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DISCUSSION PAPER SERIES

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ABSTRACT

Inequality of Opportunity in Wealth: Levels, Trends, and Drivers*

While inequality of opportunity (IOp) in earnings is well studied, the literature on IOp in individual net wealth is scarce to non-existent. This is problematic because both theoretical and empirical evidence show that the position in the wealth and income distribution can significantly diverge. We measure ex-ante IOp in net wealth for Germany using data from the Socio-Economic Panel (SOEP). Ex-ante IOp is defined as the contribution of circumstances to the inequality in net wealth before effort is exerted. The SOEP allows for a direct mapping from individual circumstances to individual net wealth and for a detailed decomposition of net wealth inequality into a variety of circumstances; among them childhood background, intergenerational transfers, and regional characteristics. The ratio of inequality of opportunity to total inequality is stable from 2002 to 2019. This is in sharp contrast to labor earnings, where ex-ante IOp is declining over time. Our estimates suggest that about 62% of the inequality in net wealth is due to circumstances. The most important circumstances are intergenerational transfers, parental occupation, and the region of birth. In contrast, gender and individuals' own education are the most important circumstances for earnings.

JEL Classification: D63, J62, D31, J24

Keywords: inequality, wealth, inequality of opportunity, decomposition

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1. Introduction

Do the circumstances of our birth determine our destiny, or are our life outcomes the result of our own decisions and actions? This question gets at the heart of why intergenerational mobility is a major topic of research and public debate. If the circumstances of birth create almost insurmountable barriers for disadvantaged people, what can be done to promote equality and provide incentives for social and economic participation? This paper examines the contribution of such circumstances to the inequality of wealth. Wealth plays a major role in intergenerational mobility and an even more important role than variables like income. By nature, wealth is intergenerational. While income and education are highly persistent across generations in many countries, wealth is the only outcome that can be—and often is—directly transferred from one generation to the next. Wealth is also a resource that can shape the course of people's lives, allowing them to achieve goals such as buying a home or starting a business (Nykvist 2008; Acolin et al. 2016) For these reasons, there is a lively and emerging body of economic literature studying and documenting the intergenerational mobility of wealth (see Adermon, Lindahl, and Waldenström 2018; Boserup, Kopczuk, and Kreiner 2018; Black et al. 2020; Fagereng, Mogstad, and Rønning 2021).

Measuring the intergenerational association between parental and child wealth is clearly important. We argue, however, that it is essential to track not only this association, but also the degree to which the individual's position in the wealth distribution is predetermined by immutable characteristics, which are referred to in the literature on inequality of opportunity as *circumstances* (Roemer 1998). Since this predetermined part of wealth is beyond the individual's control, and therefore in a fundamental sense unearned, it is referred to as the *unfair* component of wealth. Thus, the equality of opportunity framework extends the core insight of the intergenerational mobility literature to other circumstances beyond the parental position in the wealth distribution. Within this framework, we can answer more specific questions relating to intergenerational mobility: How much wealth inequality is determined by the circumstances of birth? What are the forces driving unfair wealth inequality? And what are potential policies to address these forces?

Research Question. In this paper, we use the ex-ante inequality of opportunity (IOp) framework to study the unfair component of net wealth (Ferreira and Gignoux 2011; Roemer and Trannoy 2016; Ramos and Van de gaer 2016; Peichl and Ungerer 2016;

Brunori and Neidhöfer 2021). We predict individuals' positions in the wealth distribution based on a broad set of circumstances, calculate the wealth inequality implied by these predictions, and relate this to observed wealth inequality over a period of almost two decades. The IOp framework allows us to study the individual contributions of individual circumstances to unfair wealth inequality, which extends our understanding of the intergenerational determination of wealth. Further, we break wealth down into its main components—financial, real estate, and business wealth—to study which of these drive current trends in unfair wealth inequality. We also contrast IOp in net wealth against IOp in gross labor earnings. We do this because wealth is a complex construct with diverse sources of variation: Unlike labor income, it can be decomposed into transfers (bequests), savings, and capital gains. Savings varies in similar ways to income but is only one possible source of variation. There are also forces that drive wealth and income positions apart. All else equal, we would expect that a positive unearned income shock—for example, through a bequest—would decrease labor supply when income effects are non-negligible. This shock would increase wealth but decrease current labor income (Doorley and Pestel 2020; Cesarini et al. 2017; Imbens, Rubin, and Sacerdote 2001; Kindermann, Mayr, and Sachs 2020), which shows that knowledge about labor income inequality does not directly imply knowledge about wealth inequality.

Despite its relevance for the study of intergenerational mobility, wealth has rarely been the object of research in the IOp literature due to data limitations and methodological hurdles. There exist almost no data providing high-quality information on *individual* net wealth in conjunction with a broad set of circumstances. Methodological difficulties arise because net wealth includes non-positive values, and thus most methods from the literature on earnings IOp do not generalize to wealth.

Data and Methods. Our data source, the Socio-Economic-Panel (SOEP), is able to address all data limitations encountered in the research to date. The SOEP is a representative panel of German households and a prime data source for researchers to track income and wealth inequality in Germany (Biewen 2000; Schröder et al. 2020; König, Schröder, and Wolff 2020; Albers, Bartels, and Schularick 2022). Since 2002, this panel contains detailed information on individuals' assets and liabilities, which allows for the calculation of net wealth. In addition, due to the retrospective information on individuals' biographies as well as the study's genealogical design, the SOEP contains a rich set of life circumstances. To address the methodological issues we face, we focus on ex-ante IOp in net wealth (Ferreira and Peragine 2016; Ferreira and Gignoux 2011;

Ferreira, Gignoux, and Aran 2011) and decompose unfair wealth inequality measured using the Gini index into relative contributions of circumstances using the Shapley decomposition (Sastre and Trannoy 2002; Shorrocks 2013). We estimate ex-ante IOp in a regression framework, which delivers qualitatively and quantitatively equivalent results compared to the alternative of a tree-learner-based model (Brunori, Hufe, and Mahler 2023). To make the differences between what we know about IOp in wealth and income explicit, we contrast our results with established results in the literature regarding ex-ante IOp in gross labor earnings (e.g. Peichl and Ungerer 2016).

Results. Our substantial findings are as follows: IOp in net wealth, as measured by the ratio between the actual to the counterfactual IOp-Gini coefficient, remained relatively stable at around 62% between 2002 and 2019. That is, our estimates suggest that if it were not for unfair factors driving wealth inequality, wealth inequality would be at least 62% lower. For gross labor earnings, however, IOp has declined by roughly 10 percentage points (from about 70% in 2002 to 60% in 2019). We identify intergenerational transfers (inheritances and inter-vivos gifts), parental occupation, and the region of birth as the most important circumstances for wealth inequality.[1] This is in sharp contrast to earnings, which gender and education affect most. The difference in the role of gender can be explained by the composition of wealth: In our data, up to 75% of net wealth inequality is accounted for by housing wealth. Decomposing IOp into the three wealth components real estate, business wealth, and financial wealth, we find that gender does not matter, as real estate wealth is generally shared equally between spouses or partners. For IOp in business and financial wealth, gender has a slightly more important role, but the contribution is never higher than 10%.

Literature. So far, very few studies have focused on IOp in wealth. Salas-Rojo and Rodríguez (2022) calculate ex-ante IOp in household wealth in the United States, Spain, Italy, and Canada, relating inheritances and parental education to the household's financial and non-financial wealth. They estimate an IOp ratio of over 60% in the United States and Spain and over 40% in Canada and Italy and find that IOp is higher for financial wealth than for non-financial wealth. Palomino et al. (2021) estimate ex-post IOp in the United States, France, Spain, and Great Britain and find that relative IOp ranges from 36% in Great Britain to 49% in the United States. Further, they report Shapley

[1] In addition, for both income and wealth, age accounts for significant fractions of IOp, as discussed below.

decomposition results to show that the marginal contribution of inheritances alone amounts to a third of overall wealth inequality in the United States, France, and Spain. Hufe et al. (2022) analyze the association between family background characteristics and the joint distribution of income and wealth using a multidimensional measure of inequality in the United States and find that IOp in the joint distribution increased by 78% between 1983 and 2016.

We also build on a rich literature on IOp in labor income Peichl and Ungerer (2016); Hufe, Kanbur, and Peichl (2022); Björklund, Jäntti, and Roemer (2012); Aaberge, Mogstad, and Peragine (2011); Ramos and Van de gaer (2016); Brunori, Ferreira, and Neidhöfer (2023). A smaller related strand of literature deals with IOp in health (e.g. Kovacic and Orso 2022; Davillas and Jones 2020). Our work is also closely related to the literature on intergenerational mobility in general Lee and Solon (2009); Solon (1992); Bratberg et al. (2017); Nybom and Stuhler (2016). In the IOp framework, parental earnings or parental wealth can be thought of as one circumstance (Lee and Solon 2009; Solon 1992; Bratberg et al. 2017; Nybom and Stuhler 2016). In comparison, the ex-ante framework can be thought of as mapping many circumstances into a scalar. While sibling correlations can accomplish a similar goal (see for instance Anger and Schnitzlein 2017; Björklund, Jäntti, and Lindquist 2009; Solon et al. 1991), the IOp framework is more explicit about the factors driving inequality of opportunity.

Contribution. Our study brings the following novel aspects to the emerging literature on IOp in wealth: 1) We measure wealth at the level of the individual. This allows us to directly link *individual* circumstances to *individual* outcomes. 2) We decompose net wealth into its three main components and analyze levels, trends, and determinants of real estate wealth, business wealth, and financial wealth. 3) We add a new country case that is of particular importance to the existing literature: Germany is the largest economy in the European Union and has a particularly interesting wealth distribution because of its strong rental market and generous social protection. 4) We leverage the new top wealth sample of the SOEP, known as SOEP-P (Schröder et al. 2020b; Siegers, Steinhauer, and König 2021; Schröder et al. 2020a), to assess the impact of an appropriate sampling of top wealth holders on wealth IOp estimates. 5) To the best of our knowledge, this is the first study that offers a consistent and comprehensive comparison of the level, dynamics, and determinants of IOp in gross labor earnings and net wealth. 6) We use a long-running, temporally consistent database containing extensive information on the individual's circumstances, i.e., birth and background characteristics such as gender, year of birth, place of birth, migration background, place of upbringing, body height, number of siblings, upbringing in a single-parent household, parents' education, parents' occupation, whether the individual received an inheritance or gift, and their own education (consistent with the view that children's actions are due to either nature or nurture, both of which are beyond their control).

The paper is structured as follows. In Section 2, we introduce the ex-ante IOp framework and detail how we apply it in our estimation strategy. Section 3 introduces our database, the construction of our focal variables, and the selection of our estimation sample. In Section 4, we present the results. Section 5 concludes.

2. Empirical strategy

Ex-ante IOp. According to Roemer (1998), outcomes—like wealth—are determined by individuals' *efforts*, *circumstances*, and, as a residual concept, *luck*. This distinction is derived from the commonly held moral view that individuals are, at least partially, responsible for their efforts but not for their circumstances (Ferreira and Peragine 2016). Therefore, differences in resources between individuals with the same set of circumstances are typically judged to be fair if the remaining variation is attributable to effort. Conversely, differences between individuals exerting identical effort are judged to be unfair if they are due to differences in circumstances.

Based on this, we introduce a production function for individual i's net wealth at time t: Wealth y_{it} is a function of circumstances C_i and effort E_{it}. Circumstances, because they are determined at birth or in childhood, are assumed to be unaffected by effort and time-constant. However, effort is potentially constrained by individuals' circumstances. For example, the social network of the parents could constrain the occupations or firms that individuals can enter. Thus, we can write the wealth production function as:

$$y_{it} = h(C_i, E_{it}(C_i, v_{it}), u_{it}). \tag{1}$$

In Equation 1, v_{it} and u_{it} are unobserved error terms. These error terms are often referred to as "luck" (Lefranc, Pistolesi, and Trannoy 2009; Lefranc and Trannoy 2017). v_{it} represents the random variation in effort that is independent of the circumstances C_i and u_{it} corresponds to the random variation in the outcome that is independent of circumstances C_i and effort E_{it}. The function $h(\cdot)$ maps effort, circumstances, and luck onto individuals' net wealth or labor earnings.

Using Equation 1, we can decompose wealth into direct and indirect contributions of effort and circumstances. In this study, we implement an *ex-ante* approach, that is, we are interested in the inequality of net wealth that is attributable to circumstances in an expected value sense (Ferreira and Peragine 2016). Note that this expectation will also include expected effort based on circumstances.

Determining types. If we had unlimited data at our disposal, we would estimate the counterfactual wealth distribution based on all possible combinations of the circumstances we observe, that is, for all types of circumstances. In reality, many of these type-cells are populated only sparsely and interpretations would be limited because of the curse of dimensionality.

