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Inequality of Opportunity in Wealth - Measurement from Germany

Viola Hilbert
(DIW Berlin, Germany)
vhilbert@diw.de

Daniel Graeber
(DIW Berlin, Germany)
dgreaber@diw.de

Johannes König
(DIW Berlin, Germany)
jkoenig@diw.de

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Inequality of opportunity in wealth - Measurement from Germany

Daniel Graeber*, Viola Hilbert†, Johannes König‡

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Abstract

Concerns about the sources of wealth inequality are an important topic in the current debate on wealth inequalities. In this paper, we estimate the ex-ante inequality of opportunity in net wealth for Germany using the Socio-Economic Panel. We show that relative inequality of opportunity in wealth amounts to around 60% for the last two decades. The most important circumstances in inequality of opportunity in net wealth are inheritances or gifts, parental occupation, and the region individuals are born in. These differ considerably from inequality of opportunity analyses focusing on earnings, where gender and individuals' own education tend to be most important.

Keywords: Inequality, Wealth, Inequality of Opportunity.
JEL codes:

*DIW Berlin, CEPA and BSE, German Institute for Economic Research (DIW Berlin), Mohrenstrasse 58, 10117 Berlin, Germany. Email: dgraeber@diw.de.

†DIW Berlin, BSE, German Institute for Economic Research (DIW Berlin), Mohrenstrasse 58, 10117 Berlin, Germany. Email: vhilbert@diw.de.

‡DIW Berlin, German Institute for Economic Research (DIW Berlin), Mohrenstrasse 58, 10117 Berlin, Germany. jkoenig@diw.de.

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1 Introduction

Wealth inequality has increased steadily since the second half of the last century (Chancel et al., 2021). A new branch of research documenting this rise has emerged and has ignited academic and public debates about the underlying causes of wealth inequality (Alvaredo et al., 2017; Saez and Zucman, 2016; Zucman, 2019). Not only is wealth inequality on the rise, but wealth distributions in many developed and developing countries share a common feature: wealth is highly concentrated at the top of the distribution, while the bottom holds almost no wealth at all. For example, in the US the top 10% of the population hold more than 70% of total wealth, while the bottom 50% only hold around 1% (Saez and Zucman, 2016, 2020). These extreme disparities appear worrying, since wealth is one of the crucial factors determining the material well-being of individuals next to income (Davies and Shorrocks, 2000; König et al., 2020). Further, through intergenerational transmission, wealth can determine the material well-being of not just the current but also the next generation (Black et al., 2020; Boserup et al., 2016, 2018).

It is this intergenerational persistence of wealth inequality that is especially concerning. If wealth begets wealth, certain sections of society may be permanently locked out of opportunities to shape their life-course. For example, because of incomplete financial markets due to asymmetric information, individuals with low wealth face credit constraints that prevent them from becoming home-owners or entrepreneurs (Acolin et al., 2016; Nykvist, 2008). Further, as a consequence of not being able to buy a house or start a business and reaping the returns from these choices, individuals with low wealth may not be able to transmit relevant amounts of wealth to their children. Thus, wealth inequality is not just an important economic phenomenon to be studied by academics, but it also matters deeply for our judgement of how capable our societies are to provide opportunities for everyone.

However, not all of the inequality in wealth is necessarily unfair. Cross-sectional wealth inequality also depends on individual's preferences, such as differential willingness to work and save, which most observers would consider fair (De Nardi and Fella, 2017; Hendricks, 2007). Because of this, it is important to focus on that part of the inequality in wealth that can be attributed to characteristics that are beyond an individual's control.

To do this, we make use of the inequality of opportunity (IOp) framework in this paper (Brunori and Neidhöfer, 2021; Ferreira and Gignoux, 2011; Peichl and Ungerer, 2016; Ramos and Van de gaer, 2016; Roemer and Trannoy, 2016). The IOp framework enables us to decompose wealth inequality into two parts: one that can be attributed to an individual's immutable characteristics and a residual that is due to other factors, such as an individual's effort. Thus, the IOp framework delivers precisely what is needed to discern the extent of wealth inequality in the light of fairness considerations.

Until now, wealth has not been the object of study in the IOp literature because of data limitations and methodological hurdles. As concerns data limitations, there are almost no data sets with high quality data 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 income inequality of opportunity do not straightforwardly apply to wealth.

We address the data limitations by relying on the Socio-Economic-Panel (SOEP). The SOEP is a representative panel of German households. Since 2002, this panel contains detailed information on individuals' net wealth. In addition, due to its genealogical design as well as the retrospective information on individuals' biographies, the SOEP provides a rich set of circumstances. We focus on ex-ante inequality of opportunity in net wealth (Ferreira et al., 2011; Ferreira and Peragine, 2016; Ferreira and Gignoux, 2011) and apply the Lerman and Yitzhaki (1985) decomposition to decompose inequality of opportunity in net wealth. We also contrast our results with established results in the literature in ex-ante inequality of opportunity in gross labor income.

