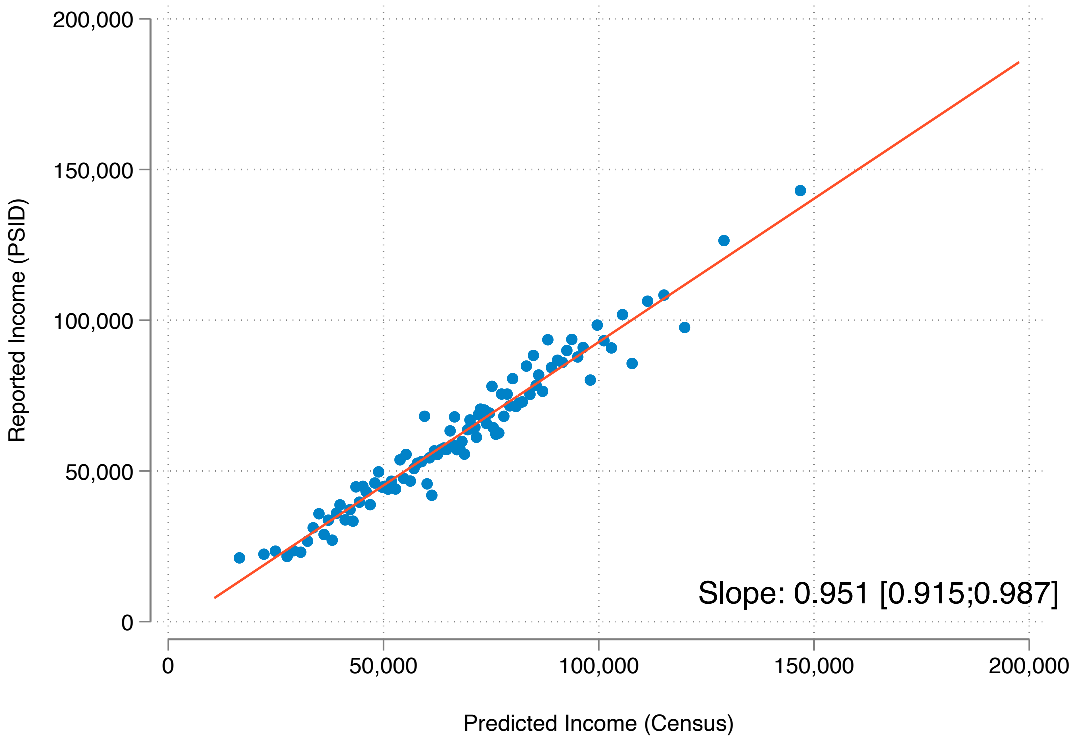
How well does our imputation procedure capture parental income during childhood? Jácome et al. (2025) provide a battery of tests to assure that imputed parental incomes based on retrospective information provided by survey respondents are not distorted by recall bias. They also use data from the 1997 PSID wave to show that a regression of self-reported paternal income in 1970 on imputed paternal income yields a regression coefficient of close to one, indicating that their imputed measure of paternal income is forecast unbiased. We conduct a similar analysis for all available birth cohorts in our sample. In particular, we use the subsample with intergenerational links (birth cohorts 1950-1980) to compare reported parental income with our imputed measure of parental income. Figure 2 shows that the linear relationship between imputed and reported parental income is also close to one, suggesting that our imputation procedure yields an accurate measure of parental income during childhood.

Estimation sample. To obtain our core analysis sample, we drop all observations with missing information on income, wealth, or imputed parental income. Furthermore, we focus on the working-age population and therefore restrict observations to individuals aged 30-59. We average all available income and wealth information over this age range to reduce the influence of transitory changes on the outcomes of interest (Charles and Hurst, 2003; Fagereng et al., 2021). We non-parametrically residualize income and wealth of age effects to account for within-cohort lifecycle variation in monetary resources.[14]

We are conscious that the PSID is subject to selective survey attrition across waves and that our data restrictions may distort our sample through selective item non-response. Therefore, we follow Meyer et al. (2015) and adjust the provided cross-sectional PSID sampling weights to match the Current Population Survey (CPS) concerning age, race, and gender. We use these

[14] Specifically, we estimate average income (wealth) for each age $m \in [30; 59]$. Then, we rescale individual incomes (wealth) measured at age m with the ratio of average income (wealth) to the age-specific average income (wealth). This procedure equalizes income (wealth) across age groups, while maintaining relative differences within these groups.

FIGURE 2. Prediction accuracy of imputed parental income



Data: PSID, US Census (Ruggles et al., 2024).
Note: Own calculations. This figure shows the relationship between reported parental income in the PSID and predicted parental income from the US Census. The slope is estimated using an OLS regression on the raw data. The dots represent average reported income (PSID) and average predicted income (Census) for each percentile of the predicted income distribution. All estimates are based on the core sample described in Table 1. This sample is further restricted to observations with available parental income information in the child age range 10-19. All calculations are performed using adjusted cross-sectional PSID sampling weights. All monetary values in 2015 USD.

adjusted weights throughout our analysis unless otherwise indicated. We note that results remain unchanged when using standard survey weights provided by the PSID (Figure S.1).

Table 1 describes the resulting sample segmented by the birth cohorts of interest.

The core sample is gender balanced. There is a continuously decreasing share of non-Hispanic whites across birth cohorts, reflecting changes in the ethnic composition of the US over time. Furthermore, there is a notable age gradient across birth cohorts. Due to the sampling period (1970-2017) and our age restrictions (30-59), the average age at observation decreases from 52.91 in the 1935 cohort to 33.95 in the 1980 cohort.

This age gradient is reflected in each cohort's average income and wealth. Incomes are highest for the cohorts 1945-1970, who we observe primarily in their 40s, i.e., the prime of their earnings lifecycles. Incomes are lower for cohorts 1935-1940 and 1975-1980, which we observe at the end

TABLE 1. Descriptive statistics (Core sample)

Cohort	N	Demographics			Outcomes		Parental income	
		Male	White	Age	Income	Wealth	in USD	Rank
1935	1,217	0.48	0.81	52.91	86,954.04	326,576.66	28,284.80	24.72
1940	1,774	0.48	0.80	50.49	87,765.02	317,795.59	37,827.86	25.91
1945	3,613	0.49	0.80	49.63	93,380.44	331,141.59	48,386.58	24.87
1950	6,427	0.49	0.77	48.73	92,730.64	327,962.81	56,897.01	26.09
1955	9,068	0.49	0.74	47.85	89,192.69	304,798.22	65,826.89	25.32
1960	9,477	0.49	0.72	46.74	91,029.55	258,534.30	64,254.40	25.39
1965	7,811	0.49	0.67	43.21	86,526.92	237,249.34	59,921.09	25.06
1970	6,228	0.49	0.63	39.32	88,438.41	181,695.69	62,449.89	24.44
1975	5,630	0.49	0.58	36.24	84,928.55	123,533.32	70,084.95	24.45
1980	4,622	0.49	0.58	33.95	73,616.66	90,437.40	71,407.07	24.36

Data: PSID, US Census (Ruggles et al., 2024).
Note: Own calculations. This table displays summary statistics for our core estimation sample. All calculations are performed using adjusted cross-sectional PSID sampling weights. All monetary values in 2015 USD. Parental income distributions are partitioned into 50 cohort-specific ranks.

and beginning of their earnings lifecycles, respectively. These patterns are consistent with the well-documented hump shape of lifecycle earnings profiles (Mello et al., forthcoming; Nybom and Stuhler, 2016).

Wealth is high and relatively stable across the oldest birth cohorts (1935-1950) and then declines steadily for all subsequent birth cohorts. This pattern is consistent with evidence on steep lifecycle wealth profiles that flatten when individuals reach retirement age (Bauluz and Meyer, 2024; French et al., 2023; Poterba et al., 2018). However, since our observation sample is restricted to working-age individuals (30-59), we do not capture the flat part of wealth profiles at the end of individuals' lifecycles.

The fact that cohorts are at different points in their income and wealth lifecycle is likely to influence our cohort comparisons concerning inequality of opportunity in the US. We provide a detailed analysis of potential lifecycle biases in section 5.

Imputed parental income during childhood (10-19) is increasing for most birth cohorts. The slumps for the 1960/65 birth cohorts reflect the economic downturns in the mid-1970s and early 1980s, rooted in the oil crisis and tightening monetary policy. In our estimations, we rely on a relative measurement of family background and convert imputed parental income into 50 cohort-specific ranks. As expected, each birth cohort's average parental income rank is approximately 25.

4 RESULTS

This section presents estimates of inequality of opportunity in the US for birth cohorts 1935-1980. All estimates are based on the measure outlined in Equation (3). As described above, empirical implementation of this measure requires choices for r_q and a_t, i.e., the parameters governing inequality aversion. For our baseline estimates, we choose dimension weights $r_{Income} = r_{Wealth} = -0.2$. Furthermore, we choose linear a_t, i.e., $|a_t| = t$, where t is the rank of a type in terms of type-representative utility $-(\mu_1^t)^{r_1}(\mu_2^t)^{r_2}$, with $t = 1$ being the type with the highest utility. In section 5, we show that our main conclusions are robust to a wide range of plausible choices for both r_q and a_t.

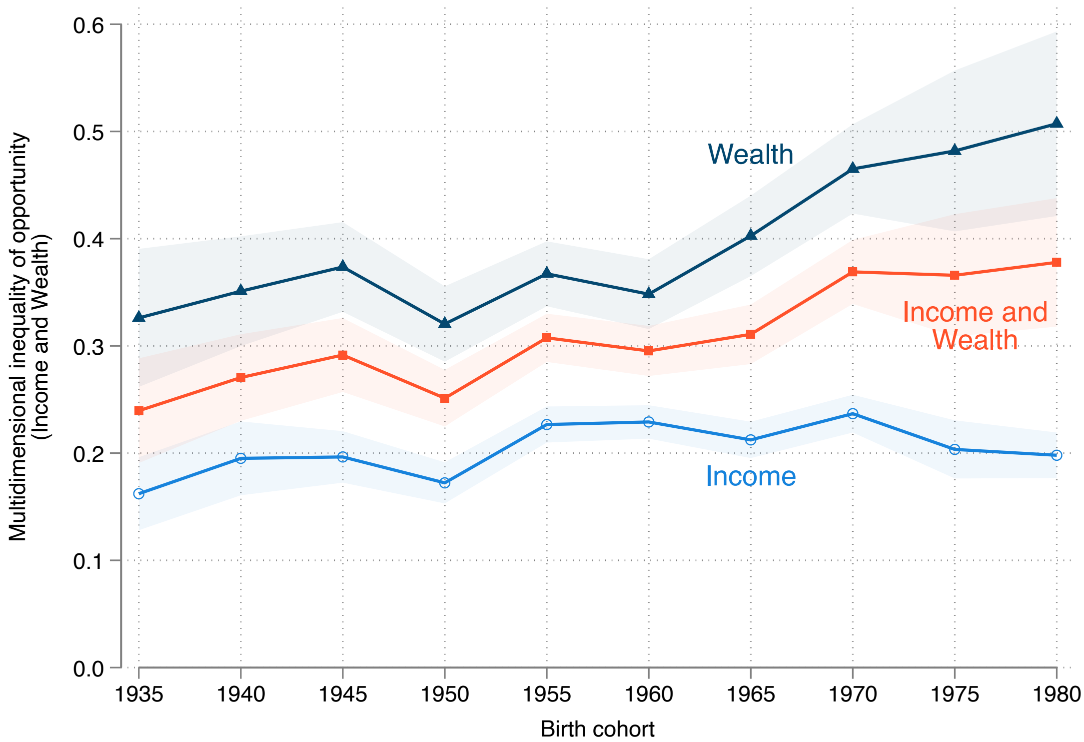
Baseline results. Figure 3 presents our main results on the development of inequality of opportunity in the US, separately for income, wealth, and the joint distribution of income and wealth. We recall that all measures are bounded on the interval $[0, 1)$ and that the values of the measures express the per-capita welfare cost of existing inequality of opportunity as a percentage of the population average of the respective outcome.