Therefore, we impose linearity in $h(\cdot)$ and $E(\cdot)$ and write

$$y_{it} = C_i\beta_t + \epsilon_{it}, \tag{2}$$

with β_t reflecting the complete contribution of the circumstances C_i to net wealth or labor earnings.[2] This includes the direct effect and the indirect effect of effort that is constrained by circumstances. This means that the estimated coefficients reflect the direct effect of circumstances and the effect of circumstances that is mediated by effort. One could also rely on non-parametric methods such as random forests to estimate the actual production function (Brunori, Hufe, and Mahler 2023; Brunori and Neidhöfer 2021). This would also capture non-linearities in the association between circumstances and wealth as well as interactions between circumstances. In Section 4.6.1, we show that results do not differ meaningfully if we use a random forest.

To analyze the inequality of outcomes across types, we predict the counterfactual wealth distribution based on the estimates of the reduced-form equation depicted in Equation 2, that is,

$$\hat{y}_{it} = C_i\hat{\beta}_t, \tag{3}$$

where $\hat{\beta}_t$ corresponds to the set of OLS coefficients on our circumstances in a linear regression of net wealth in t on the full set of circumstances. The resulting counterfactual distribution returns the variation in the outcome that is attributable to circumstances. The remaining variation in y—variation of the error term due to luck or effort—then corresponds to variation within a group defined by certain circumstances.

Inequality measurement. We apply our inequality measure $I(\cdot)$ to the distribution of $\hat{y}_{it}$ to calculate our estimate of absolute IOp.[3] Formally, absolute inequality of opportunity is

$$\mathcal{I}_a = I(\hat{y}_{it}). \tag{4}$$

[2]We index β by t because we estimate this equation year-by-year.

[3]Note that this decomposition is akin to between- and within-group decompositions of inequality. Reducing the variation in y to variation in $\hat{y}$ is essentially the same as identifying the between-group variation between types. The remaining variation in y – variation of the error term, i.e. of luck, unobserved circumstances, etc. – then corresponds to within-group variation, i.e. variation within the same type that cannot be explained by the observed circumstances.

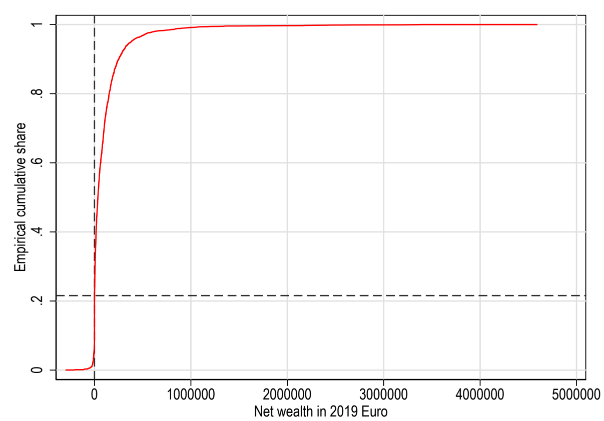
Since we are interested in the relationship between inequality of opportunity and observed, that is, total inequality, we define:

$$\delta_r = \frac{I(\hat{y}_{it})}{I(y_{it})}. \tag{5}$$

This is the IOp ratio, which we use as our relative IOp measure.

Throughout the empirical application, we choose $I(\cdot)$ to be the Gini coefficient.[4] Since we are dealing with negative values, we apply the Raffinetti, Siletti, and Vernizzi (2015) normalization of the Gini coefficient to ensure that the Gini index stays within the range [0, 1]. In 2012, for example, the share of individuals with non-positive wealth is close to 22%, as displayed in Figure 1. In Section 4.6.2, we also provide results for the MLD for reference, the measure of inequality typically chosen in related applications (Peichl and Ungerer 2016).

FIGURE 1. Cumulative distribution of net wealth in 2012



Note: Figure 1 displays the cumulative distribution function for net wealth in 2012. The figures are based on the weighted working sample. The dashed vertical line indicates the zero. The dashed horizontal line indicates the cumulative share associated with zero net wealth.

The strategy described so far provides us with at least a lower bound of the IOp because we cannot account for the complete set of circumstances. This may increase IOp or leave it unchanged. Unless the additional circumstance is not relevant, adding it to our set of circumstances will increase the inequality between groups and, therefore, the IOp estimates (Ferreira and Gignoux 2011). Thus, our estimate constitutes at least a lower bound to IOp in net wealth.

[4] The Gini coefficient entails the standard properties of anonymity, the principle of transfers, population replication, and scale invariance (Cowell 2016).

Shapley decomposition. We use the Shapley decomposition to evaluate the relative importance of circumstances on the ex-ante IOp in net wealth. The Shapley decomposition returns the marginal effects of each circumstance on $\mathcal{I}_a$, eliminating each circumstance sequentially. It assigns each circumstance its average marginal contribution in all possible elimination sequences. The resulting decomposition is appealing because it is exact, symmetric, and additive (Shorrocks 2013).

Formally, let $\mathbf{C}$ denote the set of circumstances and N the cardinality of this set. $\mathbf{F}$ indicates a randomly selected subset of s circumstances. In this case, the marginal contribution of a circumstance $k \in \mathbf{F}$ to the value of $\mathcal{I}_a(\mathbf{F} \cup \{k\})$ is defined by $\mathcal{I}_a(\mathbf{F} \cup \{k\}) - \mathcal{I}_a(\mathbf{F})$. The average marginal contribution of circumstance k to the overall IOp is given by

$$\mathcal{S}_k = \sum_{s=0}^{N-1} \sum_{\mathbf{F} \subseteq \mathbf{C} \setminus \{k\},\ |\mathbf{F}|=s} \frac{(N-1-s)!s!}{N!} \mathcal{I}_a(\mathbf{F} \cup \{k\}) - \mathcal{I}_a(\mathbf{F}). \tag{6}$$

Thus, the relative contribution of circumstance k is given by

$$\mathcal{S}_{k,r} = \frac{\mathcal{S}_k}{\mathcal{I}_a}. \tag{7}$$

3. Data

For our analysis, we use detailed data on net wealth and circumstances from the SOEP. The SOEP is a representative panel survey of households in Germany. Since 1984, the SOEP has surveyed German households, including all adult household members, on a yearly basis about their living conditions. Respondents are asked about their economic situation, education, attitudes, and many more characteristics. Today, roughly 30,000 individuals in 15,000 households participate in the survey every year (Goebel et al. 2019; Schröder et al. 2020). We use version 36 of the SOEP, which contains data on individual net wealth from 2002 to 2019.[5]

The SOEP is uniquely suited to the present analysis for four reasons: First, the SOEP is the only survey data set that contains information on assets and liabilities on the level of the individual, which enables the construction of *individual*-level net wealth. This is crucial in relating individual circumstances to individual wealth as part of a consistent and convincing analysis of IOp. Second, the biographical information and genealogical design of the SOEP permit us to use a wide range of circumstances to investigate ex-ante IOp of earnings and net wealth. Individuals in SOEP households become survey respondents as soon as they turn 18, and they remain part of the survey even after they move out and form new households of their own. This allows us to utilize information on respondents' household situation and life circumstances before they reached adulthood and began participating in the survey themselves. In addition, since 2002, the SOEP has given all respondents in the SOEP and all new survey respondents a bibliographical questionnaire. For these two reasons, we have data on an unusually rich set of circumstances. Third, the SOEP contains information on respondents' earnings as well as assets and liabilities, which allows us to contrast IOp in earnings and IOp in net wealth. Fourth, the SOEP added a new sample of top wealth holders in 2019, SOEP-P, which allows us to account for the influence of the heavy upper tail of the wealth distribution, that is, the top 1% and above, on the inequality of opportunity.

Outcomes. Our main outcome is individual net wealth. The SOEP has surveyed respondents on individual wealth with a special wealth module every five years since 2002 as well as an additional time in 2019. In the individual wealth module, individuals provide information on seven types of assets: primary residence; other real estate; financial assets such as bonds, shares, and other financial instruments; building loan contracts;

[5] DOI: 10.5684/soep.core.v37eu.

life and private pension insurance; tangible assets; and business wealth. The SOEP introduced vehicles as an eighth asset in 2019, but we disregard this to generate a consistent time series. To derive an accurate individual measure of net wealth, respondents are asked about their individual share of real estate and businesses. Individuals are also asked about three types of liabilities: outstanding debt on their primary residence; outstanding debt on other real estate; and consumer debt. A fourth liability type was introduced in 2019: student loans. Again, for temporal consistency, we disregard student loans when constructing net wealth. We calculate net wealth as gross wealth, which is the sum of the value of all asset classes, minus gross debts, calculated as the sum of the liability classes. We adjust individuals' net wealth to 2019 euros and perform a 99.98% winsorization (i.e., all data below the 0.1 percentile is set to the 0.1 percentile, and data above the 99.9 percentile set to the 99.9 percentile).

Our second outcome used to compare IOp in net wealth to gross labor earnings. Yearly gross labor earnings comprise wages and salaries from all employment including training, primary and secondary jobs, and self-employment. They also include income from bonuses, overtime, and profit-sharing.[6] Earnings are measured in 2019 euros.

Circumstances. Distinguishing between circumstances and effort is not straightforward: the decision is essentially normative. Some would limit the set of circumstances to a bare minimum and argue that most factors are in the realm of individual responsibility or effort. Others would view individuals' abilities to make meaningful choices as restricted by social circumstances, which would imply that most factors can be considered circumstances (Ferreira and Peragine 2016). In line with the literature, we consider the following variables determined at birth as circumstances: migration background, gender, and family background (Ferreira and Peragine 2016; Roemer 1993). In addition, we consider variables set before individuals reach legal age of majority as circumstances; a choice consistent with (Roemer and Trannoy 2016). One example are the individual's educational accomplishments up to the age of majority. In our baseline model, the circumstances we use are gender, migration background (native, direct, and indirect), federal state of birth, year of birth, body height, whether the individual has been officially assessed as being severely disabled or partially incapable of work for medical reasons, the number of siblings, the father's and mother's occupation at age 15 (blue collar, white collar, civil servant, self-employed, and not working or in training), the degree of urbanization of the region in which the individual spent most of their

[6] We use individual labor earnings provided in the Cross-National Equivalent File (Frick et al. 2007).

childhood up to the age of 15 (rural area, small or medium town, and large city), whether the individual has received an inheritance or gift,[7] whether the individual was (partially) raised by a single parent or in an orphanage until the age of 15, the father's, mother's, and the individual's own educational level (no degree, lower secondary, intermediate, and upper secondary).

Individual characteristics that have been found to have a causal impact on earnings should clearly have some impact on wealth by logical extension. We therefore include personal characteristics like gender (Blau and Kahn 2017; Kleven, Landais, and Søgaard 2019), height (Lundborg, Nystedt, and Rooth 2014), migration background (Blau and Kahn 2015), education (Carneiro, Heckman, and Vytlacil 2011), and year of birth (Kantarevic and Mechoulan 2006; Cotofan et al. 2023) in our set of circumstances.

Chetty, Hendren, and Katz (2016) has made a powerful case for the importance of neighborhood effects in the determination of schooling and income. We include this set of variables due to their expected impact on wealth.

Family background has been documented to impact the wealth position of children in several studies using administrative data from Scandinavian countries (Boserup, Kopczuk, and Kreiner 2018; Black et al. 2020; Fagereng, Mogstad, and Rønning 2021). These publications stress the importance of the transmission of wealth-building preferences and human capital, such as saving preferences and financial knowledge. The above-cited papers as well as Nekoei and Seim (2023) also show a significant impact of inheritances on child wealth.

In an alternative model specification, we also include the logarithm of the price-adjusted total sum of inheritances or gifts received, taking into account their capitalization factor.[8] A short description of the circumstances and potential realizations is displayed in Table B.1 in the appendix.

Sample restriction. Since we compare our results on net wealth with those based on gross labor earnings as the outcome of interest, we restrict the sample to the working-age population (25-65 years old). Further, we restrict the sample to those with full item response on the outcomes and all circumstances in the baseline model. The resulting

[7] We acknowledge that inheritances and gifts may be influenced by an individual's choices past the age of majority. Nevertheless, we find it reasonable to assume that this margin, compared to the size of the total potential inheritance, is small. In the German case, even disowned heirs have a legal right to a substantial part of the total inheritance.

[8] To avoid losing observations where the sum of inheritances/gifts is zero and its logarithm is not defined, we add one to all sums. We lose 21 observations due to missing information on the sum of inheritances/gifts, leading to n = 28,421 for this model specification.

summary statistics are displayed in Table B.2.

Including high-income-earners. In 2019, the SOEP introduced a new subsample of top wealth holders called SOEP-P. The sampling population for this subsample were substantial shareholders in companies from around the globe who reside in Germany.[9] The information on shareholding was collected from international business registers by Bureau van Dijk and provided as a special edition of the Orbis company dataset. From the about 1.5 million substantial shareholders residing in Germany, the top 600,000 with the highest value of shareholdings—representing roughly 1% of the adult population—were selected to be the sampling basis for SOEP-P.[10] SOEP-P is a stratified random sample of 1,960 individuals from these 600,000 shareholders, with stratification based on the value of the shareholdings. It is therefore a sample of top shareholders and thus top wealth holders, since top wealth holders have a higher propensity than others to invest some of their wealth in companies (Bucks et al. 2009; Bricker et al. 2017; Martínez-Toledano 2020; Wolff 2021; Smith, Zidar, and Zwick 2023). See Schröder et al. (2020) for a detailed exposition of the sampling strategy. In our main analyses, we exclude SOEP-P, but we study the relevance of its inclusion in Subsection 4.6.3.