We find that inequality of opportunity in wealth, as measured by the ratio of the actual to the counterfactual IOp-Gini coefficient, remains rather stable at around 60% between 2002 and 2019. For gross labor earnings, however, inequality of opportunity has declined over time (from 70% in 2002 to 60% in 2019). Among our standard set of circumstances, i.e. variables determining unfair inequality, we identify inheritances or gifts, parental occupation, and the region of birth as the most important circumstances for wealth inequality.[1] This is in sharp

[1]In addition, both for income and wealth, age accounts for significant fractions of inequality of opportunity, as later discussed.

contrast to our analyses focusing on income, where gender and individuals' own education matter 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 inequality in housing wealth, we find that gender does not matter. However, we find that gender matters significantly for inequality of opportunity in business and financial wealth. Further preliminary analysis confirm that the importance of the region of birth can be explained by East/West differences. That is, individuals born in the former German Democratic Republic (DDR) have lower net wealth.

Interestingly, we find that our approach to measuring inequality of opportunity in wealth is reasonable robust to biases that arise through model-misspecification, i.e., negligence of non-linearities and interactions.[2] To show that, we follow (Brunori et al., 2018) and estimate inequality of opportunity measures from random forests. Random forests are ensembles of regressions trees, which detect non-linearities and interactions via recursive partitioning. Thus the variation of net wealth explained by our set of circumstances via random forests can be thought of as an upper bound of the variation in net wealth that is explainable with our set of circumstances. Comparing the estimates based on random forests and OLS models, we find that the relative bias of inequality of opportunity in wealth of the OLS model, compared to the estimates based on random forests, never exceeds 18.41%. We believe that this provides important guidance for future studies assessing inequality of opportunity in net wealth in Germany.

Related literature examining inequality of opportunity in wealth has been developing in recent years, predominantly in Spain. Salas-Rojo and Rodríguez (2021) calculate ex-ante wealth IOp in Spain (data from the 2014 Spanish Survey of Household Finances) and the US (data from the 2016 Survey of Consumer Finances), finding that the IOp ratio is 69% in Spain and 64% in the US. They use parental education and inheritances as circumstances and find that roughly 60% of total IOp in Spain is explained by inheritances, while it is 72% in the US. The study does not use individual net wealth, but rather the log of gross, financial, or real-estate wealth on the household-level, where gross wealth is the sum of financial and

[2]Since most of our circumstances are operationalized as categorical variables, most of the bias would arise because of neglecting interactions.

real-estate wealth. Further, the authors adjust their wealth measures for gender-specific life-cycle variation from the wealth data and therefore reduce much of the variation in their wealth measures. Palomino et al. (2017) estimate ex-post net wealth IOp in Spain (data from the 2011 Spanish Survey of Household Finances) finding the IOp-ratio to be between 10-12% of observed inequality when measuring inequality using the Gini coefficient. Further, they report that they can attribute more than one third of all inequality to the influence of inheritances. The remaining circumstances are gender and parental occupation.

Our study differs from Salas-Rojo and Rodríguez (2021) and Palomino et al. (2017) in the following respects: 1) We measure wealth at the level of the individual and, thus, can tightly link individual circumstances to individual outcomes. 2) We use a long-running, temporally-consistent database with many circumstances relating to the situation into which individuals were born or in which they grew up, i.e gender, year of birth, place of birth, migration background, place of upbringing, body height, number of siblings, upbringing in a single-parent household, the parents' education, the parents' occupation, whether they 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). 3) We do not exclude non-positive wealth, because we do not impose regression models for the log of wealth. 4) We decompose the observed cross-sectional inequality in wealth into inequality of opportunity and a residual because we do not adjust our wealth measures for gender-specific life-cycle trends. 5) We develop a consistent ex-ante approach that uses circumstances determined at birth or in childhood.

The paper is structured as follows. In Section 2, we introduce the ex-ante inequality of opportunity 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

Roemer (1998) postulates the distinction between *efforts* and *circumstances*, which we can use to decompose an individual's (material) resources into fair and unfair components. We may hold individuals at least partially responsible for their efforts, but we cannot hold them responsible for their circumstances. Thus, differences in resources between individuals with the same set of circumstances are fair, as they have to be due to efforts and, conversely, differences between individuals exerting identical effort, must be unfair, as they are due to differences in circumstances.