First, inequality of opportunity in income has increased moderately over time. Starting at a level of 0.16 for the 1935 cohort, inequality of opportunity increases for the cohorts of the 1950s and 1960s to a level of approximately 0.22. For the cohorts born in the 1970s and after, inequality of opportunity in income remains stable at this level, even showing a slight decrease to 0.21 for the 1975/80 cohorts. Hence, for the last birth cohorts, the per-capita welfare cost of inequality of opportunity in income is 21% of average income in the US.

These patterns are broadly consistent with the recent literature on intergenerational income mobility time trends in the US. For example, Jácome et al. (2025) find strong decreases in intergenerational income persistence for birth cohorts 1910-1940, i.e., birth cohorts that mostly cover the period before the start of our investigation. Within our investigation window, they also detect increases in intergenerational income persistence for cohorts born in the 1950s and 1960s, followed by relative stability for cohorts born in the 1970s.[15] This finding is also consistent with Davis and Mazumder (forthcoming), who show that intergenerational income persistence increased for cohorts born in the 1960s compared to those in the 1950s, which they ascribe to the fact that the latter cohort entered the labor market after the rise in inequality in the 1980s. Similar patterns for decreasing mobility between the 1940 and 1960 cohorts are also documented in Aaronson and Mazumder (2008). Chetty et al. (2014b) focus on the birth cohorts 1970-1980, i.e., the later part of our investigation window. Consistent with our estimates, they show that intergenerational income persistence remains stable for these younger cohorts. Hartley et al.

[15] The findings of Song et al. (2020) suggest relative stability of intergenerational mobility over the time period considered by Jácome et al. (2025). Ward (2023) demonstrates that this finding is likely driven by measurement error and the focus on white males. Consistent with Jácome et al. (2025), Ward (2023) finds relative stability in intergenerational income persistence for the birth cohorts where both papers overlap (1960/70).

FIGURE 3. Inequality of opportunity in the US: Baseline estimates



Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows estimates of unidimensional (income or wealth) and multidimensional (income and wealth) inequality of opportunity in the US for the birth cohorts 1935-1980. Inequality of opportunity estimates are based on 50 cohort-specific parental income ranks. Estimates are computed based on Equation (3) with dimension weights $r_{Income} = r_{Wealth} = -0.2$. 95% confidence intervals (shaded areas) are bootstrapped using 1,000 draws. All calculations are performed using adjusted cross-sectional PSID sampling weights.

(2022) measure mobility by year of observation instead of birth cohort. However, their findings also suggest that increases in intergenerational income persistence have come to a halt in recent years.[16]

Second, inequality of opportunity in wealth has increased substantially over time. Starting at a level of 0.34 for the 1935 cohort, inequality of opportunity remains relatively stable for the birth cohorts until 1960. For the cohorts born after, inequality of opportunity in wealth increases persistently from 0.35 in the 1960 cohort to 0.51 in the 1980 cohort. Hence, for the last birth cohorts, the per-capita welfare cost of inequality of opportunity in wealth is 51% of average wealth in the US.

[16]This short review omits other papers in this literature. For example, Lee and Solon (2009) find stable intergenerational income mobility patterns for sons and suggestive evidence for increasing intergenerational income persistence of daughters in the cohorts from 1950 to 1960. Davis and Mazumder (forthcoming) and Jácome et al. (2025) include recent and comprehensive overviews of the literature on intergenerational income mobility in the US, including detailed comparisons of methodological choices and their impact on empirical results.

A direct comparison of these trends to the existing literature is complicated because data with intergenerational linkages of wealth are rare in the US. Therefore, most existing studies consider snapshot comparisons of intergenerational wealth mobility and cannot speak to trends over time (Charles and Hurst, 2003; Pfeffer and Killewald, 2018).[17] However, we can compare our estimates indirectly with other works considering trends in wealth disparities across different population groups in the US. For example, Derenoncourt et al. (2024) show that racial wealth gaps declined in the post-war period until 1980. After that, convergence has stalled, and racial wealth gaps have increased by approximately 20% in recent years. These differences are primarily driven by differences in portfolio compositions, i.e., black households' lower (higher) propensity to invest in equity (housing) and, consequently, the lower returns on their portfolios during the recent period of rising stock markets. Importantly, it is likely that this pattern extends beyond black-white differences and also encompasses other socio-economically disadvantaged groups. For example, extensive literature shows that portfolio choices and stock market participation can be linked to markers of disadvantage during childhood (Barth et al., 2020; Boserup et al., 2018; Fagereng et al., 2021; Gomes et al., 2021). Furthermore, Bauluz and Meyer (2024) show that within-cohort wealth inequality has increased markedly for birth cohorts 1900-1980. Like Derenoncourt et al. (2024), they attribute this increase to the surge of capital gains after 1980, making it likely that the detected increase in inequality also widens the wealth gaps across children from different family backgrounds who differ in their portfolio compositions. In sum, we consider our evidence on increasing inequality of opportunity in wealth for birth cohorts 1965-1980 as broadly consistent with the recent literature on time trends in wealth disparities in the US.

Third, inequality of opportunity in wealth is consistently higher than inequality of opportunity in income.[18] This finding is consistent with existing literature that presents snapshot estimates of intergenerational mobility in income and wealth in the US. For example, using the PSID Charles and Hurst (2003) estimate an intergenerational labor income elasticity of 0.30 and an intergenerational wealth elasticity of 0.37.[19] Similarly, Pfeffer and Killewald (2018) find a rank-rank correlation of 0.39 for wealth, which exceeds the estimate of 0.34 for incomes in Chetty et al. (2014a). Furthermore, the gap between inequality of opportunity estimates in income and wealth is widening over time. Starting at an initial difference of 0.17, the gap almost doubles to 0.31 in the 1980 cohort. This pattern highlights the need for a multidimensional approach when assessing time trends of inequality of opportunity in the US: unidimensional analyses of inequality of opportunity misrepresent the disparity of monetary resources across individuals

[17]See also Salas-Rojo and Rodríguez (2022) and Palomino et al. (2022) for snapshot estimates of inequality of opportunity in wealth in the US. Both papers find a strong influence of family background on wealth inequality in the US, especially through bequests and inter-vivo gifts.

[18]See also Figure S.4, where we compare the evolution of undimensional inequality of opportunity based on alternative inequality indexes.

[19]This finding is particularly noteworthy since the child generation in their dataset is relatively young, making it likely that lifecycle bias attenuates their estimate of the intergenerational wealth elasticity.

from different family backgrounds, and the scope for this misrepresentation has grown over time.

Fourth, the joint analysis of income and wealth suggests that the playing field for acquiring monetary resources has become more tilted over time. Starting at a level of 0.24 for the 1935 cohort, inequality of opportunity in the joint distribution of income and wealth reached 0.38 for the latest cohort. This shift corresponds to an increase of 58%. Importantly, the trend towards decreasing opportunities to acquire monetary resources continues for younger cohorts after 1970, i.e., for the cohorts for which the extant literature has suggested relative stability in inequality of opportunity (Chetty et al., 2014b; Hartley et al., 2022; Jácome et al., 2025). Hence, when accounting for the multidimensionality of monetary resources, one cannot reject the hypothesis that opportunities in the US have further declined for the most recent birth cohorts.

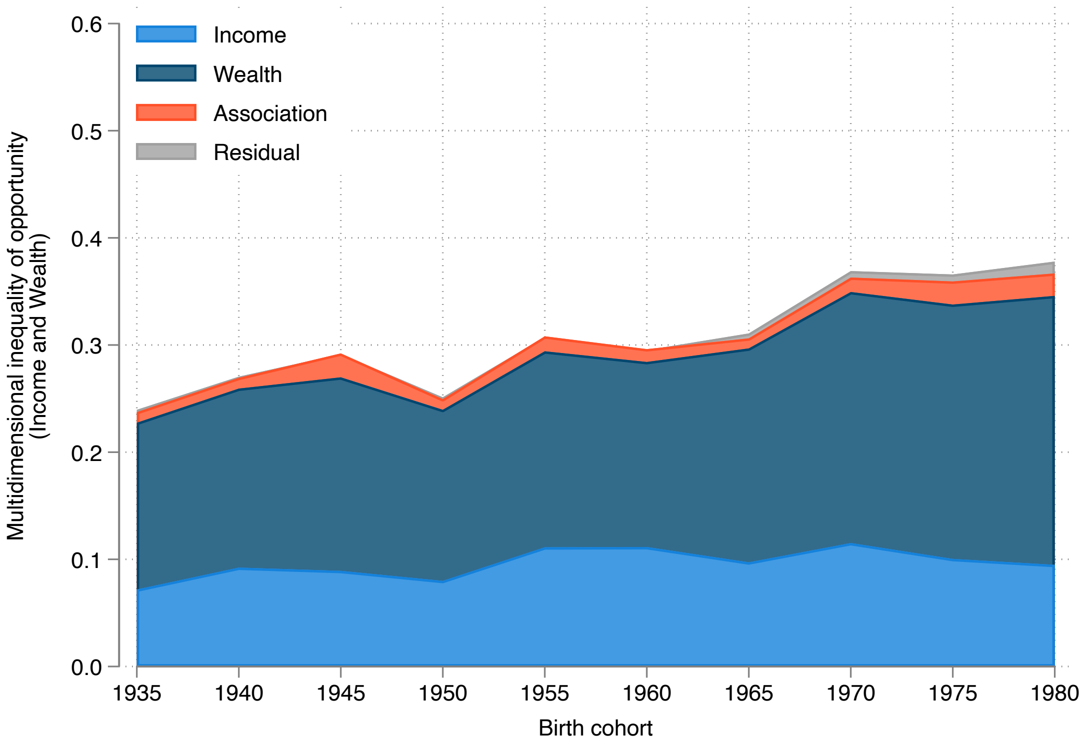
Decomposition. To develop a better understanding of these trends, we conduct an attribute decomposition, i.e., we decompose the time trend into the contributions of (i) inequality of opportunity in income, (ii) inequality of opportunity in wealth, as well as (iii) the cross-type association in both outcomes. The last dimension is particularly interesting as it cannot be analyzed in unidimensional measures of inequality of opportunity. In Appendix B we develop this decomposition and show that $I(X)$ can be split into the following components:

$$\begin{aligned} I(X) = {} & \underbrace{\tfrac{r_1}{r_1+r_2}\left(1-\left(\sum_{t=1}^{M}\tfrac{N_t a_t}{\sum_{t=1}^{M} N_t a_t}\left(\tfrac{\mu_1^t}{\mu_1}\right)^{r_1}\right)^{\frac{1}{r_1}}\right)}_{=I_1(\text{Income})} \\ & + \underbrace{\tfrac{r_2}{r_1+r_2}\left(1-\left(\sum_{t=1}^{M}\tfrac{N_t a_t}{\sum_{t=1}^{M} N_t a_t}\left(\tfrac{\mu_2^t}{\mu_2}\right)^{r_2}\right)^{\frac{1}{r_2}}\right)}_{=I_2(\text{Wealth})} \\ & + \underbrace{\tfrac{1}{r_1+r_2}\left(1-\tfrac{\sum_{t=1}^{M} N_t a_t \sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1}(\mu_2^t)^{r_2}}{\sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1}\sum_{t=1}^{M} N_t a_t (\mu_2^t)^{r_2}}\right)}_{=\kappa_I(\text{Association})} \\ & + R, \end{aligned} \tag{6}$$

where I_q is a unidimensional index of inequality of opportunity in outcome dimension q, κ_I is a measure of cross-type association in outcomes, and R is a residual resulting from linear approximation. In all our calculations, the contribution of the residual term is negligible, and we will abstract from it in the following discussion. Furthermore, note that the type weights for unidimensional measures I_q are slightly different from the corresponding weights used for the unidimensional measures presented in Figure 3. In Figure 3, type weights are calculated based on ranks in the univariate outcome distributions; in the decomposition, type weights are the same across dimensions, i.e., in both I_1 and I_2 they are based on ranks in the type utility distribution. In Figure S.5, however, we show that there are almost no differences between the unidimensional indices of inequality of opportunity in Figure 3 and those in the decomposition.