[9]Shareholders are classified as substantial by Bureau van Dijk if they hold at least 0.1% of all shares of a company.

[10]The value of shareholdings was proxied in the Orbis database using the monetized turnover of the company and the respective ownership share.

4. Results

4.1. Absolute and relative IOp in net wealth

In a first step, we regress net wealth on the set of circumstances in each year separately. The regression output is shown in Panel A.1 in the appendix. Based on these estimates, we predict the counterfactual distribution of net wealth, that is, the distribution of net wealth before the exertion of effort, calculate the Gini coefficient for each distribution in each year, and plot absolute and relative IOp. Figure 2 displays the results. The blue bars represent the Gini for the empirical distribution and the orange bars represent the Gini for the counterfactual distribution. The vertical green small bars are percentile-based 95% confidence intervals, calculated using 500 bootstrap replications.[11]

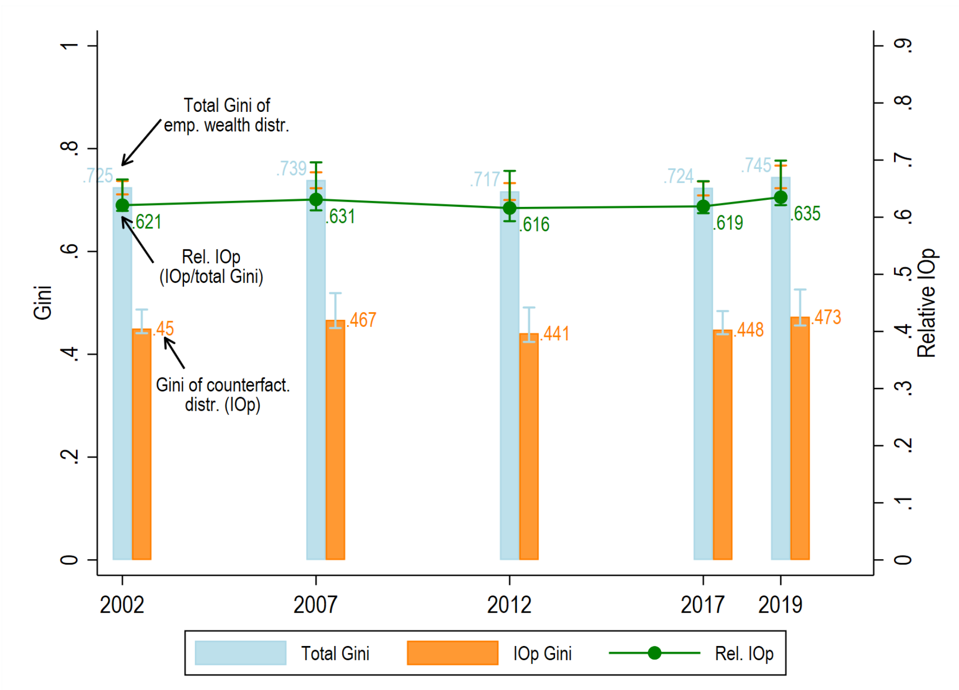
Total inequality in net wealth is high and stable throughout our observation period. Figure 2 shows that the Gini coefficient for net wealth, shown as blue bars, starts at 0.73 in 2002 and ends at 0.75 in 2019. IOp, that is, the counterfactual Gini coefficient for net wealth, ranges from 0.45 to 0.47 in 2002 and 2019, respectively. Notably, we cannot observe a decline in absolute IOp for net wealth. If anything, the point estimates indicate a small increase.

A result of the stable inequality in net wealth is that relative IOp, given by the ratio of the absolute IOp to total inequality in net wealth, is stable over the entire observation period. Relative IOp was approximately 0.62 in 2002 and remains at roughly the same level for every year that we observe.[12]

[11]Since the distribution of Ginis follows a skewed, non-normal distribution, the confidence intervals are non-symmetric.

[12]Specifying the logarithm of the total sum of inheritances/gifts instead of a dummy variable for having received any kind of transfer changes the results little, as can be seen in the appendix, Figure A.2A

FIGURE 2. The Evolution of IOp in Net Wealth



Note: The blue bars depict the Gini coefficient of the empirical net wealth distribution in the respective survey years and include orange percentile-based 95% confidence intervals from 500 bootstrap replicates. The orange bars depict the Gini coefficient of the respective counterfactual distribution, where differences in net wealth are due to circumstances alone. Blue percentile-based 95% confidence intervals from 500 bootstrap replicates are included. The green connected dots show the IOp ratio, that is, the Gini coefficient of the counterfactual IOp distribution divided by the Gini of the empirical distribution of the respective outcome. The associated vertical bars correspond to percentile-based 95% confidence intervals.

4.2. Decomposing IOp in net wealth

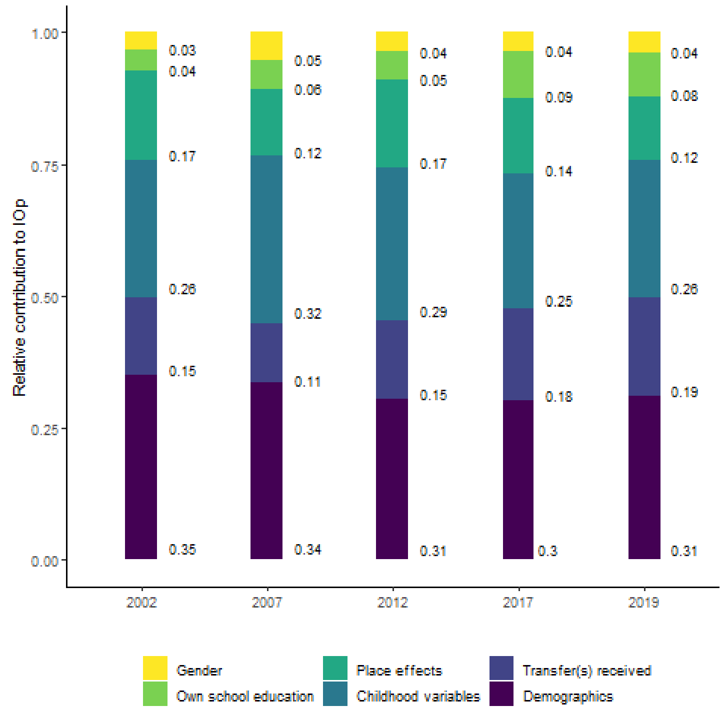
To understand the influence of various circumstances on IOp in net wealth, we apply the Shapley decomposition. To ease exposition, we aggregate circumstances into the following categories: gender, own school education, being an intergenerational transfer recipient, demographics, childhood and parental background, and place effects. An overview of the grouping of the circumstances is displayed in Table B.1 in the appendix.

The relative contributions of circumstances to IOp in net wealth are displayed in Figure 3. Clearly, gender does not contribute significantly to IOp in net wealth. The relative contribution of gender amounts to approximately 4% and remains relatively constant over time. Also, respondents' education contributes only marginally to IOp in net wealth. However, the contribution of education increases over time. The relative contribution of education more than doubles from 4% in 2002 to 8% in 2019.

Place effects and childhood circumstances contribute significantly to IOp in net wealth. Place effects contribute from 12% to 17% to IOp in net wealth. Childhood circumstances contribute 26% to 32% to IOp in net wealth. The relative contribution of childhood circumstances is relatively stable over time.

Moreover, intergenerational wealth transfers also contribute significantly to IOp in net wealth. The relative contribution of these wealth transfers increases from 15% in 2002 to 19% in 2019. This corresponds to an increase of approximately 27%. Lastly, the demographics contribute approximately 35% to 31% to IOp in net wealth, with a declining trend over time.

FIGURE 3. Shapley Decomposition of IOp in Net Wealth



Note: Stacked bar charts of the share of IOp (Gini coefficient of the counterfactual distribution) that is accounted for by circumstances in each survey year. The shares are based on Shapley values as described in Section 2. The category of demographics comprises the variables migration background, year of birth, and body height. Childhood and parental background include parents' education, parents' occupation, number of siblings, and whether an individual was raised (partially) in a single-parent household. The circumstances of the federal state in which the respondent was born and the degree of urbanization of the place of upbringing are grouped into the category of place effects.

4.3. Life-cycle trends in cross-sectional IOp estimates

Figure 3 shows that demographics, the year of birth amongst them, are one of the most relevant circumstances in explaining IOp in net wealth. Between 30% and 35% of IOp in net wealth is accounted for by demographics alone.

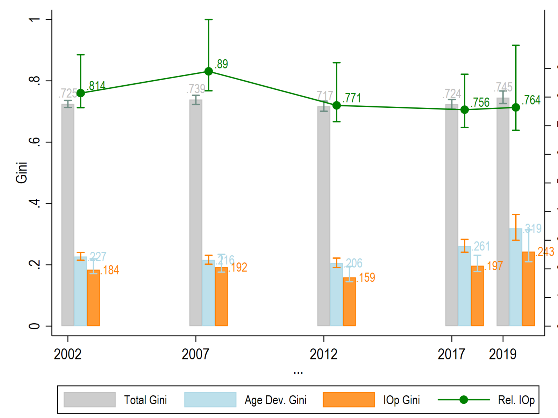
An individual cannot be held responsible for the year in which they were born. Accordingly, we consider individuals' year of birth a circumstance. However, the year of birth included in our regression analyses certainly captures both age, that is, life-cycle effects such as precautionary saving motives and bequest motives, as well as cohort effects, that is, different labor market and educational opportunities. Thus, inequality between types also arises from the fact that we compare individuals at different stages of their lives. These differences can arise even in a setting with no inequalities associated with circumstances, independent of year of birth or age.

Therefore, in a different model specification, we follow Brunori and Neidhöfer (2021) and calculate each respondent's deviation from their expected value in net wealth, given their age. We predict this expected value by pooling the data for all years and regressing net wealth on a second-order polynomial of age. Hence, we derive an average age trend for all respondents observed between 2002 and 2019. The individuals' deviation from their expected value is measured in absolute terms, subtracting the average outcome in the respective age reference group from individuals' observed level of net wealth.

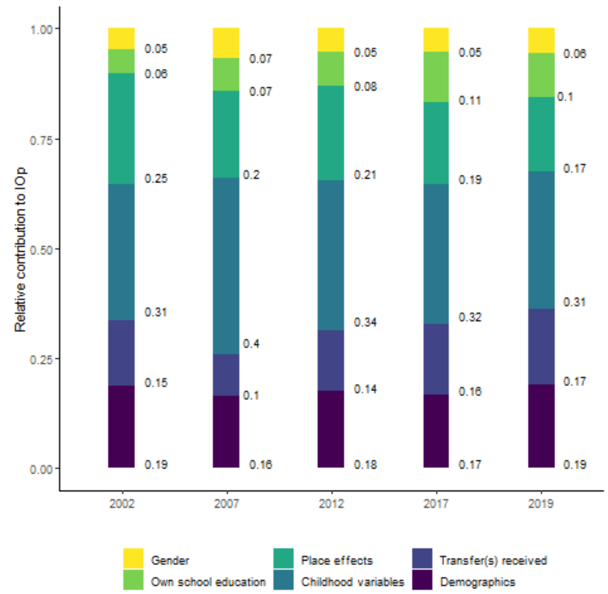
Results are shown in Figure 4. As illustrated in Figure 4A, the Gini coefficients of the counterfactual distribution are now closer to the Gini coefficients of the distribution where we measure absolute deviations from a general age trend, leading to higher estimates of relative IOp. However, the estimates also vary more widely across survey years, compared to our main estimates. In Figure 4, estimates range between 76% and 89%. Moreover, in this analysis, the point estimates are consistent with a moderately declining trend, although the confidence intervals are too large to rule out the absence of a trend with certainty.

Turning to Figure 4B, which displays the relative contribution of circumstances to IOp in net wealth, we find that the set of demographics are less important than in our main analysis displayed in Figure 3; contributing between 16% and 19% to IOp. In contrast, childhood variables and place effects are considerably more important than in our main analysis. Childhood variables have increased substantially in relevance, with contributions now ranging from 40% to 31%. Place effects are also noticeably more relevant than in our main analysis, with contributions now ranging from 17% to 25%. Our finding that transfers explain close to one fifth of IOp and that their contribution to IOp is increasing over time remains robust to this alternative model specification. Generally, the main qualitative findings of our baseline analysis are confirmed in this analysis.

FIGURE 4. IOp of age-adjusted net wealth



A. IOp



B. Circumstances' contribution to IOp

Note: Figure A. shows IOp estimates for the model specification where the outcome of interest is the absolute deviation from predicted net wealth levels, given an individual's age. The grey bars depict the Gini coefficient of the empirical net wealth distribution in the respective survey years and include percentile-based 95% confidence intervals constructed using 500 bootstrap replicates. The blue bars depict the Gini coefficient of the distribution of deviations in net wealth from predicted wealth levels, given individuals' age, with orange, percentile-based 95% confidence intervals. The orange bars depict the Gini coefficient of the respective counterfactual distribution, where differences in the age deviation distribution are due to circumstances alone, with blue, percentile-based 95% confidence intervals. The green connected dots show relative IOp, that is, the Gini coefficient of the counterfactual IOp distribution divided by the Gini of the distribution of deviations in net wealth from predicted wealth levels, given individuals' age. Figure B. shows the decomposition of IOp using Shapley values in the age deviation distribution.