Following the IOp literature, we operationalize these concepts by introducing a production function for individuals i's net wealth at time t: wealth y_{it} is a function of circumstances C_i and effort E_{it}. Circumstances, since they are determined at birth or in childhood in our models, are assumed to be unaffected by effort and time-constant, but effort is constrained by individuals' circumstances. Thus, we write:

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

In Equation 1, v_{it} and u_{it} are unobserved error terms. In the literature, these error terms are often referred to as "luck" (Lefranc et al., 2009; Lefranc and Trannoy, 2017). The term v_{it} represents the random variation in effort that is independent of the circumstances C_i and u_{it} the random variation that is independent of circumstances C_i and E_{it}.

In general, the structure in Equation 1 permits the decomposition of the outcome into direct and indirect contributions of effort and circumstances. In this study, we implement an ex-ante approach. Further, we are interested in estimating IOp in wealth as a share of total inequality in wealth. Therefore, assuming additive separability and linearity in $h(\cdot)$ and $E(\cdot)$, we 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. This includes the direct effect and the indirect effect through effort that is constrained by circumstances.

Ex-ante equality of opportunity is realised if all individuals face the same opportunity set, no matter what their circumstances are, and before effort and the outcomes are realized. Thus, the ex ante approached requires only information about the circumstances and no information on effort. Based on the circumstances, we estimate the opportunity set for every individual as the mean of the outcomes, i.e, as $E(y_{it}|C_i)$.

In our application, we estimate ex ante inequality of opportunity as inequality in a counterfactual situation, in which all inequalities are accounted for by differences in circumstances. Ideally, one would like to replace each individual's net wealth with the type specific mean net wealth, where types are defined by combinations of circumstances. We use predictions based on the reduced form depicted in Equation 2, i.e.,

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

where $\hat{\beta}_t$ corresponds to the set of OLS coefficient on our circumstances in a linear regression of net wealth in t on the full set of circumstances. Based on this counterfactual distribution, i.e., the distribution of $\hat{y_{it}}$, we then apply our inequality measure $I(\cdot)$ to this distribution to estimate the absolute inequality of opportunity:

$$\delta_a = I(\hat{y_{it}}). \tag{4}$$

Most importantly, we are interested in the share of inequality of opportunity among the overall inequality in net wealth:

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

Since one of our goals is to contrast the relative inequality of opportunity in net wealth and labor earnings, we also calculate the relative inequality of opportunity in labor earnings.

Throughout, our inequality measure is the Gini coefficient[3]. Typically, researchers rely

[3]Since we are dealing with negative values, we apply the Raffinetti et al. (2015) normalization of the Gini coefficient, to ensure a Gini index with range $[0, 1]$.

on mean log deviations (MLD) to estimate inequality in the respective distributions. However, the support of net wealth distribution includes negative and many zero values. We would discard essential features of the net wealth distribution by relying on the MLD. In the appendix, we also provide results for the MLD.

The strategy described so far provides us with a lower bound of inequality of opportunity because we cannot account for the complete set of circumstances. Additional circumstances will partition the population into more types. This will not cause the between-group inequality to decrease. On the contrary, unless the additional circumstance is not relevant, adding an additional circumstance to our set of circumstances will increase the between-group inequality and hence, the inequality of opportunity estimates (Ferreira and Gignoux, 2011). Thus, our estimate constitutes a lower bound to inequality of opportunity in net wealth.

2.1 Source decomposition of inequality and inequality of opportunity

We are also interested in how the various circumstances contribute to inequality of opportunity. For this, assume that individuals' wealth (income) Y is made up of K components, such that $Y = \sum_{k=1}^{K} Y_k$, where Y_k is the wealth (income) from source k. Lerman and Yitzhaki (1985) show that the contribution of each component to the overall inequality is:

$$G = \sum_{k}^{K} S_k R_k G_k, \tag{6}$$

where $S_k = \mu_k/\mu$ is the share of component k in the overall income (wealth) and G_k is the Gini coefficient of variable k.

$$R_k = cov(y_k, F)/cov(y_k, F_k), \tag{7}$$

is the "Gini correlation" between income (wealth) component k and total income (wealth), where $cov(y_k, F)$ is the covariance of component k with the cumulative distribution of the outcome. (Schechtman and Yitzhaki, 1999) show that the range of the Gini correlation is $[-1, 1]$ for any given marginal distributions. Hence, the Gini correlation R_k determines whether the component k increases or decreases the overall inequality.

We can use this source decomposition for decompositions by wealth components, e.g. housing or financial wealth, but also for decompositions with respect to the circumstances in the wealth production function.