The results of this decomposition are shown in Figure 4. 17% and 69% of the overall increase

FIGURE 4. Multidimensional inequality of opportunity in the US: Decomposition by outcome dimension



Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows a decomposition of multidimensional inequality of opportunity for birth cohorts 1935-1980. Inequality of opportunity estimates are based on 50 cohort-specific parental income ranks. Estimates are computed based on Equation (3) with dimension weights $r_{Income} = r_{Wealth} = -0.2$. The decomposition is based on the attribute decomposition derived in Appendix B. All calculations are performed using adjusted cross-sectional PSID sampling weights.

in inequality of opportunity can be explained by trends in unidimensional inequality of opportunity in income and wealth, respectively. The cross-type association of income and wealth explains only 8% of the overall increase in unequal opportunities. This finding is somewhat surprising since recent research indicates an increased correlation between income and wealth in the US (Berman and Milanovic, 2024; Kuhn and Ríos-Rull, 2016; Kuhn et al., 2020). Our results suggest that these increases at the individual level are driven mainly by increased correlation within family background types. In contrast, the association of these outcomes across family background types remains relatively stable. However, we note that the relative stability of cross-type association κ_I depends on the parameter choices for a_t and r_q. In Table S.2, we show the decomposition of time trends under different plausible assumptions for r_q. The results show that the contribution of cross-type associations increases with increasing r_q, i.e., a higher sensitivity to outcomes in the lower tail of the distribution. For example, if we set $r_{Income} = r_{Wealth} = -0.5$, κ_I explains up to 20% of the overall increase in unequal opportunities. This finding indicates that the association has become stronger in the lower tails of the income and wealth distribution: children who grew up in poorer families in later birth cohorts have become more resource-constrained in *both income and wealth* than those who grew up in poorer families in earlier birth cohorts.

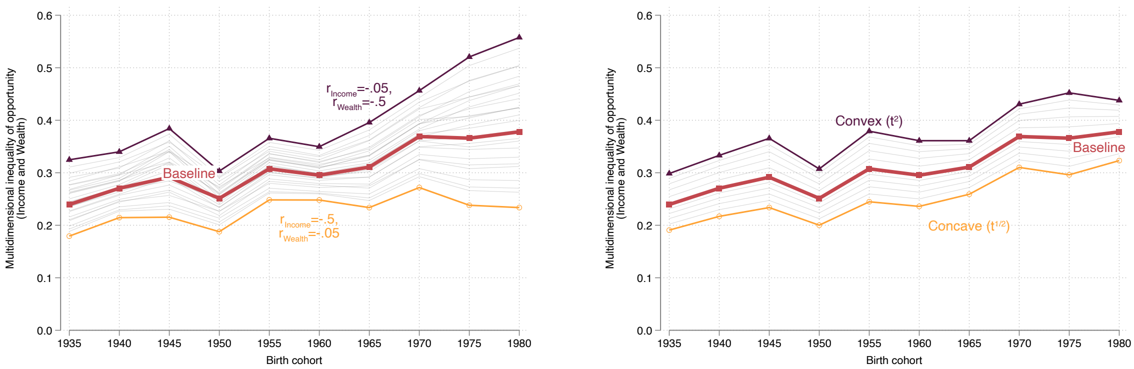
5 SENSITIVITY ANALYSES

In this section, we probe the robustness of our conclusions by varying the measurement parameters r_q and a_t. Furthermore, we change some core data choices concerning the coding of outcome variables, the measurement of family background, and the selection of our analysis sample. In Appendix D, we present additional sensitivity analyses implementing different restrictions on cell sizes in the US Census, using different sampling weights and treatments of extreme values in the income and wealth distributions.

Parameter choices. We assess the sensitivity of our main conclusions to changes in the measurement parameters, i.e., dimension weights r_q and type weights a_t. Alternative parameter choices correspond to different normative assumptions about inequality aversion. Therefore, they will lead to level shifts in the extent of inequality of opportunity—a property that is well-known in the literature (Atkinson, 1970). However, we are mainly concerned with the development of inequality of opportunity over time. Therefore, we will abstract from levels in the following discussion and focus on whether changes in unequal opportunities are sensitive to different assumptions about these parameters.

First, in our baseline estimates, we give both dimensions equal weight and choose $r_{Income} = r_{Wealth} = -0.2$. However, there may be good reasons to give different weights to different dimensions of monetary resources. For example, one could argue that wealth should receive a higher weight due to its insurance value. Conversely, one could argue that wealth should receive a lower weight since it is less liquid and might not be available for instantaneous consumption. Panel (A) of Figure 5 shows alternative results for all pairwise combinations over the parameter grid $r_q \in (-0.05, -0.1, -0.2, -0.3, -0.4, -0.5)$. The lowest estimates of inequality of opportunity are obtained for $r_{Income} = -0.5$ and $r_{Wealth} = -0.05$; that is, in case we place little weight on the wealth dimension and a ten times larger weight on the income dimension. Such an income-focused parameterization yields an increase of inequality of opportunity from

FIGURE 5. Multidimensional inequality of opportunity in the US: Sensitivity to parameter choices



(A) Alternations in dimension weights (r_q)

(B) Alternations in type weights (a_t)

Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows estimates of multidimensional inequality of opportunity in the US for the birth cohorts 1935-1980 under different parameter choices. Inequality of opportunity estimates are based on 50 cohort-specific parental income ranks. Estimates are computed based on Equation (3). Panel (A) shows the sensitivity to alterations in r_q. We display are all pairwise combinations of $r_{Income} \in (-0.05, -0.1, -0.2, -0.3, -0.4, -0.5)$ and $r_{Wealth} \in (-0.05, -0.1, -0.2, -0.3, -0.4, -0.5)$. The thick red line replicates our baseline estimates from Figure 3, where we use $r_{Income} = r_{Wealth} = -0.2$. Panel (B) shows the sensitivity to alterations in a_t. We construct convex (concave) weights as t^x where $x \in (0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.2, 1.4, 1.6, 1.8, 2.0)$. The thick red line replicates our baseline estimates from Figure 3, where we use linear weights $x = 1$. All calculations are performed using adjusted cross-sectional PSID sampling weights.

0.18 to 0.23 and a flat trend for more recent birth cohorts. This result is close to our estimates of unidimensional inequality of opportunity in Figure 3 and consistent with existing work on intergenerational income mobility (Chetty et al., 2014b; Hartley et al., 2022; Jácome et al., 2025). However, even small increases in the wealth focus lead to upward corrections in inequality of opportunity estimates and overturn the conclusion of flat time trends for later cohorts. For example, increasing r_{Wealth} to a value of -0.2, steepens the time trend considerably: starting at a level of 0.21 for the 1935 birth cohort, inequality of opportunity increases to a level of 0.32 in the last birth cohort. The highest estimates of inequality of opportunity are obtained for $r_{Income} = -0.05$ and $r_{Wealth} = -0.5$; that is, in case we place more weight on the wealth dimension and little weight on the income dimension.

Second, type weights a_t determine the degree of inequality aversion between types. In our baseline estimates, we choose linear $|a_t| = t$ with t being the weight of a type that is t-th worst in the type utility ranking. Panel (B) of Figure 5 shows alternative results for non-linear specifications of these weights. The highest estimates are obtained for convex type weights $|a_t| = t^2$, i.e., when the inequality aversion coming from type weights is higher. The lowest estimates are obtained for concave type weights $|a_t| = t^{0.5}$, i.e., when the type inequality aversion is lower. Despite changes in levels, our conclusions concerning time trends are insensitive to parameter choices in a_t.

Third, we compute the results for the extended measure $\tilde{I}$ in Equation (5), allowing for higher degrees of substitution between income and wealth than in our baseline case. In Figure S.6, we report results for $\beta \in (0.0, 0.2, 0.5, 0.8)$, where $\beta = 0$ corresponds to our baseline case and $\beta = 0.8$ is close to the case of perfect substitutability. We combine alterations in β with different degrees of inequality aversion, from small $\epsilon = -0.1$ to large $\epsilon = -1$. Treating income and wealth as more substitutable does not affect the time trend of inequality of opportunity in the US. In our baseline case ($r_{Income} = r_{Wealth} = -0.2$ or $\epsilon = -0.4$), the difference between $\beta = 0$ and $\beta = 0.8$ in terms of average inequality of opportunity over time is only about 0.01 and for other ϵ values it is at most 0.02. Similarly, our main conclusions about the time trends are also not affected by changes in β.

Fourth, as mentioned in section 2, there are two sources of inequality aversion in our measure: ϵ and type weights a_t. Therefore, we provide further analyses to illustrate the sensitivity of our results with respect to these two sources. We present these additional analyses in terms of our baseline measure using the representation of Equation (4). In Figure S.7, we report results when using constant $|a_t| = 1$ for all t and varying ϵ from -0.1 to -1. Thereby, we shut down the influence from type weights a_t, and ϵ is the sole parameter governing inequality aversion, varying from low levels of inequality aversion to medium levels often found in the literature. Results show level shifts in total inequality of opportunity with increasing ϵ; however, our conclusions regarding the time trend remain unaffected. Conversely, we check the sensitivity of our results against very large levels of inequality aversion coming from type weights while keeping ϵ at our baseline level. We use more and more convex type weights, i.e., $|a_t| = t^x$ with x ranging from 2 to 14.[20] The results are reported in Figure S.8. The time trend becomes flatter for very high levels of convexity. However, it is important to emphasize that the very large weight put on the least well-off type also increases the noise in the data, making it harder to detect time trends in a statistically reliable way. Finally, we increase the inequality aversion coming from ϵ to large levels. Figure S.9 shows results for ϵ varying from -0.4 to -4 and interacting with linear, convex, and concave type weights. The results show that the importance of the type weights a_t decreases with increasing ϵ. For example, for $\epsilon = -2$ the results are very similar regardless of whether we use linear, concave, or convex weights; for $\epsilon = -4$ they are almost the same. Our general conclusion about increases in inequality of opportunity in the US remains unaffected.

In summary, the results considered in this paragraph show that our conclusion of increasing inequality of opportunity in the US is robust to a wide range of plausible parameter choices for our measure, even for extreme values that are outside the range typically considered in the literature.

[20]Note $x = 2$ is already considered in Panel (B) of Figure 5.