4.4. Decomposition of wealth IOp for the portfolio components

The portfolio components of net wealth differ in how they are accumulated and what purpose they serve. To understand whether IOp in wealth stems from a specific portfolio component, we decompose wealth into three main sources: housing, business, and financial wealth. Housing net wealth includes the value and outstanding debt on the respondents' primary residence and other real estate. We define as financial wealth all assets and liabilities apart from business and real estate net wealth, that is, financial assets (stocks, bonds, etc.), building loan contracts, life and private pension insurance, tangible assets, and consumer debts.

Relevance of different wealth components. Figure 5 shows the composition of the wealth portfolio and the relative contribution of the portfolio components to total net wealth inequality over time.[13] By far the most important wealth asset is real estate net wealth. Housing net wealth increases from an average value of 69,950 euros in 2002 to 98,070 euros in 2019, an increase of about 40%. This corresponds to an increase from 65% in 2002 to 67% of the average wealth portfolio in 2019. Further, real estate net wealth inequality accounts for around 64% to 66% of overall net wealth inequality in the years 2002 to 2019. Financial wealth is more important than business wealth by about a factor of around two. Financial wealth inequality accounts for at least one fifth and as much as a fourth of total net wealth inequality. The differential relevance and different ways these different wealth stocks accumulate emphasizes how important it is to analyze IOp for these wealth components specifically.

IOp in different wealth components. We compare total inequality in each of the three wealth assets to their respective absolute IOp estimates. Figure 6A depicts the results for net housing wealth. Total inequality in net housing wealth is similar to total inequality in net wealth, measured at Gini coefficient levels of around 0.77 for all observed time periods. Absolute IOp in real estate wealth is close to 0.45-0.47 for survey years 2002-2019. As a result, relative IOp amounts to approximately 0.59 for real estate wealth and is relatively stable for the entire period of observation.

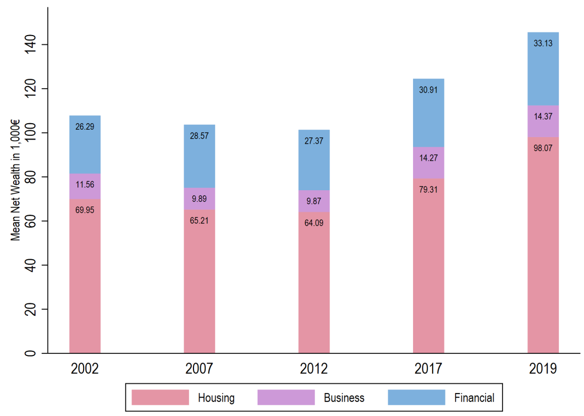
IOp in financial wealth is fairly similar to IOp in housing wealth in both trends and levels. This is depicted in Figure 6B. Total inequality in financial wealth is close to 0.75, and absolute IOp is close to 0.45 for most years in our survey period. Consequently, relative IOp is close to 0.60 and stable for all survey years in our period of observation.

For business wealth, we find results that differ from the other two wealth components. As illustrated in Figure 6C, total business wealth inequality is stable for our period of observation and is approximately 0.99, a value of near-perfect inequality, since the maximum possible value the Gini coefficient can take on is one.[14] The reason for this finding is that most of the variation happens at the extensive margin. Most respondents

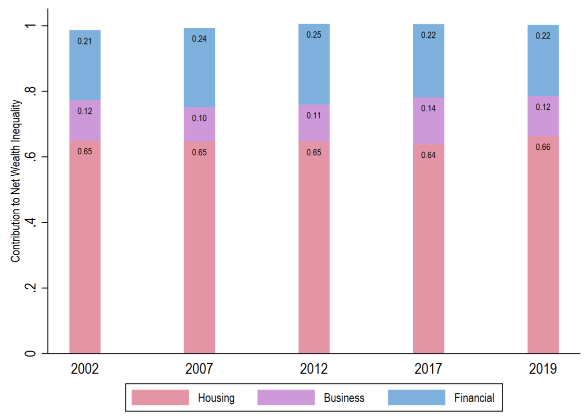
[13] To calculate the assets' contribution to net wealth inequality, we use the Lerman and Yitzhaki (1985) decomposition, in whichtotal net wealth $Y = \sum_{k=1}^{K} Y_k$ is the sum of wealth components k and the contribution of each component to the overall inequality is $G = \sum_{k}^{K} S_k R_k G_k$. Here, $S_k = \mu_k/\mu$ is the share of component k of total net wealth, G_k is the component-specific Gini coefficient, and $R_k = cov(y_k, F)/cov(y_k, F_k)$ is the "Gini correlation" between wealth component k and net wealth (with $cov(y_k, F)$ being the covariance of component k with the cumulative distribution of net wealth).

[14] As mentioned in Section 2, we normalize the Gini coefficient to ensure that it lies in the range [0, 1] in spite of negative values in the empirical wealth distribution.

FIGURE 5. Wealth (inequality) by asset



A. Mean Wealth and its components

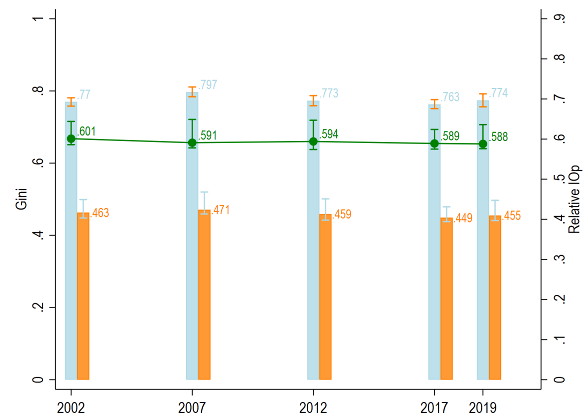


B. Share of asset Gini in total net wealth Gini

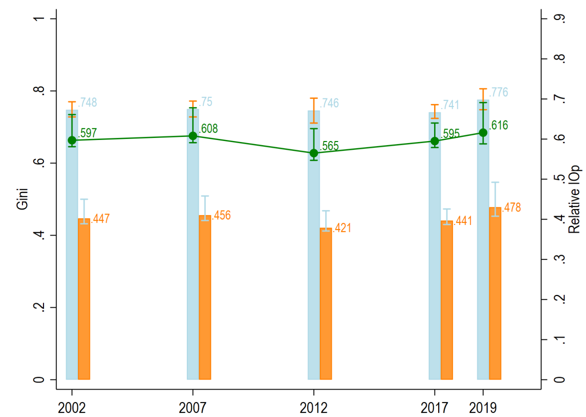
Note: Stacked bar charts of (A.) mean net wealth, broken down to mean wealth in the asset categories housing, business, and financial net wealth; and (B.) the share of total empirical inequality in net wealth (measured by the Gini coefficient) that is accounted for by inequality in the respective wealth asset category (housing, business, and financial net wealth), in each survey year. These shares are computed using the Gini decomposition by source following Lerman and Yitzhaki (1985).

do not own any business wealth. Absolute IOp for business wealth starts at 0.64 in 2002, peaks in 2007 at 0.68, and after 2007, the absolute IOp declines slightly to 0.64 in 2019. Due to the empirical inequality being close to one, relative IOp largely co-moves with the level of absolute IOp and varies from 0.60 to 0.68 in our period of observation. Overall, we find that the *level* of relative IOp does not vary much across wealth components. However, in the next part of this section, we perform a Shapley decomposition of the IOp of each wealth component to understand how IOp emerges in each wealth component.

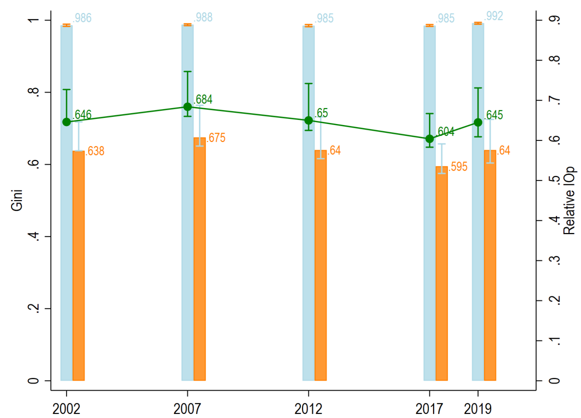
FIGURE 6. IOp for the components of the net wealth portfolio



A. Housing



B. Financial



C. Business

Note: The blue bars depict the Gini coefficient of each empirical wealth portfolio distribution in the respective survey years and include orange, percentile-based 95% confidence intervals drawn from 500 bootstrap replicates. The orange bars depict the Gini coefficient of the respective counterfactual distribution, where differences in respective wealth levels are due to circumstances alone. Blue, percentile-based 95% confidence intervals from 500 bootstrap replicates are included. The green connected dots show the IOp ratio, that is, the Gini coefficient of the counterfactual IOp distribution divided by the Gini of the empirical distribution of the respective outcome. Vertical bars correspond to percentile-based 95% confidence intervals.

Decomposing IOp into Circumstances. Our decomposition of IOp in the three wealth components reveals sharp differences in the relative contributions of different circumstances to IOp across wealth components. We apply a Shapley decomposition to IOp in each of the three wealth assets to quantify the relative importance of the various groups of circumstances. The results are shown in Figures 7A, 7B, and 7C. We find that inheritances matter more for housing wealth than for financial or business wealth.

Between 13% to 20% of IOp in housing wealth are attributable to having received an inheritance or gift. For business wealth, this share amounts to 7% in 2002 and increases to 16% in 2019. Similarly, in 2002, the share of IOp in financial assets attributable to inheritances and gifts amounted to 7% and increased to 9% in 2019.

The role of childhood variables also varies significantly across the assets classes. In our observation period, 23% to 30% of IOp in housing wealth is attributable to childhood circumstances. These figures are 28% to 38% for financial assets and 23% to 30% for business assets.

For the contribution of place effect to real estate wealth, IOp varies between 13% and 20%. The influence on IOp in financial wealth is smaller, with shares ranging from 12% to 16%. For IOp in business wealth, the shares are very stable at 11% to 14%.

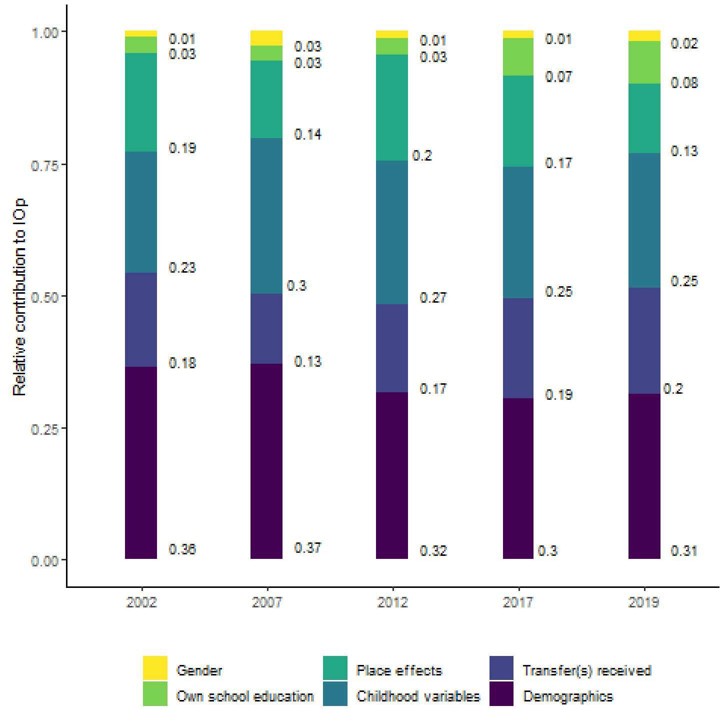
Education contributes from 3% to 8% to IOp in real estate wealth. Note that its share in real estate wealth increases over the observation period. Education contributes between 1% and 7% to IOp in financial wealth. Its contribution to business wealth ranges from 10% in 2002 to 16% in 2019.

The contribution of gender to IOp in net real estate wealth is close to zero. This is likely due to the fact that couples in Germany usually hold real estate assets jointly (Nutz 2022; Kapelle et al. 2022). In Figure A.4 in the appendix, we show the mean ownership of the primary residence and other real estate by gender, as well as the mean value of these real estate assets among owners. In line with Sierminska, Piazzalunga, and Grabka (2019), we observe that men are more likely than women to own both the primary residence and other real estate, but this difference decreases over time. There is no significant difference in the mean value of the primary residence between male and female homeowners in 2012, 2017, and 2019. For other real estate, men's assets are worth significantly more on average, but this does not seem to affect IOp estimates in real estate wealth, since the ownership of other real estate is so much lower on average than ownership of the primary residence.