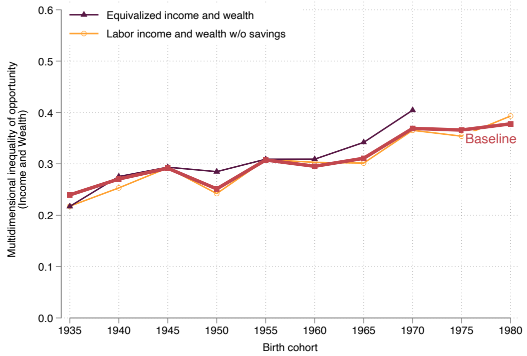
Data choices. In Figure 6, we furthermore document that our main conclusions are robust to a variety of different data choices. We recall that our multidimensional index is only defined for type-specific income and wealth that are positive, i.e., $\mu_r^t > 0, \ \forall r, t$. Some of the following robustness analyses are based on data modifications that lead to a violation of this requirement. For example, when splitting by more granular parental income ranks, types get smaller, which increases the risk of having types with negative income or wealth. Similarly, when adjusting outcomes for family size, incomes get drawn towards zero, again increasing the risk of having types with negative income or wealth. Therefore, we cannot show all robustness analyses for the complete time series from 1935 to 1980.

First, we consider different definitions of our outcome variables. Our baseline estimates consider family income and wealth without adjusting these variables for household size. Therefore, our findings may be driven by differential changes in household compositions across individuals from different family backgrounds. To address this concern, we repeat our calculations while deflating income and wealth by the modified OECD equivalence scale. Panel (A) of Figure 6 shows that our conclusion of increasing inequality of opportunity in the US remains unaffected by this alternation, suggesting that time trends in inequality of opportunity are not driven by differences in fertility and household size across individuals from different family backgrounds. Among others, this finding is also consistent with Derenoncourt et al. (2024) and Fagereng et al. (2021), who show that trends in racial wealth differences in the US and the intergenerational transmission of wealth in Norway are not due to differences in household size.

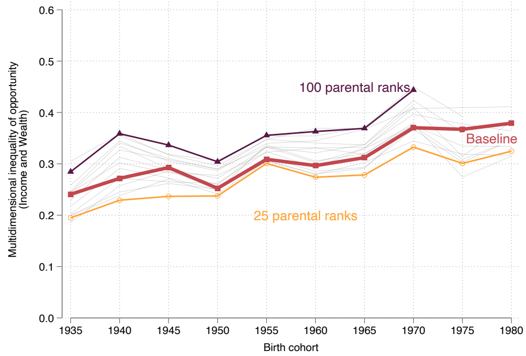
Furthermore, our baseline estimates use a definition of disposable household income that includes asset flows and a definition of household net worth that includes contemporaneous savings of households. Therefore, our estimates may be driven by mechanical relationships between income and wealth. To address this concern, we adjust both concepts as follows: first, we replace disposable household income with household labor market earnings, i.e., we use an income concept that is not mechanically related to the volume and composition of asset portfolios. Second, we adjust household net worth by deducting active savings in a given year, i.e., we use a wealth concept that is not mechanically related to contemporaneous income and saving.[21] Panel (B) of Figure 6 shows that our time series for inequality of opportunity in the US is not sensitive to these adjustments, suggesting that mechanical relationships between income and wealth are not the primary driver of our results. We also note that this finding is consistent with the small contribution of cross-type associations of income and wealth in the attribute decomposition of Figure 4 and the important role of asset price fluctuations as a driver of wealth inequality in the US (Bauluz and Meyer, 2024; Derenoncourt et al., 2024; Kuhn et al., 2020).

[21] We follow the definitions and imputation protocol of Bosworth and Anders (2008) to derive a measure for active savings in the PSID. We thank the authors for sharing the details of their imputation method with us.

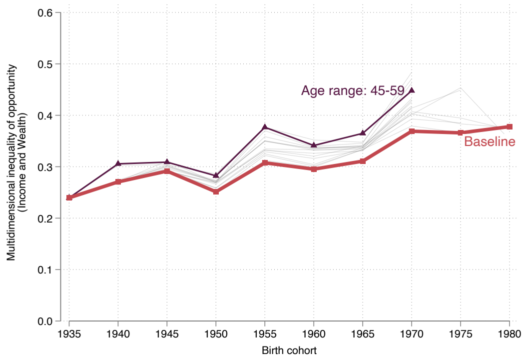
FIGURE 6. Multidimensional inequality of opportunity in the US: Sensitivity to data choices



(A) Alternative income and wealth concepts



(B) Alternative type partition



(C) Alternative age ranges

Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows estimates of multidimensional inequality of opportunity in the US for the birth cohorts 1935-1980 under different data choices. Estimates are computed based on Equation (3) with dimension weights $r_{Income} = r_{Wealth} = -0.2$. Panel (A) shows estimates based on equivalized household income and wealth, and labor income and wealth without active savings. The thick red line replicates our baseline estimates from Figure 3, where we use disposable household income and net wealth without applying an equivalence scale. Panel (B) shows estimates while varying the granularity of the partition of parental income distributions from 25 to 100 cohort-specific ranks. The thick red line replicates our baseline estimates from Figure 3, where we use 50 cohort-specific parental income ranks. Panel (C) shows estimates while increasing the minimum age restriction from 30 to 45 years. The thick red line replicates our baseline estimates from Figure 3, where we use a minimum age restriction of 30 years. All calculations are performed using adjusted cross-sectional PSID sampling weights.

Second, we consider different definitions of our measure of family background. In our baseline estimates, we partition the cohort-specific distribution of parental incomes into 50 ranks. However, finer or coarser type partitions are conceivable. On the one hand, a finer type partition may lead to more accurate estimates of inequality of opportunity since we can make more nuanced differentiations between advantageous and disadvantageous family backgrounds. On the other hand, a finer type partition decreases the sample size within each parental income rank, increasing the noise of our estimates—see Brunori et al. (2023) and Escanciano and Terschuur (2023) for a detailed discussion of the bias-variance trade-off in the context of inequality of opportunity estimations. To address this concern, we repeat our estimations for type partitions between 25 and 100 ranks.[22] Panel (A) of Figure 6 shows that our conclusion of increasing inequality of opportunity in the US remains unaffected by the granularity of the type partition. On the one hand, our estimates are lower, and the time trend becomes slightly flatter when we opt for a coarser partition. This result is mechanical: at the limit, we would consider the entire population as one type, and estimates of inequality of opportunity would be consistently zero in all birth cohorts. On the other hand, our estimates are higher, and the time trend becomes more erratic when we opt for a finer partition—especially for the birth cohorts 1935/40 where sample sizes are substantially smaller than for other cohorts (Table 1). Yet, the overall conclusion of increasing inequality of opportunity in the US remains unaffected by these changes.

Third, we consider different age restrictions for our analysis sample. As described in section 3, we measure income and wealth at different points of the lifecycle of the birth cohorts of interest. This fact might raise concerns that lifecycle effects drive the estimated time trends. Such concerns may be particularly pertinent for the last birth cohorts, which we observe at the beginning of their lifecycle wealth profiles. Ideally, we would like to observe all birth cohorts in a narrow age range, representing their average income and wealth during their prime working years (30-59). Evidently, we cannot do this for the last cohorts since we are restricted to the available data. However, we can address this concern by restricting our analysis to a narrower age range for all earlier birth cohorts and by assessing how such an age harmonization affects our estimates for these cohorts. In Panel (C) of Figure 6, we repeat our analysis while narrowing the admissible age range stepwise from 30-59 to 45-59.[23] This restriction excludes younger birth cohorts from our estimates. For older birth cohorts, the age harmonization leads to an upward correction of inequality of opportunity. This pattern suggests that current levels of unequal opportunities in the younger cohorts will increase as they progress in their lifecycle, further amplifying the detected increase of inequality of opportunity in the US.[24]

We conclude that the level of inequality of opportunity and the magnitude of its increase vary with different measurement choices. However, the main conclusion of increasing inequality of opportunity in the US for birth cohorts 1935-1980 is robust.

[22] Note that we normalize type weights a_t in coarser partitions such that they represent approximately the average type weights in the finest partition with 100 types. For example, in the finest partition, types 100 and 99 receive type weights 100 and 99, respectively. In the partition with 50 types, these types are represented in type 50, which we assign a weight of $(100 + 99)/2 = 99.5$. Therefore, results for coarser/finer type partitions cannot be driven by shifts in the value of weights.

[23] In Table S.3, we show that narrowing age ranges indeed decreases cross-cohort differences in income and wealth.

[24] This finding is also consistent with income profiles that "fan out" over the lifecycle (Mello et al., forthcoming).

6 CONCLUSION

In this paper, we study inequality of opportunity for the acquisition of monetary resources in the US for the birth cohorts 1935-1980. In contrast to existing work, we account for the multidimensionality of monetary resources by targeting the joint distribution of income and wealth.

Our results show that unidimensional analyses may miss important information when analyzing the playing field in the US. First, we document a more unequal distribution of opportunities when complementing income with the wealth dimension. Second, recent increases in inequality of opportunity are predominantly driven by a less opportunity-egalitarian distribution of wealth, which goes unnoticed in analyses that focus on income only.

When using our multidimensional approach, we find consistent increases in inequality of opportunity for the birth cohorts 1935-1980, suggesting that the US has moved further away from a level playing field in recent decades.

We see the potential for various interesting extensions. First, the analysis could be extended to include other important determinants of individual well-being beyond monetary resources (e.g., Kahneman and Deaton, 2010). Second, it could be interesting to analyze patterns by gender to account for the fundamental changes to female labor force participation and family formation in the post-war period (e.g., Autor et al., 2019; Shenhav, 2021). Furthermore, we contend that equality of opportunity only provides one normative criterion to judge the fairness of outcome distributions. Therefore, it would be interesting to extend the multidimensional approach applied in this paper also to other fairness criteria beyond equality of opportunity (e.g., Hufe et al., 2022).

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Multidimensional Equality of Opportunity in the United States

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Supplementary Material
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A MEASUREMENT

In this appendix, we present examples that illustrate the workings of major axioms mentioned in section 2 and we derive the extended measure presented in Equation (5).

A simple example. Consider a society with two types that are of equal size. Both income and wealth are unequally distributed. Since (i) inequality in both dimensions is exactly the same, and (ii) both dimensions are perfectly correlated across types, inequality of opportunity in monetary resources is exactly the same (0.17) regardless of whether we focus on income (I_{Income}) or wealth (I_{Wealth}) in isolation, or whether we focus on the joint distribution of income and wealth ($I_{Income,Wealth}$).

We now consider three alternative societies in which unidimensional and multidimensional measures of inequality of opportunity diverge. As in the main part of the paper, estimates are computed based on Equation (3) with dimension weights $r_{Income} = r_{Wealth} = -0.2$ and linear a_t.

	Income	Wealth
Type 1	50	500
Type 2	100	1,000

$I_{Income} = 0.17$
$I_{Wealth} = 0.17$
$I_{Income,Wealth} = 0.17$

(a)

	Income	Wealth
Type 1	60	600
Type 2	90	900

$I_{Income} = 0.09$
$I_{Wealth} = 0.09$
$I_{Income,Wealth} = 0.09$

(b)

	Income	Wealth
Type 1	50	1,000
Type 2	100	500

$I_{Income} = 0.17$
$I_{Wealth} = 0.17$
$I_{Income,Wealth} = 0.06$

(c)

	Income	Wealth
Type 1	40	1,100
Type 2	110	400

$I_{Income} = 0.27$
$I_{Wealth} = 0.27$
$I_{Income,Wealth} = 0.12$

(a) We equalize outcomes across types in both dimensions. Therefore, I_{Income} and I_{Wealth} decrease and the multidimensional measure $I_{Income,Wealth}$ decreases. This case illustrates the measure's *sensitivity to Pigou-Dalton transfers between types*.

(b) We maintain inequality across types but reverse the cross-type association of income and wealth. Therefore, both I_{Income} and I_{Wealth} stay the same, but the multidimensional measure $I_{Income,Wealth}$ decreases. This case illustrates the measure's *sensitivity to correlation-increasing transfers*.

(c) We increase inequality across types in both dimensions, but reverse the cross-type association of income and wealth. Therefore, I_{Income} increases, and I_{Wealth} increases, however, the multidimensional measure $I_{Income,Wealth}$ decreases. This case illustrates that unidimensional and multidimensional measures can lead to opposing conclusions. While the former would detect an increase in inequality of opportunity in comparison to the baseline, the latter would detect a decrease in unequal opportunities.

Derivation of the extended measure. Let us derive $\tilde{I}$ from Equation (5) along the lines of the proof in Kobus et al. (2024) (p. 41). Let us consider the general case of K outcomes.

By additivity of the welfare function, we write:

$$-\left[\sum_{t=1}^{M} N_t a_t \left(\sum_{j=1}^{K} \alpha_j (\delta\mu_j)^{\beta}\right)^{\frac{\epsilon}{\beta}}\right]^{\frac{1}{\epsilon}} = -\left[\sum_{t=1}^{M} N_t a_t \left(\sum_{j=1}^{K} \alpha_j (\delta_t \mu_j^t)^{\beta}\right)^{\frac{\epsilon}{\beta}}\right]^{\frac{1}{\epsilon}}$$

$$\delta^{\epsilon}\left[\sum_{t=1}^{M} N_t a_t \left(\sum_{j=1}^{K} \alpha_j (\mu_j)^{\beta}\right)^{\frac{\epsilon}{\beta}}\right] = \sum_{t=1}^{M} N_t a_t \delta_t^{\epsilon} \left(\sum_{j=1}^{K} \alpha_j (\mu_j^t)^{\beta}\right)^{\frac{\epsilon}{\beta}}.$$

Thus,

$$\delta = \left[\frac{\sum_{t=1}^{M} N_t a_t \delta_t^{\epsilon} \left(\sum_{j=1}^{K} \alpha_j (\mu_j^t)^{\beta}\right)^{\frac{\epsilon}{\beta}}}{\sum_{t=1}^{M} N_t a_t \left(\sum_{j=1}^{K} \alpha_j (\mu_j)^{\beta}\right)^{\frac{\epsilon}{\beta}}}\right]^{\frac{1}{\epsilon}}.$$

In this paper, we only consider the case of no within-type inequality, so $\delta_t = 1$ for all types t, in which case the inequality of opportunity index is the following:

$$\tilde{I}(X) = 1 - \left[\sum_{t=1}^{M} \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t} \left(\frac{\sum_{j=1}^{K} \alpha_j (\mu_j^t)^{\beta}}{\sum_{j=1}^{K} \alpha_j (\mu_j)^{\beta}}\right)^{\frac{\epsilon}{\beta}}\right]^{\frac{1}{\epsilon}}.$$

Now, in the first stage, the type-average outcomes are evaluated via a CES utility function with outcome weights α_j and a degree of substitution β (i.e., Cobb-Douglas is a special case for $\beta = 0$). The normalisation factor is the value of the CES utility function at the population mean. In the second stage, the evaluation is done via the CES function with parameter ϵ. The sensitivity of the welfare function to the multi-attribute Pigou-Dalton transfer axiom, as in Kobus et al. (2024), restricts the range of parameter values to $\beta < 1, \epsilon < 1$, and the sensitivity to correlation-increasing transfers further restricts it to $\epsilon < \beta$ (e.g., Seth, 2013). Building on various characterisations of the class of double-CES welfare functions (and their subclasses) in the literature (e.g., Decancq and Ooghe, 2010; Seth, 2013; Vega and Urrutia, 2011), the class of welfare functions from which $\tilde{I}$ is derived can be axiomatised. Compared to the class with Cobb-Douglas utility in the first stage, ratio scale invariance can be relaxed to using the same scaling factor for all dimensions and a new axiom has to be added, e.g., weak dimension separability (Vega and Urrutia, 2011), additive separability in dimensions (Seth, 2013) or generalised quasilinearity Eichhorn (1978).

For $K = 2$ outcomes as in the paper, the $\tilde{I}$ measure is the following

$$\tilde{I}(X) = 1 - \left[\sum_{t=1}^{M} \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t} \left(\frac{\alpha(\mu_1^t)^\beta + (1-\alpha)(\mu_2^t)^\beta}{\alpha(\mu_1)^\beta + (1-\alpha)(\mu_2)^\beta} \right)^{\frac{\epsilon}{\beta}} \right]^{\frac{1}{\epsilon}}.$$

B ATTRIBUTE DECOMPOSITION

In this appendix, we derive and prove the attribute decomposability of $I(X)$ as defined in Equation (3). Our derivation is based on results presented in Abul Naga and Geoffard (2006). For the exposition, we focus on the case of two outcome dimensions with $K = 2$. However, we note that this restriction can be easily relaxed. With $K = 2$, X consists of two submatrices X_1 and X_2 that denote outcome matrices for dimensions 1 and 2, respectively. Recall that μ_q^t denotes a type mean in outcome dimension q. Given the notation with two submatrices, an element x_{i1} (x_{i2}) of matrix X_1 (X_2) equals μ_1^t (μ_2^t), i.e., the mean value of dimension 1 (dimension 2) in type t to which individual i belongs. Finally, recall that μ_q denotes the population mean of dimension q.

Attribute decomposability. In general, $I(X) = 1 - \delta(X)$, where $\delta(X) \in [0, 1)$. $I(X)$ is attribute decomposable if and only if

$$\delta(X) = f_1(\gamma_1(X_1)) + f_2(\gamma_2(X_2)) + f_3(\kappa(X)), \tag{7}$$

where f_1, f_2, f_3 are increasing functions ($\mathbb{R}_+ \mapsto \mathbb{R}_+$), γ_1 and γ_2 are unidimensional equality indices, and κ is a measure of association between X_1 and X_2.

Proposition 1. *$\delta(X)$ is attribute decomposable as follows:*

$$\ln \delta(X) = \frac{r_1}{r_1 + r_2} \ln \gamma_1(X_1) + \frac{r_2}{r_1 + r_2} \ln \gamma_2(X_2) + \frac{1}{r_1 + r_2} \ln \kappa(X), \tag{8}$$

where

$$\gamma_1(X_1) = \left(\sum_{t=1}^{M} \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t} \left(\frac{\mu_1^t}{\mu_1} \right)^{r_1} \right)^{\frac{1}{r_1}},$$

$$\gamma_2(X_2) = \left(\sum_{t=1}^{M} \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t} \left(\frac{\mu_2^t}{\mu_2} \right)^{r_2} \right)^{\frac{1}{r_2}},$$

$$\kappa(X) = \frac{\sum_{t=1}^{M} N_t a_t \sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1} (\mu_2^t)^{r_2}}{\sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1} \sum_{t=1}^{M} N_t a_t (\mu_2^t)^{r_2}}.$$

Proof. Formally, let $w_0 := W(X) = \sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1} (\mu_2^t)^{r_2}$ denote the level of welfare (measured by a utilitarian welfare function W) associated with X. This follows from the fact that Kobus et al. (2024) derive measures of inequality of opportunity from welfare functions, following the approach of Atkinson (1970), Kolm (1969), and Sen (1973). First, let $\delta(X)$ be the proportion of mean outcomes required to achieve the same level of welfare if all attributes were equally distributed across types, i.e., $w_0 = \sum_{t=1}^{M} N_t U^t(\delta\mu_1, \delta\mu_2)$. Second, let ρ_1 be the proportion of μ_1 needed to reach w_0 if (i) the first attribute were equally distributed across types and (ii) the distribution of the second attribute across types remained unchanged. Formally, $w_0 =$

$\sum_{t=1}^{M} N_t U^t(\rho_1, \mu_1, \mu_2^t)$. Third, let γ_1 be the proportion of μ_1 that is required to reach w_0 if (i) the first attribute were equally distributed across types, and (ii) the second attribute were equally distributed across types. Formally, $w_0 = \sum_{t=1}^{M} N_t U^t(\gamma_1\mu_1, \rho_2\mu_2)$.

It follows that

$$w_0 = \sum_{t=1}^{M} N_t a_t (\delta\mu_1)^{r_1} (\delta\mu_2)^{r_2} = \sum_{t=1}^{M} N_t a_t (\gamma_1\mu_1)^{r_1} (\rho_2\mu_2)^{r_2}.$$

After modification, we get $\delta^{r_1+r_2} = (\gamma_1)^{r_1}(\rho_2)^{r_2}$, and we obtain

$$\ln(\delta) = \frac{r_1}{r_1+r_2}\ln(\gamma_1) + \frac{r_2}{r_1+r_2}\ln(\gamma_2) + \frac{1}{r_1+r_2}\ln\left(\rho_2/\gamma_2\right)^{r_2}, \tag{9}$$

which is the desired decomposition with $\kappa := (\rho_2/\gamma_2)^{r_2}$.

We now need to derive functional forms of γ_1, γ_2, and κ.

Note that $w_0 = \sum_{t=1}^{M} N_t a_t (\gamma_1\mu_1)^{r_1} (\rho_2\mu_2)^{r_2} = \sum_{h=1}^{M} N_t a_t (\mu_1^t)^{r_1} (\rho_2\mu_2)^{r_2}$. Solving for γ_1 yields:

$$\gamma_1 = \left(\sum_{t=1}^{M} \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t} \left(\frac{\mu_1^t}{\mu_1}\right)^{r_1}\right)^{\frac{1}{r_1}}.$$

Proceeding in analogy, for γ_2 we get:

$$\gamma_2 = \left(\sum_{t=1}^{M} \frac{N_t a_t}{\sum_{t=1}^{M} N_t a_t} \left(\frac{\mu_2^t}{\mu_2}\right)^{r_2}\right)^{\frac{1}{r_2}}.$$

Furthermore, we use $w_0 = \sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1} (\rho_2\mu_2)^{r_2} = \sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1} (\mu_2^t)^{r_2}$ to obtain

$$\rho_2 = \left(\frac{\sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1} (\mu_2^t)^{r_2}}{\sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1} (\mu_2)^{r_2}}\right)^{\frac{1}{r_2}}.$$

Finally, substituting the expressions for γ_2 and ρ_2 into $\kappa := (\rho_2/\gamma_2)^{r_2}$ we get:

$$\kappa = \frac{\sum_{t=1}^{M} N_t a_t \sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1} (\mu_2^t)^{r_2}}{\sum_{t=1}^{M} N_t a_t (\mu_1^t)^{r_1} \sum_{t=1}^{M} N_t a_t (\mu_2^t)^{r_2}}.$$

□

Linear approximation. Collecting terms and reversing the log-linearization of $\delta(X)$, we obtain the attribute decomposition of $I(X)$ displayed in Equation (7):

$$I(X) = 1 - (\gamma_1)^{\frac{r_1}{r_1+r_2}} (\gamma_2)^{\frac{r_2}{r_1+r_2}} (\kappa)^{\frac{1}{r_1+r_2}}. \tag{10}$$