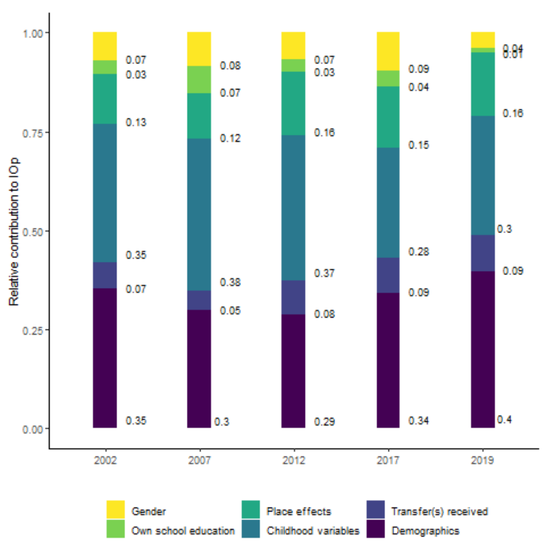
In contrast, gender is relevant for IOp in financial wealth. As illustrated in Figure 7B, the share of IOp in financial wealth explained by gender is 7% in 2002 and increases to about 9% in 2017 before declining to 4% in 2019. Turning to the relevance of gender for IOp in business wealth, we find that its relative contribution amounts to 7% in 2002 and decreases to 4% in 2019.

Overall, we find a diverse pattern of circumstance-contributions within the asset classes. Nevertheless, there are some themes tying the asset classes together: Childhood variables play a large role for all the classes—contributing between 20% and 40%

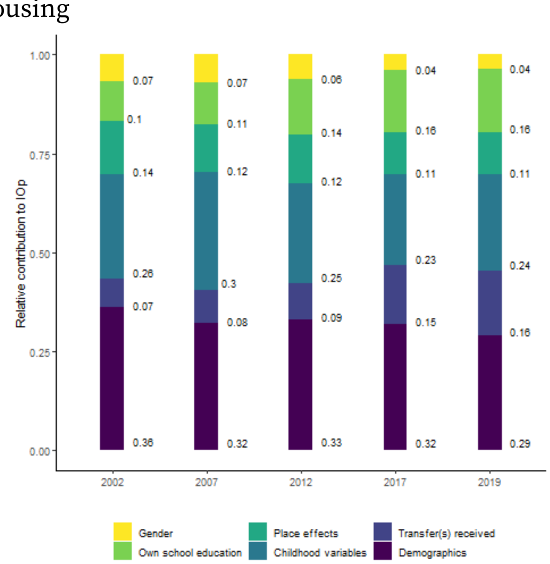
FIGURE 7. The contribution of circumstances to IOp in wealth assets



A. Housing



B. Financial



C. Business

Note: Bar charts of the share of IOp of each wealth portfolio (as measured by the Gini coefficient of the counterfactual distribution) which is accounted for by individual circumstances in each survey year.

depending on the year and class. However, for financial and business wealth, the role of childhood variables diminishes over time. This, in itself, would be an encouraging finding if it were not for the other unifying trend: The contribution of intergenerational transfers to IOp in all the asset classes increases over time.

4.5. Comparison to IOp in gross labor earnings

The comparison of IOp in net wealth to IOp in gross labor earnings reveals stark differences in relative IOp between the two outcomes.

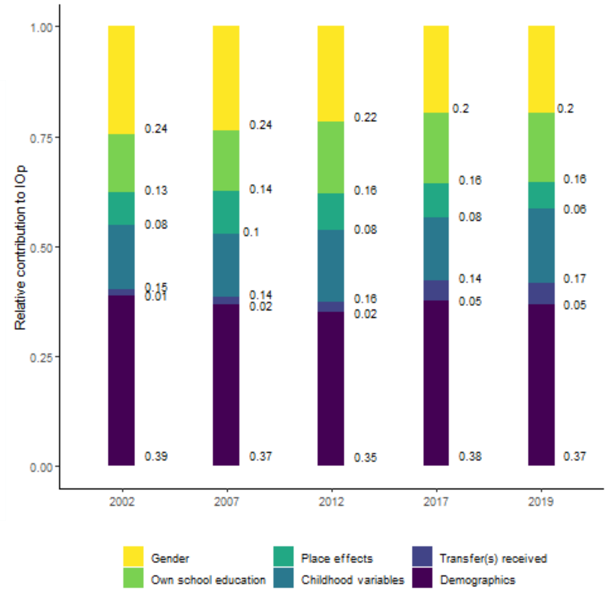
Figure 8 displays the results for gross labor earnings. Note that the sample in the main analysis and this analysis coincide. Figure 8A displays IOp in gross labor earnings from 2002 until 2019. Figure 8B displays the relative Shapley values for IOp in gross labor earnings for each year. Initially, the relative IOp in gross labor earnings is higher than for net wealth in 2002. The value for gross labor earnings is 0.71 whereas it is 0.62 for net wealth. But in contrast to the relative IOp in net wealth, relative IOp is declining for gross labor earnings over time. In 2019, relative IOp is equal to 0.63.

We also find the different sets of circumstances contribute significantly differently to IOp in net wealth compared to gross labor earnings. For instance, gender and education are significantly more important for gross labor earnings than for net wealth. Depending on the year of observation, gender is five to eight times more important for IOp in gross labor earnings than for IOp in net wealth. Similarly, education is two to three times as important for IOp in gross labor earnings than for IOp in net wealth.

On the contrary, the relevance of place effects is approximately half as important for IOp in gross labor earnings as for IOp in net wealth. Similarly, the relevance of childhood characteristics is about twice as large for IOp in net wealth as for IOp in labor earnings. Notably, transfer receipt is not relevant for IOp in gross labor earnings compared to IOp in net wealth. Finally, demographics are of similar importance for IOp in gross labor earnings and for IOp in net wealth.

FIGURE 8. IOp in gross labor earnings

A. IOp



B. Decomposition

Note: In Figure 8A, the blue bars depict the Gini coefficient of the empirical (A.) gross labor earnings and (B.) net wealth distribution in the respective survey years and include orange, percentile-based 95% confidence intervals from 500 bootstrap replicates. The orange bars depict the Gini coefficient of the respective counterfactual distribution, where differences in a) gross labor earnings and b) net wealth are due to circumstances alone. Blue, percentile-based 95% confidence intervals from 500 bootstrap replicates are included. The green connected dots show the IOp ratio, i.e., the Gini coefficient of the counterfactual IOp distribution divided by the Gini of the empirical distribution of the respective outcome. The green vertical bars correspond to percentile-based 95% confidence intervals. Figure 8B displays the relative Shapley values of a Shaplye decomposition of IOp, for each year seperately.

4.6. Sensitivity analysis

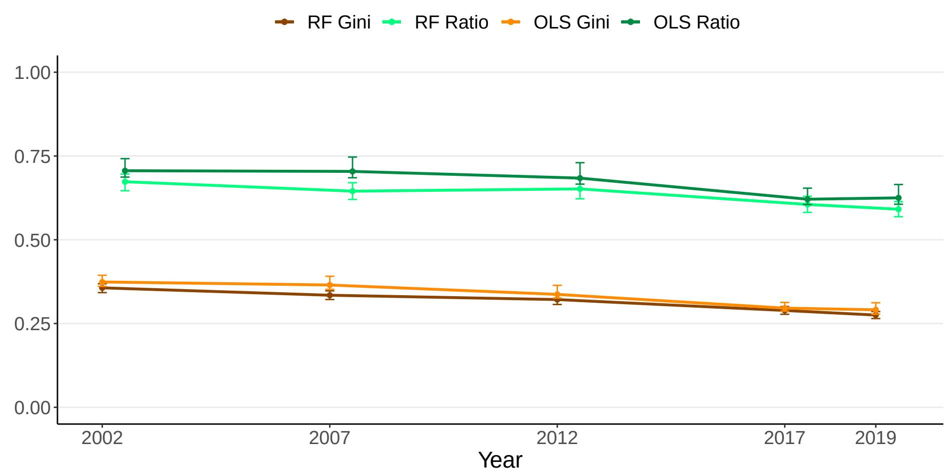
4.6.1. IOp measurement based on regression forests

Until now, we have estimated the counterfactual distribution of net wealth based on the categorization of types via a linear OLS regression, that is, we impute the expected net wealth of a given type based on a linear model of net wealth. As in any econometric application, the correct model specification is not known. For instance, the true model may include interactions or nonlinear terms of the circumstances. The misspecification may lead to incorrect predictions of expected net wealth. To address this, we apply random forests (Brunori, Hufe, and Mahler 2023). Random forests are a convenient method to account for (unknown) nonlinearities and interactions, as the researcher does not have to specify a model ex-ante. The predictions from random forests are based on ensembles of decision trees. Decision trees, in turn, account for nonlinearities and interactions between circumstances via successive partitioning.[15]

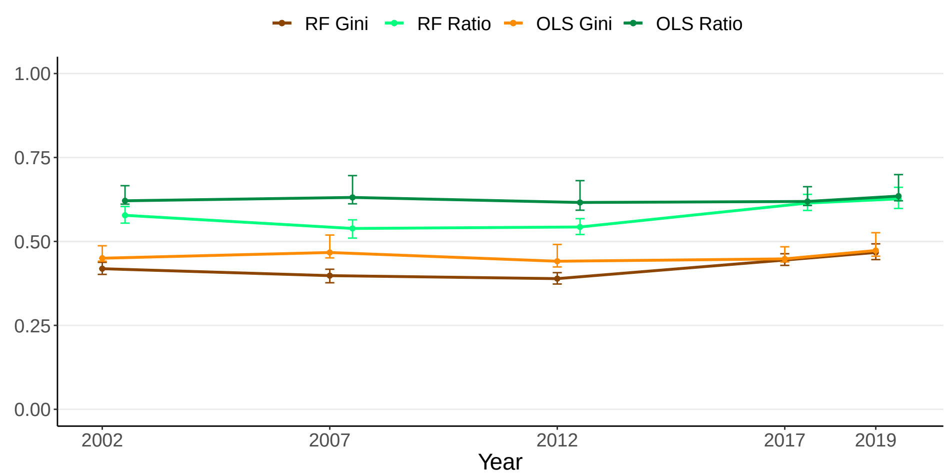
Figure 9 displays the time series for the counterfactual Gini and the relative IOp for gross labor earnings and net wealth based on the random forest predictions. For both gross labor earnings and net wealth, we find that the point estimates do not diverge substantially from the OLS-based estimates in either level or trend. In addition, the associated 95% confidence intervals suggest that the OLS-based estimates generally do not differ statistically from the random forest estimates. We therefore choose to rely on the more parsimonious OLS specification.

[15] For a short description of random forests, please refer to Section C in the appendix. A more extensive treatment is contained in Hastie, Tibshirani, and Friedman (2009). We tune the hyperparameters of the random forests using cross-validated grid search and predict the counterfactual outcomes based on the optimally tuned forest. We use the R package **ranger** (N. Wright, Wager, and Probst 2022).

FIGURE 9. IOp - accounting for non-linearities and interactions



A. Gross labor earnings



B. Net wealth

Note: Time series of absolute IOp and IOp ratio estimates based on regression forests. 95% confidence intervals are computed based on percentiles of 200 bootstrap replicates of the counterfactual IOp Gini for every respective year. Estimates are based on 1000 tree-learners within each forest. Regression forest hyperparameters (*mtry*, *sample fraction*, and *minimum node size*) were optimally tuned using cross-validated grid search.

4.6.2. Alternative inequality measure: MLD

Since most of the literature for IOp in earnings relies on the mean log devation (MLD) as an inequality measure, we replicate our main analysis using the MLD. The MLD belongs to the family of entropy measures and exhibits moderate inequality aversion. Nonetheless, we should caution that all inequality measures have different transfer effects.[16] Further, the MLD cannot handle non-positive values. Thus, the only option for using the MLD is a transformation of the distribution in the range of the non-positive values. We consider two: 1) We set all non-positive values to 1, and 2) we drop all non-positive observations. In this analysis, we also include gross labor earnings, as it is comforting that we can replicate the finding in Peichl and Ungerer (2016) of declining relative IOp in gross labor earnings. Both because of the change in inequality measure and because of the transformation of non-positive values, the IOp exercise is not directly comparable to our main analysis. However, we can identify some broad trends.

Figure 10 shows the absolute and relative IOp using the MLD and setting non-positive values to 1. For earnings, both overall inequality and absolute IOp decline over time, making the trend comparable to the trend we showed in Figure 8A. Overall inequality, however, decreases more strongly than absolute IOp, so that relative IOp increases over time. Yet this increase is rather mild and goes from 0.10 in 2002 to about 0.11 in 2019.

For net wealth, overall inequality rises slightly during our sample period, while absolute IOp stays close to constant with a slight rise at the end of the sample period. As a result, relative IOp remains close to 0.17 over the entire observation period.