Applying a linear approximation around the point of perfect equality (i.e., $\gamma_1 = \gamma_2 = \kappa = 1$), we get the linear decomposition displayed in Equation (6):

$$\begin{aligned} I(X) &= \tfrac{r_1}{r_1+r_2}(1-\gamma_1) + \tfrac{r_2}{r_1+r_2}(1-\gamma_2) + \tfrac{1}{r_1+r_2}(1-\kappa) + R, \\ &= \tfrac{r_1}{r_1+r_2} I_1 + \tfrac{r_2}{r_1+r_2} I_2 + \tfrac{1}{r_1+r_2}\kappa_I + R. \end{aligned} \tag{11}$$

C ADDITIONAL TABLES

TABLE S.1. Descriptive statistics: Core sample vs. intergenerational links

Cohort	Core sample						Sample with intergenerational links					
	N	Male	White	Age	Par. (USD)	Par. (Rank)	N	Male	White	Age	Par. (USD)	Par. (Rank)
1935	1,217	0.48	0.81	52.91	28.28	24.72	–	–	–	–	–	–
1940	1,774	0.48	0.80	50.49	37.83	25.91	–	–	–	–	–	–
1945	3,613	0.49	0.80	49.63	48.39	24.87	–	–	–	–	–	–
1950	6,427	0.49	0.77	48.73	56.90	26.09	2,685	0.49	0.79	48.09	67.69	33.24
1955	9,068	0.49	0.74	47.85	65.83	25.32	8,428	0.49	0.76	47.67	68.13	26.65
1960	9,477	0.49	0.72	46.74	64.25	25.39	8,432	0.50	0.74	46.60	67.40	27.23
1965	7,811	0.49	0.67	43.21	59.92	25.06	6,275	0.50	0.72	43.08	64.60	28.18
1970	6,228	0.49	0.63	39.32	62.45	24.44	5,198	0.49	0.68	39.29	65.11	26.07
1975	5,630	0.49	0.58	36.24	70.08	24.45	5,006	0.48	0.64	36.26	72.07	25.58
1980	4,622	0.49	0.58	33.95	71.41	24.36	4,491	0.50	0.59	33.94	72.22	24.71

Data: PSID, US Census (Ruggles et al., 2024).
Note: Own calculations. This table displays summary statistics of our core estimation sample and a restricted subsample with available parental income information in the child age range 10-19. All calculations are performed using adjusted cross-sectional PSID sampling weights. All monetary values in 2015 USD. Parental income distributions are partitioned into 50 cohort-specific ranks.

TABLE S.2. Multidimensional inequality of opportunity in the US: Attribute decomposition under alternative parameterizations

Change 1935-1980	Dimension weight		Contribution of ... (in %)			
	Income	Wealth	Income	Wealth	Association	Residual
0.19	-0.5	-0.5	10	68	20	3
0.17	-0.4	-0.4	12	68	16	4
0.15	-0.3	-0.3	14	69	12	5
0.14	-0.2	-0.2	17	69	8	6
0.13	-0.1	-0.1	20	69	4	7

Data: PSID, Ruggles et al. (2024).
Note: Own calculations. This table displays the relative contribution of I_{Income}, I_{Wealth}, and κ_I to the increase in multidimensional inequality of opportunity for birth cohorts 1935-1980 under different parameter choices for r_q. The absolute increase in inequality of opportunity is shown in the first column. The decomposition is based on the attribute decomposition derived in Supplementary Material B. All calculations are performed using adjusted cross-sectional PSID sampling weights.

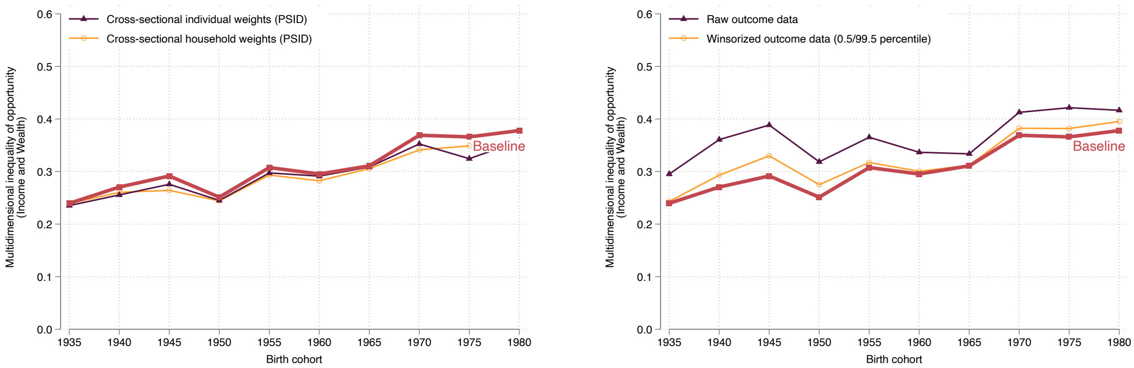
**TABLE S.3. Descriptive statistics:
Income and wealth with different age restrictions**

	30-59		35-59		40-59		45-59	
	Inc.	Wealth	Inc.	Wealth	Inc.	Wealth	Inc.	Wealth
1935	86,954.04	326,576.66	86,954.04	326,576.66	86,954.04	326,576.66	86,954.04	326,576.66
1940	87,765.02	317,795.59	87,765.02	317,795.59	87,765.02	317,795.59	88,037.22	331,302.44
1945	93,380.44	331,141.59	93,380.44	331,141.59	95,053.79	351,305.03	96,011.23	380,897.47
1950	92,730.64	327,962.81	94,695.32	344,380.44	96,928.23	370,091.47	99,440.62	402,888.06
1955	89,192.69	304,798.22	91,369.59	326,202.66	93,356.38	348,665.88	94,145.33	366,824.31
1960	91,029.55	258,534.30	92,882.25	272,568.41	94,410.32	283,923.72	93,948.05	295,439.69
1965	86,526.92	237,249.34	88,015.96	250,437.94	88,735.10	265,671.25	86,609.59	257,977.31
1970	88,438.41	181,695.69	91,389.55	197,814.92	93,130.32	196,474.38	96,332.67	219,514.66
1975	84,928.55	123,533.32	89,056.85	137,782.33	94,783.39	166,939.45	–	–
1980	73,616.66	90,437.40	80,870.14	118,561.66	–	–	–	–

Data: PSID, US Census (Ruggles et al., 2024).
Note: Own calculations. This table displays income and wealth in our core estimation sample using different age restrictions. All calculations are performed using adjusted cross-sectional PSID sampling weights. All monetary values in 2015 USD.

D ADDITIONAL FIGURES

FIGURE S.1. Multidimensional inequality of opportunity in the US: Sensitivity to sampling weights and extreme values

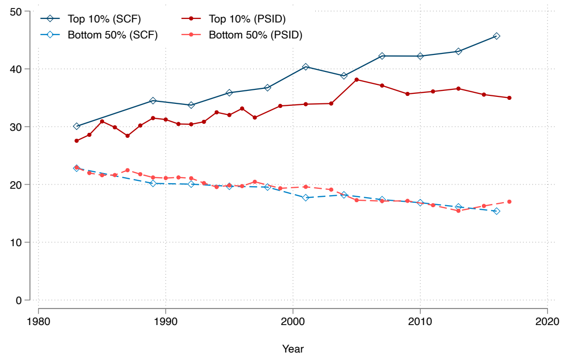


(A) Alternations sampling weights

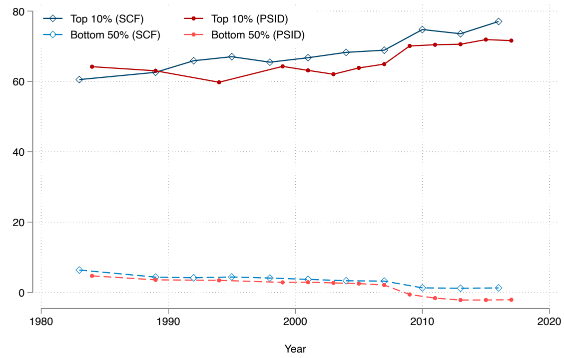
(B) Alternations treatment of extreme values

Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows estimates of multidimensional inequality of opportunity in the US for the birth cohorts 1935-1980 under different sample weighting schemes and under different treatments of extreme values of income and wealth. Panel (A) shows estimates based on cross-sectional individual weights and cross-sectional household weights provided by the PSID. The thick red line replicates our baseline estimates from Figure 3, where we use adjusted cross-sectional sampling weights to match the CPS. Panel (B) shows estimates using winsorized or raw data for income and wealth. The thick red line replicates our baseline estimates from Figure 3, where we trim the year-specific income and wealth distributions at the 0.5 and 99.5 percentiles. Calculations in Panel (B) are performed using adjusted cross-sectional PSID sampling weights.

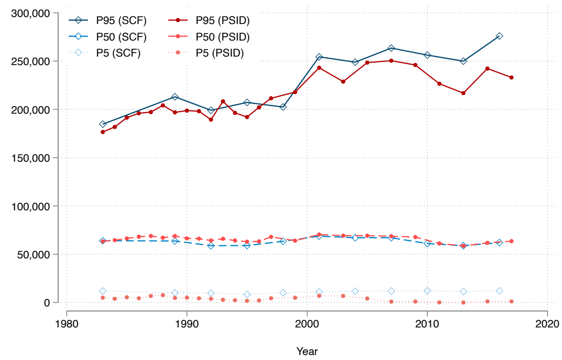
FIGURE S.2. Household income and wealth in PSID and SCF, 1983-2016



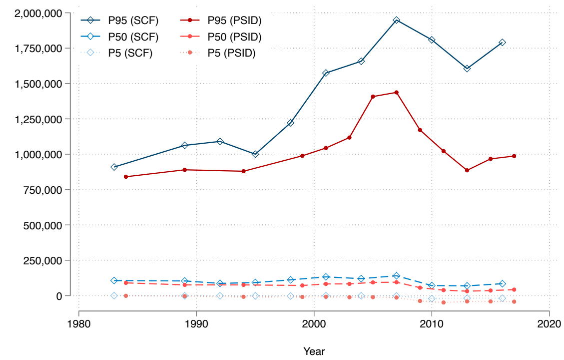
(A) Wealth shares at bottom and top (in %)



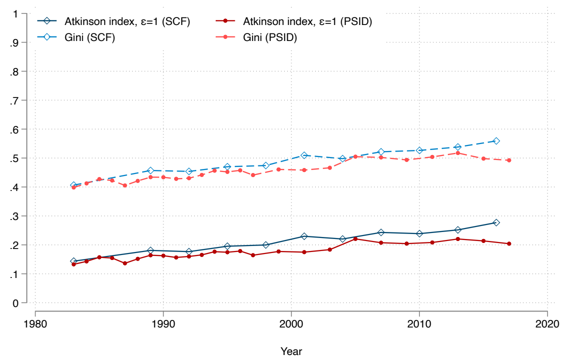
(B) Income shares at bottom and top (in %)



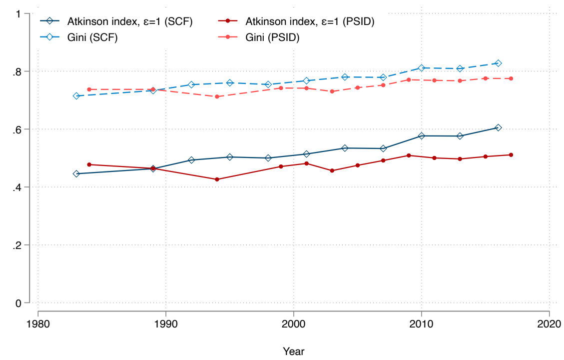
(C) Income percentiles (in USD)