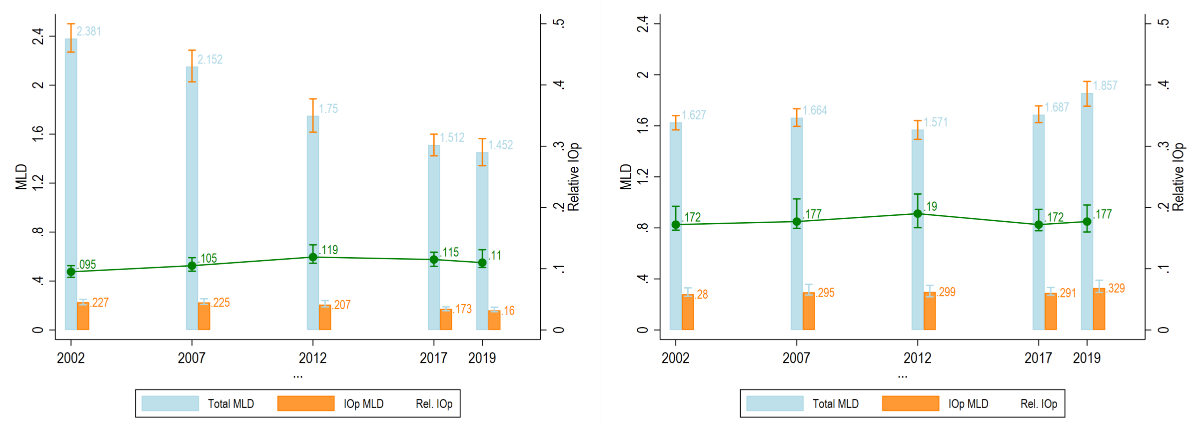
Thus, although for both earnings and net wealth, relative IOp differs strongly in magnitude compared to when we measure it using the Gini, time trends, at least for net wealth, are comparable as relative IOp stays roughly constant.

Figure 11 shows the analogous results for the data where observations with non-positive net wealth values have been dropped. For earnings, this leads to a strong decrease in overall inequality, compared to the distribution where non-positive values were replaced with the value of 1. The MLD now varies between .31 and .34. The absolute IOp is also smaller, but much less than the overall MLD. Relative IOp now starts at a much higher level—roughly 0.47 in 2002—but decreases to about 0.33 in 2019. The trend is now aligned with our main results.

For net wealth, overall inequality has also dropped in all periods, while absolute IOp has declined only slightly. For relative IOp, again, the level has increased now to

[16] This may result in major differences in inequality judgments. Inequality rankings of distributions will not necessarily be consistent across measures.

FIGURE 10. Net wealth IOp measures using MLD—non-positive values converted

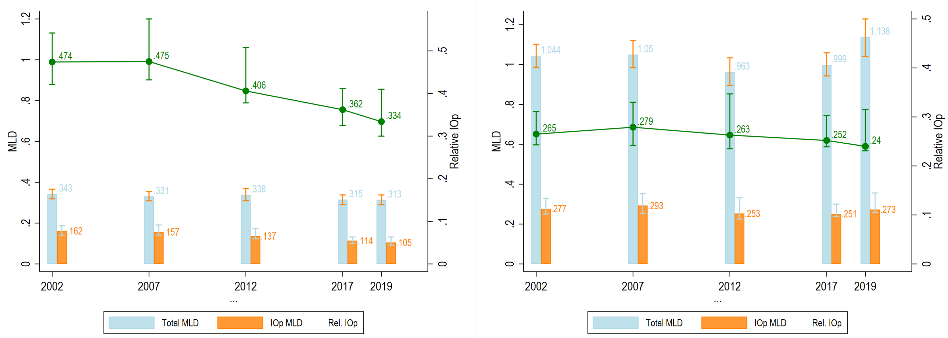


A. Gross labor earnings

B. Net wealth

Note: IOp estimates for (A.) gross labor earnings and (B.) net wealth, using the mean log deviation (MLD) instead of the Gini coefficient as measure of inequality. Since the mean log deviation uses a logarithmic transformation of the values of the distribution, it cannot handle negative or zero values. Therefore, we converted all zero or negative values in both the gross labor earnings and the net wealth distributions to 1. The blue bars depict the MLD of each empirical wealth portfolio distribution in the respective survey years. The orange bars depict the MLD of the respective counterfactual distribution, where differences in respective wealth levels are due to circumstances alone. The green connected dots show the relative IOp, that is, the MLD of the counterfactual IOp distribution divided by the MLD of the empirical distribution of the respective outcome. Percentile-based 95% confidence intervals from 500 bootstrap replicates are included.

FIGURE 11. Net wealth IOp measures using MLD—non-positive values dropped



A. Gross labor earnings

B. Net wealth

Note: IOp estimates for (A.) gross labor earnings and (B.) net wealth, using the mean log deviation (MLD) instead of the Gini coefficient as measure of inequality. Since the mean log deviation uses a logarithmic transformation of the values of the distribution, it cannot handle negative or zero values. Therefore, we dropped all zero or negative values from the sample. The blue bars depict the MLD of each empirical distribution in the respective survey years. The orange bars depict the MLD of the respective counterfactual distribution, where differences in respective wealth levels are due to circumstances alone. The green connected dots show the relative IOp, that is, the MLD of the counterfactual IOp distribution divided by the MLD of the empirical distribution of the respective outcome. Percentile-based 95% confidence intervals from 500 bootstrap replicates are included.

approximately 0.25, but the (absence of a) trend is similar to our main analysis.

For completeness, we show IOp estimations for the sample where non-positive values of earnings and/or net wealth were dropped but using the Gini coefficient as inequality measure in Figure A.3 in the appendix. As expected, both the total Gini and the IOp Gini are smaller in the sample with positive values only. However, relative IOp in net wealth is slightly overestimated compared to the full sample. For earnings, relative IOp is slightly overestimated in the years 2000 and then shows a steeper decline in the years 2010. Again, the overall time trends in IOp both in earnings and net wealth show the same pattern as in our main analysis.

To sum up, we find that the use of the MLD does not result in substantially different trends in terms of the absolute and relative IOp of net wealth.

4.6.3. Including the top wealth sample

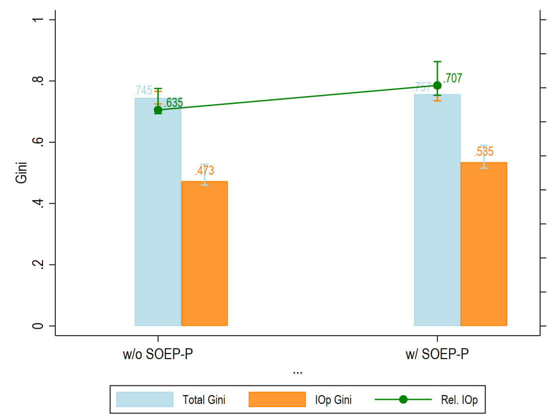
In the main analysis we exclude SOEP-P, a sample of top wealth holders, because it would prohibit us from examining a consistent time series of IOp.[17] However, it is useful to compare our results in 2019 with and without SOEP-P to see whether a more accurate representation of top wealth holders influences our results. This analysis also adds great value to the literature, since it relies heavily on survey data. Typically, due to high opportunity costs or confidentiality concerns, high-wealth individuals are less inclined to voluntarily participate in surveys (Vermeulen 2018; Bach, Thiemann, and Zucco 2019; Schröder et al. 2020b).

Figure 12 shows the IOp results and the contributions of circumstances with and without SOEP-P for 2019, the first year in which the SOEP-P data are available. Panel A. shows that total inequality, as well as absolute and relative IOp, increase when SOEP-P is included. Most noticeably, when we include SOEP-P, relative IOp increases from 0.64 to about 0.71. This change is explained by the starker increase of absolute IOp. Panel B. shows that the main circumstance that gains importance is gender, while transfers and place effects lose importance.

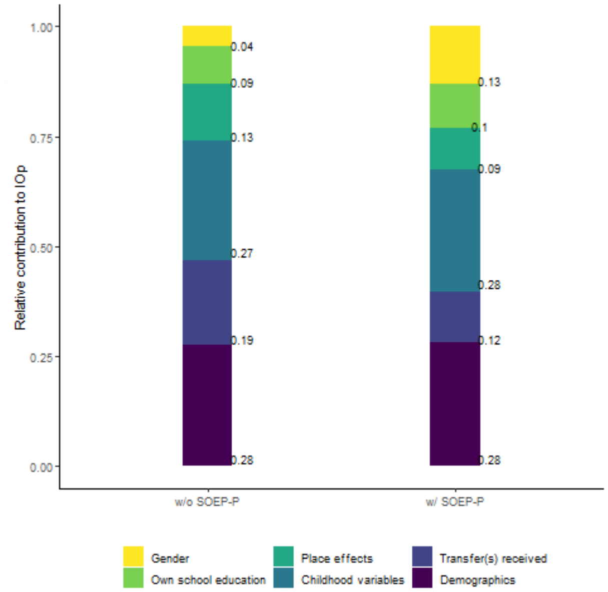
In sum, the inclusion of SOEP-P does not lead to large qualitative changes in our results. Relative IOp increases by a moderate 11%, but it is likely that this would be a time-constant effect that we would find in all periods. This change is driven by an increase in IOp. Thus, we may slightly underestimate the level of absolute and relative IOp in our main analysis. Further, it may be that gender plays a more significant role

[17] Further, use of SOEP-P prohibits the inclusion of body height measurements, as these were not collected for SOEP-P in 2019.

FIGURE 12. Net wealth IOp including top wealth holders



A. Inequality of Opportunity



B. Circumstances' contribution to IOp

Note: Figure A. shows IOp estimates for the year 2019, comparing the usual sample (restricted) to the sample where the SOEP sample P, that is, the group of top wealth holders, is included. The blue bars depict the respective Gini coefficient of the empirical net wealth distribution, with orange confidence intervals. The orange bars depict the Gini coefficient of the respective counterfactual distribution, where differences in net wealth are due to circumstances alone, with blue, percentile-based 95% confidence intervals. The green connected dots show relative IOp, that is, the Gini coefficient of the counterfactual IOp distribution divided by the Gini of the empirical distribution. Figure B. shows the decomposition of IOp using Shapley values for the two respective samples. Note that due to many missing observations, body height has been excluded from the set of explanatory variables used to estimate IOp.

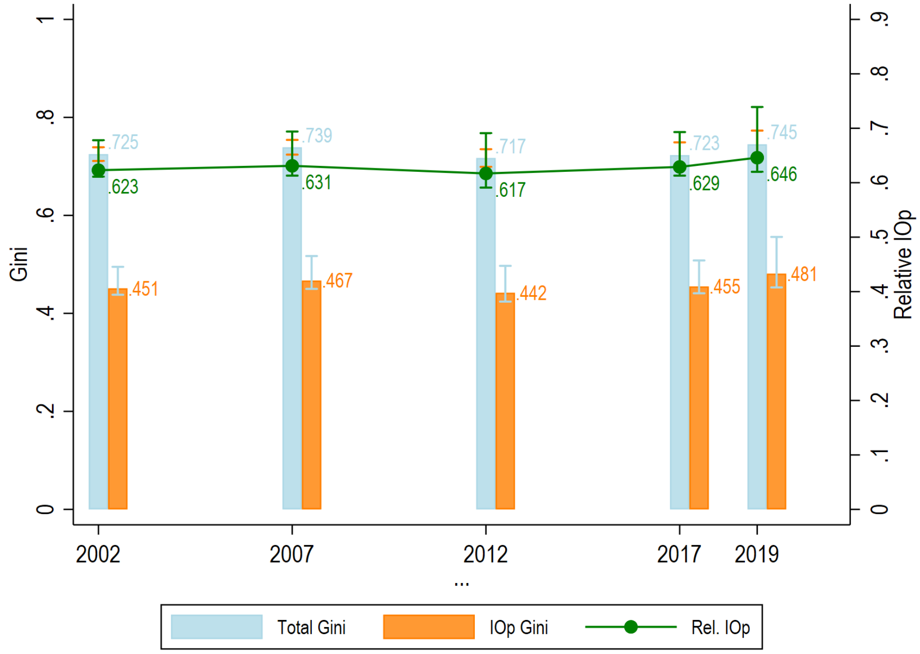
when the top of the wealth distribution is properly accounted for, but that role is still not nearly as large as it is in the case of earnings.

4.6.4. Equal sample size per year

Since we analyze IOp at several points in time, our temporal comparison might be influenced by different sample sizes in the cross-sections. In our analysis, the sample size per cross-section varies between 4,470 (2007) and 7,732 (2017). For larger sample sizes, IOp estimates might be mechanically inflated. To ensure that the variation in sample size does not affect our results, we randomly draw (without replacement) a sample of minimal sample size (4,470) for the years 2002, 2012, 2017, and 2019 and estimate IOp based on this minimal sample size.[18] Figure 13 shows the average IOp estimate after

[18] We are grateful to Daniel G. Mahler for this suggestion.

FIGURE 13. Net Wealth IOp, holding the sample size constant



Note: IOp estimations across survey years, where each year, the sample size is held constant at the minimum sample size of 4,470. For survey years other than 2007 (year with minimal sample size), a random subset of 4,470 observations is drawn without replacement. The orange bars depict the mean IOp estimates from 500 bootstrap replicates. Vertical bars indicate percentile-based 95% confidence intervals associated with 500 bootstrap replicates.