(D) Wealth percentiles (in USD)



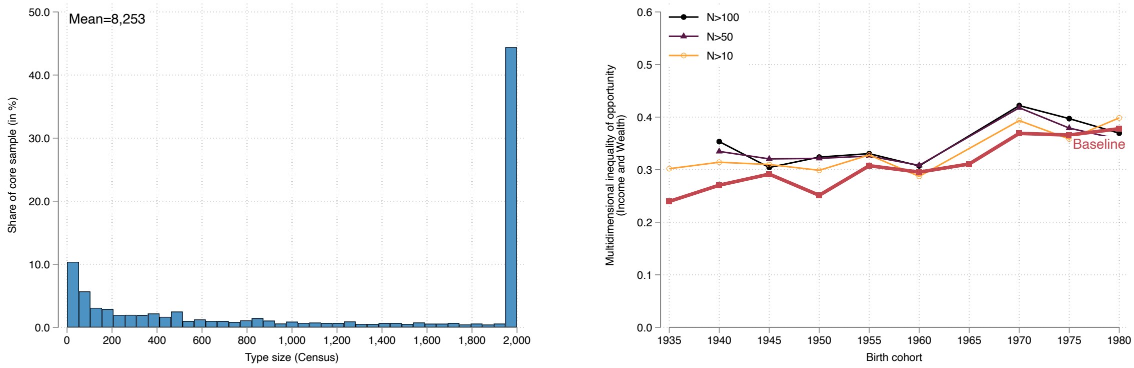
(E) Income inequality



(F) Wealth inequality

Data: PSID, SCF+ (Kuhn et al., 2020).
Note: This figure compares income and wealth distributions between the PSID and the Survey of Consumer Finances (SCF). Samples are restricted to household heads. Gini and Atkinson indices are calculated by dropping all negative income or wealth observations. See section 3 for detailed definitions of income and wealth. All calculations are performed using cross-sectional household sampling weights provided by the PSID and SCF. All monetary values in 2015 USD.

FIGURE S.3. Multidimensional inequality of opportunity in the US: Sensitivity to type sizes in the US Census

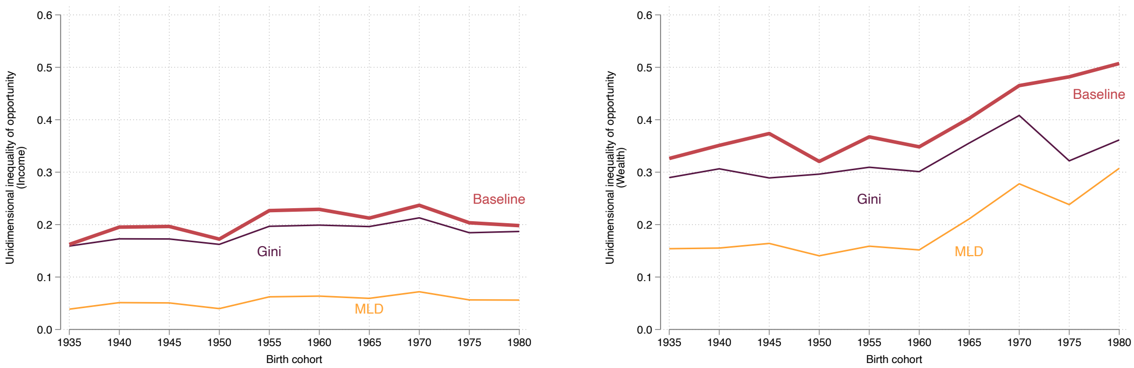


(A) Distribution of type sizes in US Census

(B) Time trend of inequality of opportunity in the US

Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure displays information on the sensitivity of our estimates to small cell sizes in the US Census. Panel (A) shows the distribution of type sizes in the US Census. We censor the distribution at $N = 2,000$ for better visibility. Panel (B) shows estimates of multidimensional inequality of opportunity in the US for the birth cohorts 1935-1980 using different restrictions on the minimal cell size in the US Census. Inequality of opportunity estimates are based on 50 cohort-specific parental income ranks. Estimates are computed based on Equation (3) with dimension weights $r_{Income} = r_{Wealth} = -0.2$. The thick red line replicates our baseline estimates from Figure 3, where we impose no restrictions on minimal type sizes in the US Census. Calculations in Panel (B) are performed using cross-sectional PSID sampling weights.

FIGURE S.4. Unidimensional inequality of opportunity in the US: Sensitivity to different inequality indexes

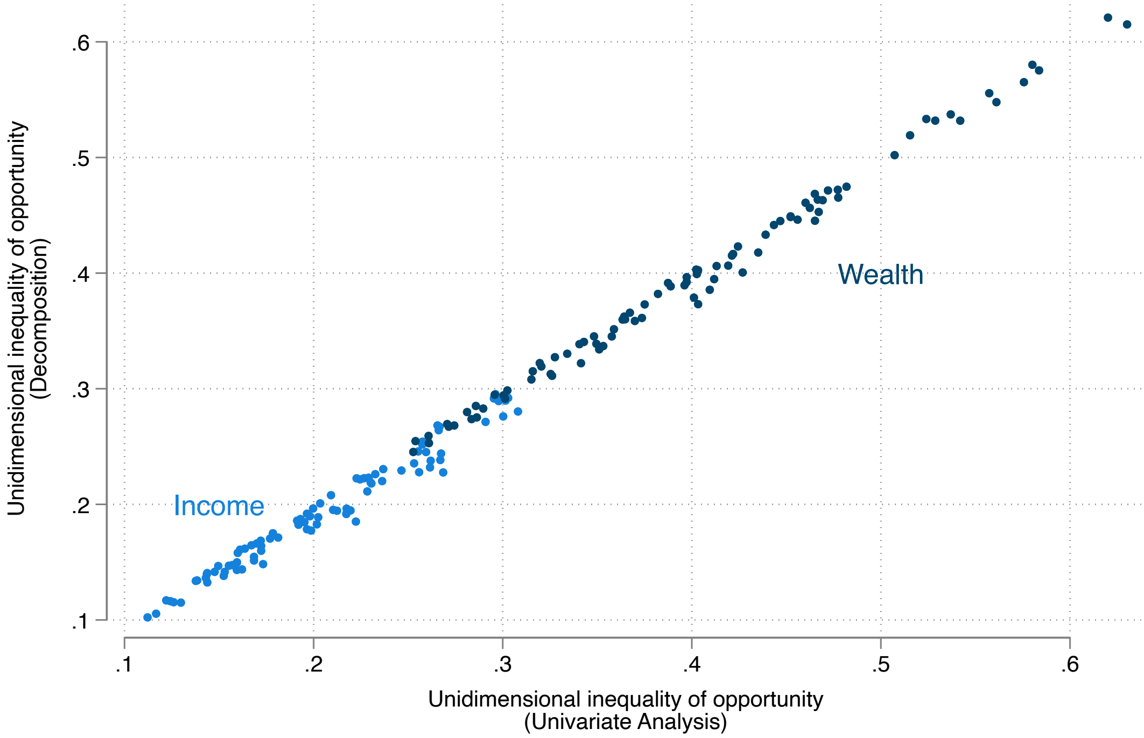


(A) Unidimensional inequality (Income)

(B) Unidimensional inequality (Wealth)

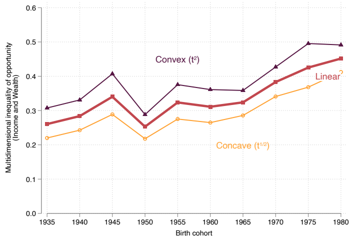
Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows estimates of unidimensional inequality of opportunity in the US for the birth cohorts 1935-1980 using different inequality indexes. Panel (A) (Panel [B]) shows estimates for income (wealth). The thick red line replicates our baseline estimates from Figure 3. All calculations are performed using adjusted cross-sectional PSID sampling weights.

FIGURE S.5. Unidimensional inequality of opportunity in the US: Univariate analysis versus decomposition results

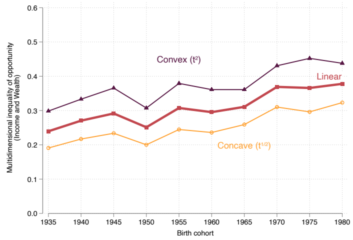


Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure compares estimates of unidimensional inequality of opportunity from a univariate analysis (see Figure 3) to estimates of unidimensional inequality of opportunity from the decomposition (see Figure 4). Inequality of opportunity estimates are based on 50 cohort-specific parental income ranks. We construct this figure using a selection of estimates for all cohorts (1935-1980) based on different parameterizations of $r_{Income} = r_{Wealth} \in (-0.05, -0.2, -0.5)$ and t^x where $x \in (0.5, 1.0, 2.0)$. All calculations are performed using adjusted cross-sectional PSID sampling weights.

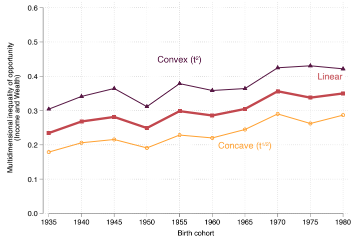
FIGURE S.6. Multidimensional inequality of opportunity in the US: Sensitivity to β