500 iterations of random draws of minimal sample size (for 2007, the estimate from the full sample is shown). Comparing these estimates to those depicted in Figure 2, it becomes clear that the different sample size across years does not have an impact on the results—if anything, the IOp ratio estimates in the analysis with equal sample sizes are minimally higher.

5. Discussion and conclusion

In this paper, we present the first, long-run time series for IOp in net wealth in Germany. We have decomposed IOp in net wealth into its components and contrasted our results to IOp in gross labor earnings. We show that the IOp ratio of net wealth is at a similar level to gross labor earnings at roughly 62%. Unlike gross labor earnings, we do not find a decline in total or relative IOp in net wealth over time.

Discussion. When we decompose the IOp in net wealth and labor earnings into contributions by circumstances, we find that gender contributes between 20% and 24% to IOp in gross labor earnings. For net wealth IOp, the relative contribution of gender is very close to zero, with values smaller than 5%. It stands to reason that the large contribution for earnings reflects wage losses from care work (see, e.g., Kleven, Landais, and Søgaard 2019) as well as gender-based discrimination in labor markets (Blau and Kahn 2017). In addition, there exists evidence that women tend to work less than men to adhere to specific gender norms (Bertrand, Kamenica, and Pan 2015). We have discussed at the outset that wealth is a function of earnings, but far from fully determined by them. Thus, we would expect only partial pass-through of these effects. We have seen that housing wealth contributes the lion's share to observed wealth inequality. When it comes to housing, couples are likely to adhere to an equal sharing rule (Sierminska, Piazzalunga, and Grabka 2019). Thus, for the most important component driving wealth inequality, gender has a muted role. Further, even though women suffer substantial earnings penalties, they generally inherit the wealth of their husbands as they tend to live longer (Regan and Partridge 2013). This is another major force curtailing the influence of gender on wealth inequality (Edlund and Kopczuk 2009).

Childhood variables, such as parental education and occupation, are important for labor earnings but even more so for net wealth, contributing from a fourth to about a third of the IOp Gini. This contribution trended down to a fourth over our observation period. An important mechanism behind this finding may be occupational following, especially among entrepreneurs (Lentz and Laband 1989, 1990). The importance of entrepreneurship for wealth creation and as a driver of wealth inequality has been widely discussed (e.g. Cagetti and De Nardi 2006; De Nardi and Fella 2017), so it stands to reason that the acquisition of human capital with respect to entrepreneurship from one's parents is an important mechanism driving wealth differences. The diminishing influence of parental variables is countervailed by a rise in the contribution of intergenerational transfers to IOp: These explain up to one fifth of the IOp in net wealth. As discussed in Boserup, Kopczuk, and Kreiner (2018), this finding may not only be due the direct effect of the wealth transfers, but also due the associated transmission of savings behavior.

While region of birth plays only a minor role in the IOp in gross labor earnings, it is considerably more important for net wealth. This speaks to the literature on the role of place effects in intergenerational mobility (Chetty, Hendren, and Katz 2016; Chetty and Hendren 2018). Although this literature is not fully conclusive on the causes of place or neighborhood effects, some mechanisms are prime candidates: 1) the functioning of local institutions such as public administration or schools, 2) peer effects and the transfer of otherwise unattainable human and social capital, and 3) the diffusion of relevant information about business and job opportunities within neighborhoods. An other explanation could be the former separation of Germany into the German Democratic Republic (GDR), a former state within Germany's current borders, and the Federal Republic of Germany (FDR). As the GDR was a socialist state, individuals living there had fewer opportunities to accumulate wealth prior to Germany's unification (Fuchs-Schündeln 2008).

Another stark difference we document is the role of individuals' education. While this is an important contributor to IOp in gross labor earnings, its role in IOp in net wealth is much smaller. On the labor market, education either reflects productivity or contains signals about the type of individual. For IOp in net wealth, these two channels are not directly applicable. If anything, education may be relevant for individuals' investment choices. Hence, while the mechanisms of selection on education are very direct for earnings, they are much less direct for wealth.

Finally and unsurprisingly, we find that the age profile contributes more to IOp in wealth than to the IOp labor earnings, emphasizing the important role of the precautionary motive for the cross-sectional inequality of net wealth.

Conclusion. We have documented that the level of IOp in net wealth is high, as the IOp-ratio lies above 62% throughout our sample period. Unlike in the case of earnings, we do not see a declining trend. Based on these data, it appears sensible to infer that unfair inequality in wealth will persist at this high level if its underlying causes are not addressed.

In contrast to our findings for earnings, unfair wealth inequality is driven by intergenerational transfers, parental occupations, and region of birth. These findings are worrying because there exist only a few policy tools to meaningfully address them. The exception are intergenerational transfers, which can be made subject to taxation. Evidence collected by Nekoei and Seim (2023) suggests that wealth differences due to inheritances are persistent and, therefore, wealth taxation may be able to reduce long-run wealth inequality. However, an adequate design of wealth taxation faces many challenges both conceptually and practically, starting with the issue of the assessment of the value of certain wealth items (Bastani and Waldenström 2020). It is unclear how policy makers should address neighborhood effects. Moving everyone to a "good" neighborhood is not feasible. The policy recommendations depend on the source of the neighborhood effects: If the sources are local institutions such as public administration or schools, it may be feasible to improve these in underperforming neighborhoods. If they are peer effects and social capital, straightforward policy solutions may be out of reach. Similar arguments apply to the influence of parental occupations.

Seen from another perspective, our findings also highlight that when policy makers tackle the causes of unfair inequalities in earnings—for example, by addressing the gender wage gap—spillovers to wealth will be small. Since a different set of circumstances determines the IOp in net wealth, a different policy toolkit is required. Accordingly, there are also implicit trade-offs when addressing unfair inequalities: If policy makers focus their efforts on addressing IOp in earnings, they may miss out on the more intergenerationally relevant concept of wealth. Our findings therefore also call for more caution in considering the consequences of certain policy tools.

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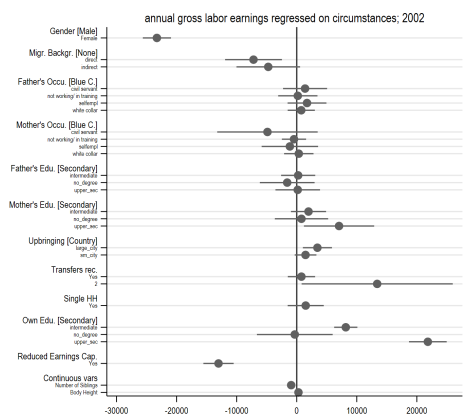
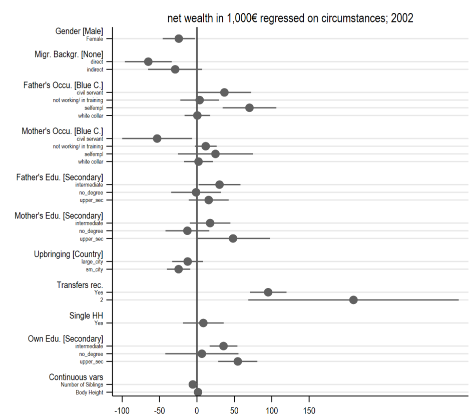
Appendix

A. Figures

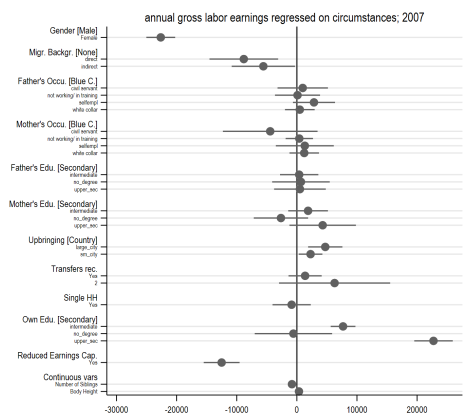
FIGURE A.1. Coefficient plots of gross labor earnings and net wealth regressed on circumstances



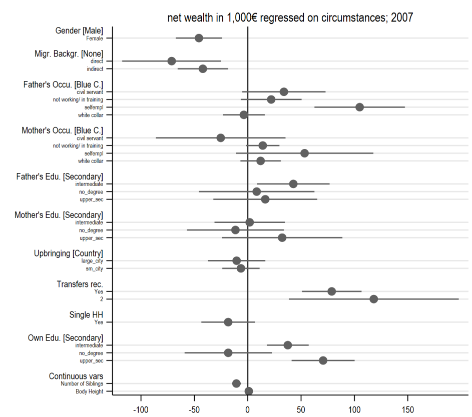
A. Gross labor earnings 2002



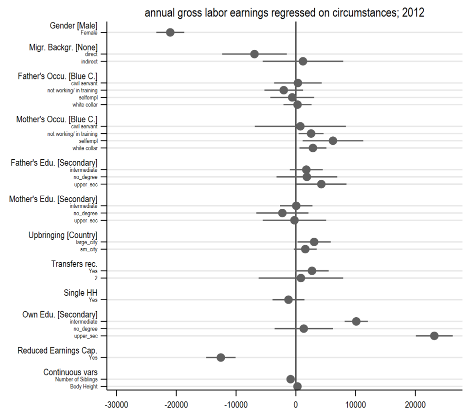
B. Net wealth 2002



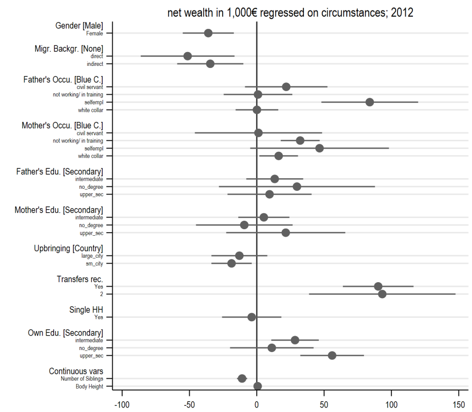
C. Gross labor earnings 2007



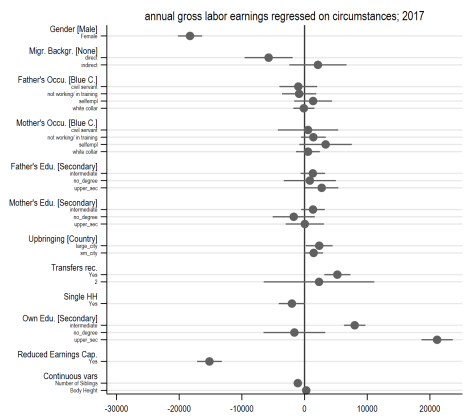
D. Net wealth 2007



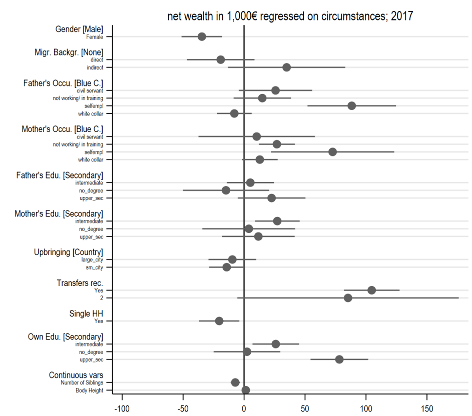
E. Gross labor earnings 2012



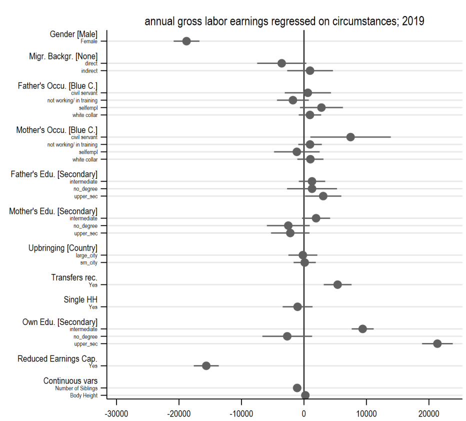
F. Net wealth 2012



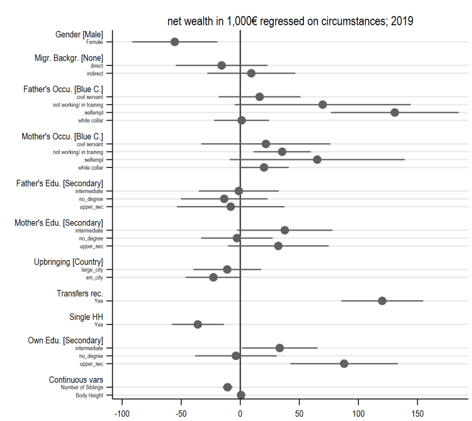
G. Gross labor earnings 2017



H. Net wealth 2017



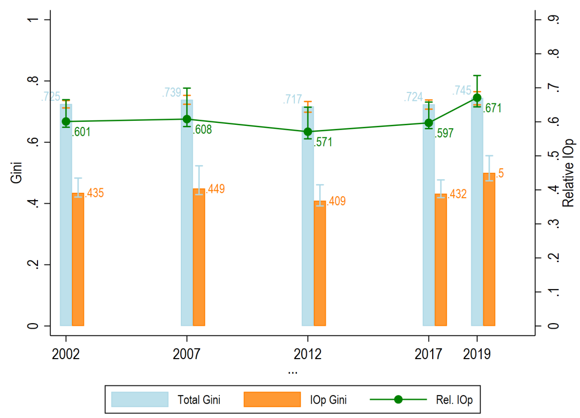
I. Gross labor earnings 2019



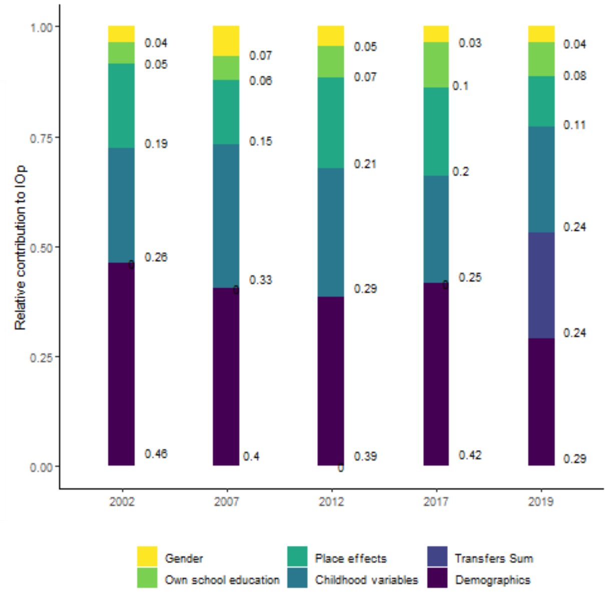
J. NW 2019

Note: Panel A.1 displays the coefficient estimates of gross labor earnings and net wealth (in 1,000s), for each year separately.