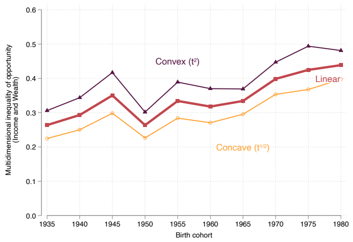
(A) $\beta = 0, \epsilon = -1$



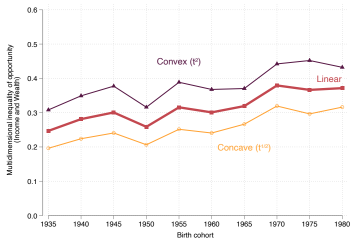
(B) $\beta = 0, \epsilon = -0.4$



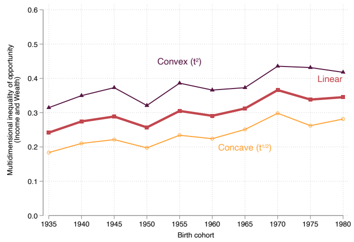
(C) $\beta = 0, \epsilon = -0.1$



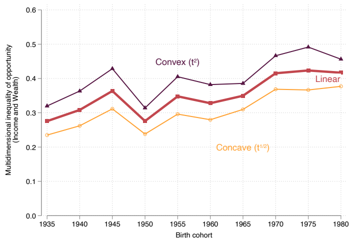
(D) $\beta = 0.2, \epsilon = -1$



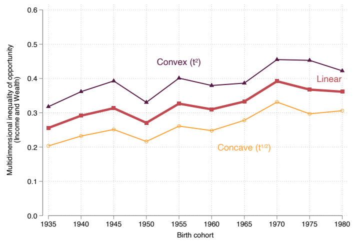
(E) $\beta = 0.2, \epsilon = -0.4$



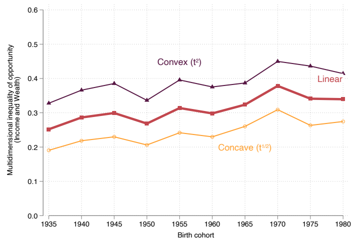
(F) $\beta = 0.2, \epsilon = -0.1$



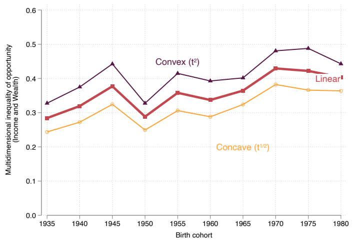
(G) $\beta = 0.5, \epsilon = -1$



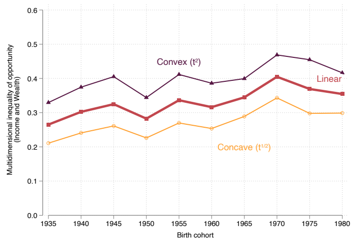
(H) $\beta = 0.5, \epsilon = -0.4$



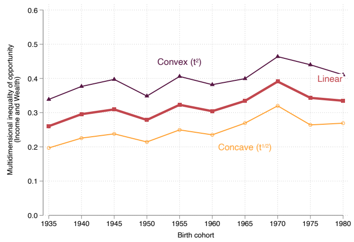
(I) $\beta = 0.5, \epsilon = -0.1$



(J) $\beta = 0.8, \epsilon = -1$



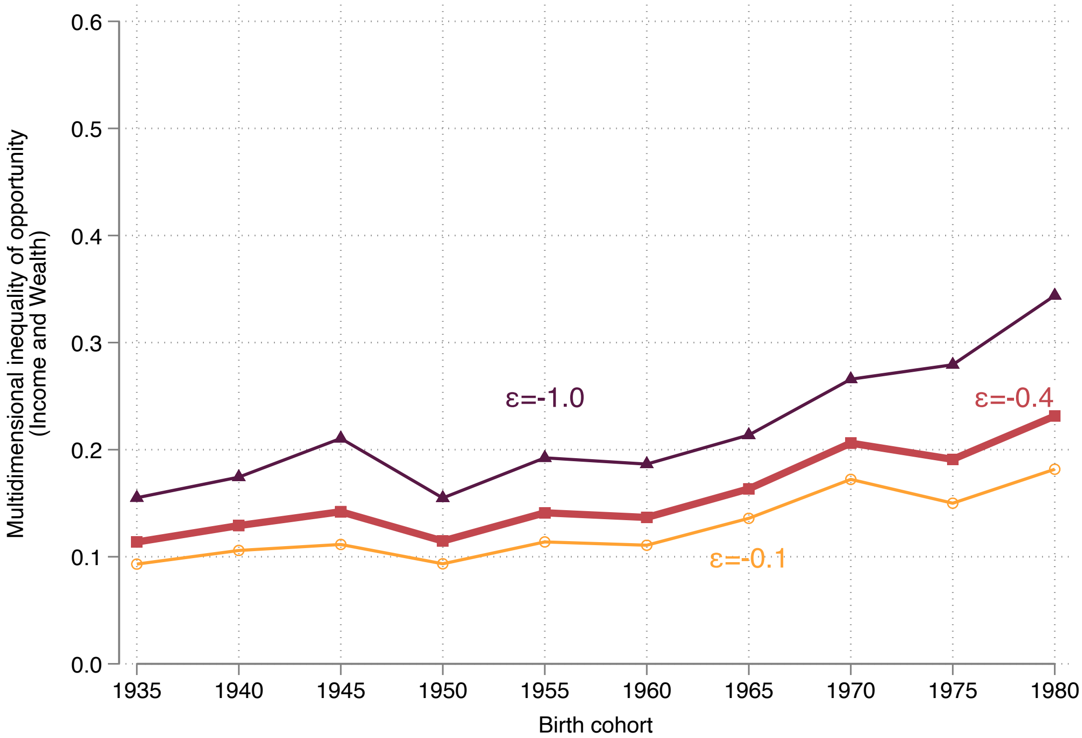
(K) $\beta = 0.8, \epsilon = -0.4$



(L) $\beta = 0.8, \epsilon = -0.1$

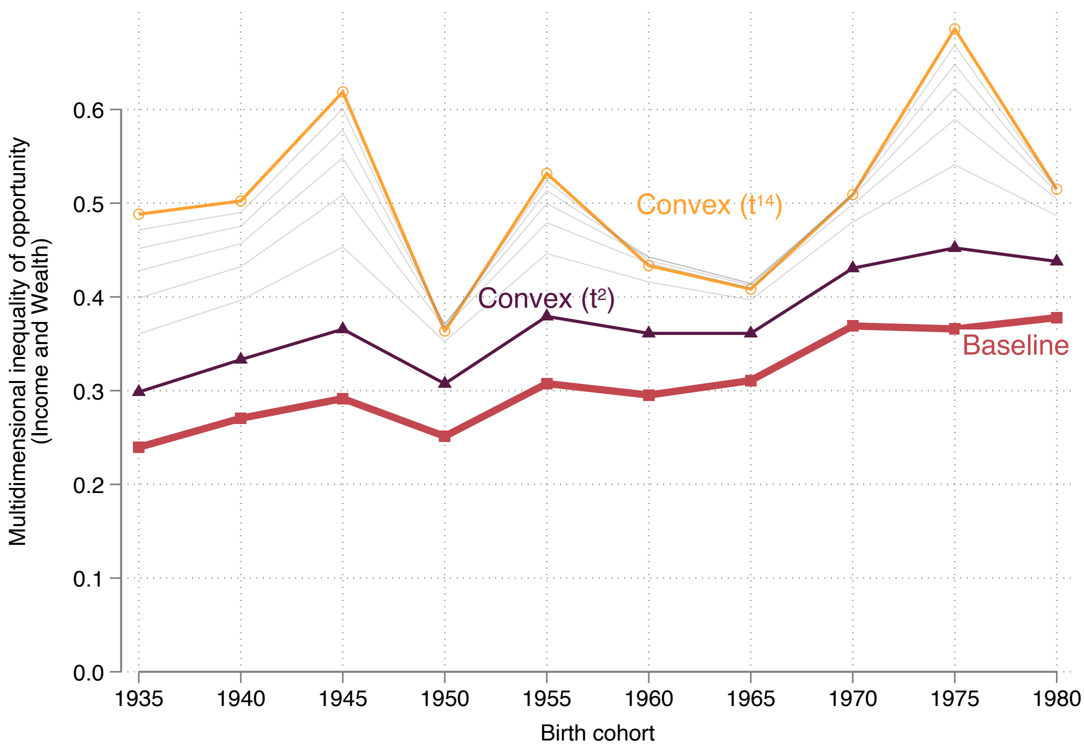
Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows estimates of multidimensional inequality of opportunity in the US for the birth cohorts 1935-1980 under different parameter choices. Inequality of opportunity estimates are based on 50 cohort-specific parental income ranks. Estimates are computed based on Equations (4) - (5) with $\alpha = 1 - \alpha = 0.5$. Other parameter choices are indicated in the figure subtitles and the graph annotation. We construct convex, linear, and concave weights as t^x where $x \in (0.5, 1.0, 2.0)$. All calculations are performed using adjusted cross-sectional PSID sampling weights.

FIGURE S.7. Multidimensional inequality of opportunity in the US: Time trends for constant type weights a_t



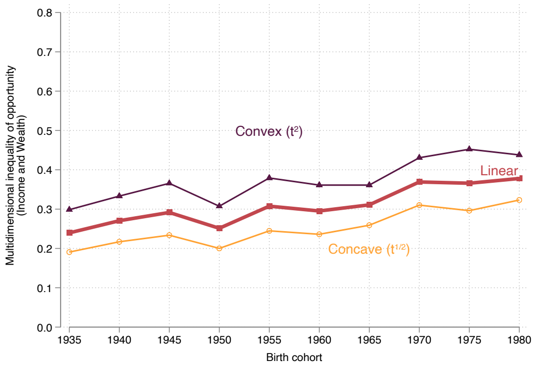
Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows estimates of multidimensional inequality of opportunity in the US for the birth cohorts 1935-1980 under different parameter choices. Inequality of opportunity estimates are based on 50 cohort-specific parental income ranks. Estimates are computed based on Equation (4) with $\alpha = 1 - \alpha = 0.5$. Other parameter choices are indicated in the graph annotation. We construct constant weights as t^x where $x = 0$. All calculations are performed using adjusted cross-sectional PSID sampling weights.

FIGURE S.8. Multidimensional inequality of opportunity in the US: Time trends for highly convex type weights a_t

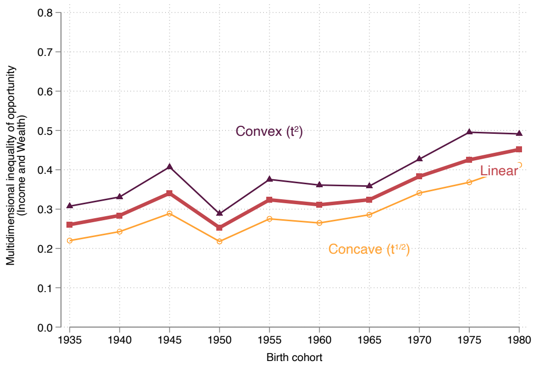


Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows estimates of multidimensional inequality of opportunity in the US for the birth cohorts 1935-1980 under different parameter choices. Inequality of opportunity estimates are based on 50 cohort-specific parental income ranks. Estimates are computed based on Equation (4) with $\alpha = 1 - \alpha = 0.5$ and $\epsilon = -0.4$. We construct convex weights as t^x where $x \in (2, 4, 6, 8, 10, 12, 14)$. All calculations are performed using adjusted cross-sectional PSID sampling weights.

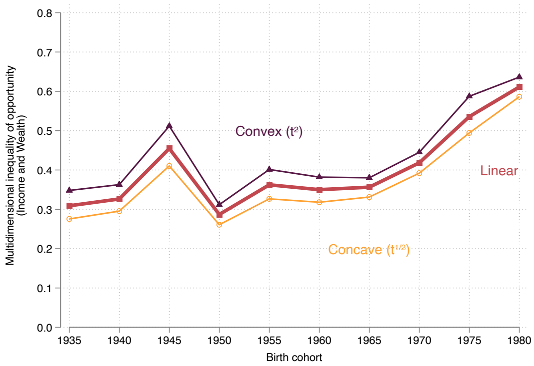
FIGURE S.9. Multidimensional inequality of opportunity in the US: Interaction of ϵ and a_t



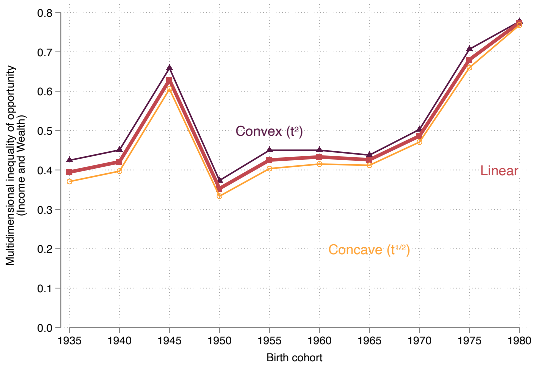
(A) $\epsilon = -0.4$



(B) $\epsilon = -1$



(C) $\epsilon = -2$



(D) $\epsilon = -4$

Data: PSID, US Census (Ruggles et al., 2024).
Note: This figure shows estimates of multidimensional inequality of opportunity in the US for the birth cohorts 1935-1980 under different parameter choices. Inequality of opportunity estimates are based on 50 cohort-specific parental income ranks. Estimates are computed based on Equation (4) with $\alpha = 1 - \alpha = 0.5$. Other parameter choices are indicated in the figure subtitles and the graph annotation. We construct convex, linear, and concave weights as t^x where $x \in (0.5, 1.0, 2.0)$. All calculations are performed using adjusted cross-sectional PSID sampling weights.

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