FIGURE A.2. IOp estimates considering the sum of inheritance



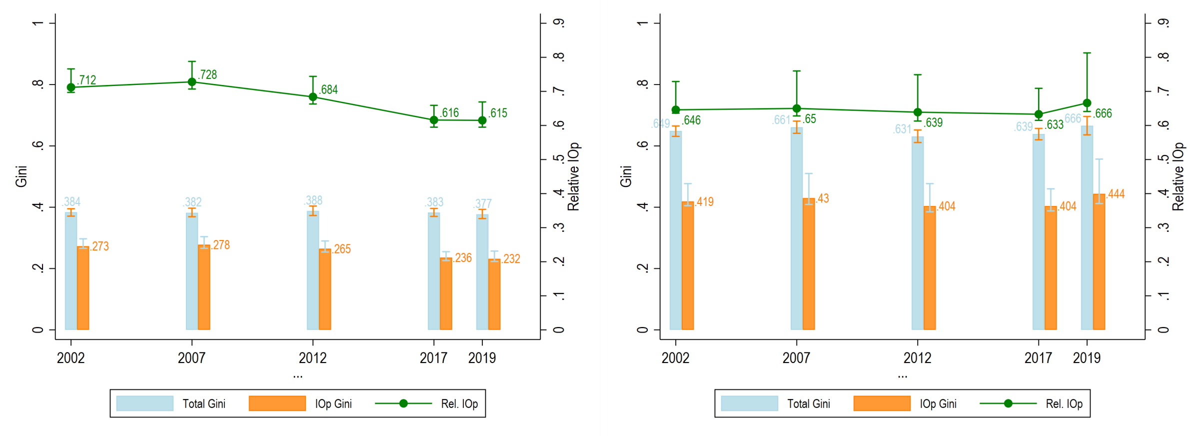
A. Inequality of opportunity estimates



B. Circumstances' contribution to IOp

Note: (a) Estimates of inequality of opportunity using the set of circumstances as defined in base model (demographics, childhood variables, place effects, an individual's own school education, and gender), but specifying the total sum of inheritances/gifts received prior to the respective survey year (instead of a dummy variable indicating whether and individual has received any kind of transfer), adjusted to 2019 prices, as well as their capitalization factor; (b) Shapley decomposition results based on model as specified in (a).

FIGURE A.3. Gini IOp estimates – non-positive values dropped

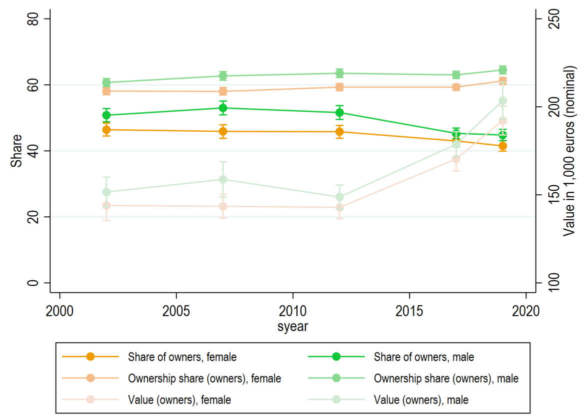


A. Gross labor earnings

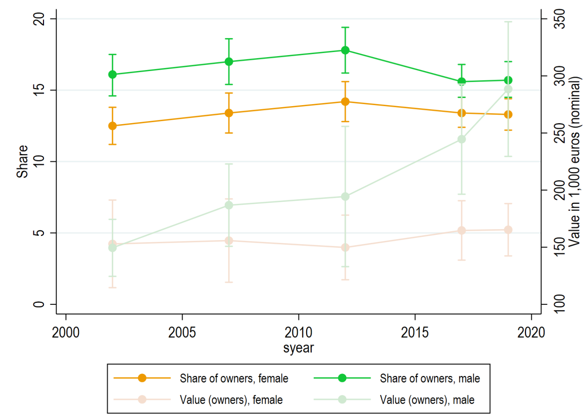
B. Net wealth

Note: Inequality of opportunity estimates for (a) gross labor earnings and (b) net wealth, measured by the Gini coefficient and using a restricted sample where non-positive values have been dropped. The blue bars depict the Gini of each empirical distribution in the respective survey years. The orange bars depict the Gini of the respective counterfactual distribution, where differences in respective wealth levels are due to circumstances alone. The green connected dots show the relative IOp, i.e. the Gini of the counterfactual IOp distribution divided by the Gini of the empirical distribution of the respective outcome. 95% percentile confidence intervals from 500 bootstrap replicates are included.

FIGURE A.4. Housing wealth by gender



A. Primary residence



B. Other real estate

Note: Housing wealth by gender, with respect to (a) an individual's primary residence and (b) other real estate. The darkest estimates depict the share of respondents indicating that they own the respective asset; the lightest lines plot the mean share of value in nominal euros of the respective asset, conditional on being an owner (values are shown on the right y-axis). For the primary residence, the mean share of ownership among owners is shown additionally, i.e. the mean percentage of ownership of joint asset, conditionally on being an owner (the share is equal to 100% for sole ownership). The vertical bars depict 95% confidence intervals.

B. Tables

Table B.2. Summary statistics of pooled sample

	Mean	S.d.	Min.	Max.	Obs.
Outcomes:					
Individual wealth:					
Net wealth	135584.60	333739.71	-720760	15770000	28685
Real estate net wealth	87463.38	192849.85	-129532	5360000	28685
Business net wealth	14639.73	183383.21	0	15000000	28685
Financial net wealth	33481.49	88616.20	-747354	3450000	28685
Gross labor earnings	32738.76	35786.84	0	780000	28685
Circumstances:					
Gender:					
Female	0.53	0.50	0	1	28685
Paternal occupation at age 15:					
Blue collar	0.42	0.49	0	1	28685
Civil servant	0.09	0.29	0	1	28685
Not working or training	0.07	0.26	0	1	28685
Selfemployed	0.12	0.33	0	1	28685
White collar	0.29	0.46	0	1	28685
Maternal occupation at age 15:					
Blue collar	0.20	0.40	0	1	28685
Civil servant	0.03	0.16	0	1	28685
Not working or training	0.40	0.49	0	1	28685
Selfemployed	0.06	0.24	0	1	28685
White collar	0.32	0.47	0	1	28685
Paternal school degree:					
Intermediate	0.20	0.40	0	1	28685

No degree	0.03	0.17	0	1	28685
Secondary	0.61	0.49	0	1	28685
Upper secondary	0.15	0.36	0	1	28685
Maternal school degree:					
Intermediate	0.24	0.42	0	1	28685
No degree	0.04	0.20	0	1	28685
Secondary	0.63	0.48	0	1	28685
Upper secondary	0.09	0.29	0	1	28685
Degree of urbanity childhood:					
Countryside	0.36	0.48	0	1	28685
Large city	0.23	0.42	0	1	28685
Small city	0.41	0.49	0	1	28685
Single parent or orphanage	0.11	0.31	0	1	28685
Own school degree:					
Intermediate	0.49	0.50	0	1	28685
No degree	0.01	0.11	0	1	28685
Secondary	0.23	0.42	0	1	28685
Upper secondary	0.27	0.44	0	1	28685
Reduced earnings capacity	0.11	0.31	0	1	28685
Height in cm	172.36	9.43	120	218	28685
Year of birth	1965.26	12.53	1937	1994	28685
Number of siblings	1.96	1.66	0	17	28685
Transfer received	0.21	0.40	0	1	28685

Monetary values are expressed in 2019 Euros.

Figures are unweighted.

C. Random forest

In the domain of machine learning methods, random forests belong to supervised learning algorithms and are based on regression trees. Regression trees are generated by recursive binary splitting. Intuitively speaking, the algorithm splits the sample along covariates such that the observations in the subsamples, or *nodes*, are as similar as possible with respect to the outcome and as dissimilar as possible across nodes. The prediction is then determined as the mean within the respective nodes. Formally, for every step k, the data D are split into two nodes, $D_{k,L}$ and $D_{k,R}$. The exact split is characterized by the covariate X_j and the threshold associated with this split, $\gamma(k, j)$. Thus, the nodes $D_{k,L}$ and $D_{k,R}$ are defined as follows:

$$D_{k,L} = \{x|x_j < \gamma(k, j)\}; D_{k,R} = \{x|x_j \geq \gamma(k, j)\}. \tag{A1}$$

The predicted values are the mean values of y_i within each node, that is, $\hat{y}_{k,m} = N_{k,m}^{-1} \sum_{i|X_i \in D_{k,m}} y_i$ with $m \in \{R, L\}$. The splitting variable X_j^* and associated threshold $\gamma(k, j)^*$ for each node are determined by minimizing the sum of square errors (SSE) across nodes:

$$\min_{\forall\, x_j \in x \text{ and } \gamma(k,j) \in R_{x_j}} SSE_{k,L} + SSE_{k,R}, \tag{A2}$$

where $SSE_{k,m} = \sum_i^{N_m} (y_i - \hat{y}_i)^2$. The resulting nodes then enter the algorithm again as input. This algorithm terminates if a final number of *leaves* is reached. Clearly, not limiting the size of the tree results in overfitting. In consequence, the size of the tree is typically limited. This usually reduces the variance of the out-of-sample predictions. However, it comes at the cost of increased bias.

To avoid this trade-off, researchers often average across multiple trees. Single trees have low bias but high variance. One way to lower the variance is to average across multiple trees. However, for this to work, the trees must have low correlation. This is typically achieved by training the single trees on bootstrapped samples of the training data and considering only a separate random subset of features at each node. We determine the relevant hyperparameters in 2012, the middle of our observation period. The optimal number of regression trees for our random forests is 400 and the number of variables that are randomly selected at each split is 2. However, the results do not differ significantly if we implement the rule of thumb of $[K^{1/2}]$, where the squared brackets indicate the integer of its argument.

Table B.1. Description of circumstances

Category	**Circumstance**	**Realizations**
Demographics	year of birth	categorical (years 1937 to 1994)
Demographics	reduced earning capability (officially assessed as severely disabled or partially incapable of work for medical reasons)	indicator
Demographics	individual's body height	continuous
Demographics	individual's migration background	categorical (native, direct, indirect migration background)
Transfer(s) received	received transfer (inheritance or gift) prior to year of reference	indicator
Transfer(s) received	sum of transfers (value of inheritance or gift received prior to year of reference), adjusted to 2019 prices and capitalization factor	continuous
Childhood variables	mother's school education	categorical (no degree, secondary, intermediate, upper secondary)
Childhood variables	father's school education	categorical (no degree, secondary, intermediate, upper secondary)
Childhood variables	father's occupation when individual was 15 years old	categorical (blue collar, self-employed, white collar, civil servant, not working or in training)
Childhood variables	mother's occupation when individual was 15 years old	categorical (blue collar, self-employed, white collar, civil servant, not working or in training)
Childhood variables	(partially) raised in single-parent household (at least one year until age 15 spent with single parent or in orphanage)	indicator
Childhood variables	number of siblings	continuous
Place effects	federal state where individual was born	categorical (16 federal states; not born in Germany)
Place effects	urbanization of place of upbringing	categorical (countryside, small or medium city, large city)
Own school education	individual's own school education	categorical (no degree, secondary, intermediate, upper secondary)
Gender	female gender	indicator

Note: Table B.1 displays the description of circumstances use in our analysis. Column (1) displays the categories in which we subsume the circumstances in our decomposition analysis. Column (2) includes the description of the circumstance and column (3) describes the potential realizations of the circumstances. The actual amount of the gifts or inheritances are used only in the alternative specification, in lieu of the indicator for having received a gift or inheritance.