3 Data

For our analysis, we rely on the SOEP. The SOEP is a representative panel survey of households in Germany. Since 1984, German households and their members are interviewed about their living conditions on a yearly basis. In the SOEP, the household members are interviewed about their economic situation, education, and attitudes, among others. Today, it includes about 15,000 households with 30,000 individuals (Goebel et al., 2019; Schröder et al., 2020). We use version 36 of the SOEP.[4]

The SOEP is the uniquely suited to conduct our analysis: First, the SOEP contains information on the respondents' earnings as well as wealth. Otherwise, we would have to rely on different data sources, which would call for the the harmonization of all focal variables across these dataset. This would limit potential comparisons. Second, the genealogical design and the biographical information permit us to use a wide range of circumstances to investigate ex-ante inequality of opportunity of earnings and wealth. Individuals in SOEP households are interviewed as soon as they turn 18 and are followed thereafter, even if those individuals move out and form new households. Moreover, since 2002, individuals in the SOEP and new entrants into the SOEP respond to a bibliographical questionnaire. For these two reasons, we rely on an unusual rich set of circumstances. Third, the SOEP is the only dataset for Germany that records assets and liabilities on the level of the individual enabling the construction of *indvidual* net wealth.

Our main outcome is individuals' net wealth. Since 2002, the SOEP infers individuals' wealth with a special wealth module every five years and, out of schedule, in 2019. In the individual wealth module, individuals are asked to provide information on their assets, which comprises 7 assets: the primary residence, other real estate, financial assets (bonds, shares,

[4]DOI: 10.5684/soep.core.v36eu.

and other financial instruments), building-loan contracts, life and private pension insurance, tangible assets, and business wealth. The SOEP introduced vehicles as an eigth asset in 2019, however, we disregard it for temporal consistency. To derive an accurate individual measure of wealth, respondents are asked about their individual share of real estate and businesses. The wealth module also records , individuals are also asked about three classes of liabilities: outstanding debt on the primary residence, outstanding debt on other real estate, and consumer debt. A fourth liability class was introduced in 2019: student loans. Again, for temporal consistency reasons we disregard student loans when constructing net wealth. Net wealth is gross wealth computed from all asset classes minus debts computed from the liability classes. We adjust individuals' net wealth to 2019 Euros.

Our second outcome that we use to compare inequality of opportunity in wealth to is individuals labor earnings. Yearly labor earnings comprise wages as well as salaries from all employment including training, primary and secondary jobs, and self-employment. It also includes income from bonuses, overtime, and profit-sharing.[5] Labor earnings are measured in 2019 Euros.

When it comes to the choice of circumstances, it is not innocuous to distinguish between circumstances and effort. At its core, it is a normative decision. At the one extreme, some would limit the set of circumstances to a bare minimum and would allocate most factors into the realm of individual responsibility, i.e., effort. Others would view the individuals' abilities to make real choices as restricted by social circumstances. Thus, most factors would be considered circumstances in this latter case (Ferreira and Peragine, 2016). We decide to label those characteristics circumstances which have been labelled as most unfair in Western societies. These are the migration background, gender, and the family background (Ferreira and Peragine, 2016; Roemer, 1993). In addition, we also deem factors influenced by decisions that are taken before individuals reach the age of legal consent as circumstantial, consistent with (Roemer and Trannoy, 2016). One example is individuals' own educational accomplishments at the age of consent. In our base model, the circumstances we use to determine the types are gender (two categories: female and male), migration background (three categories: none, direct, and indirect), place of birth in Germany (indicator variable of 16 federal

[5]We use labor earnings as provided by the personal equivalence files.

states), year of birth (indicator variable), body height, the number of siblings, the father's occupation at age 15 (five categories: blue collar, white collar, civil servant, self-employed, and not working/in training), the mother's occupation at age 15 (same five categories as for the father), the place where the individual spent most of their childhood up to the age of 15 (three categories: in the country, small or medium city, and large city), whether the individual has received an inheritance or gift, whether the individual was (partially) raised by a single parent or in an orphanage until the age of 15, the father's educational level (four categories: no degree, lower secondary, intermediate, and upper secondary), the mother's educational level (same four categories as for the father), and the individual's own education (same four categories as for the parents' education).

In a different model specification, we also include the logarithm of the price-adjusted total sum of inheritances or gifts received, taking into account their capitalization factor[6].

Since we compare our results on net wealth with those based on gross labor earnings as outcome of interest, we restrict the sample to the population of working age (25-65 years old). Further, we restrict the sample to full item response on the outcome and all circumstances in the base model. The resulting summary statistics are displayed in Table 1.

4 Results

In the following, we present the first complete results for inequality of opportunity in wealth and income in Germany. In Section 4.1, we present the first measures of inequality of opportunity for both gross labor earnings and net wealth for Germany. In Section 4.2, we decompose the relative inequality of opportunity into sources based on circumstances and in section 4.4 we decompose by sources based on the portfolio composition.

4.1 Evolution of the IOp ratios of income and wealth

In a first step, we regress gross labor earnings and net wealth on the set of circumstances. The regression output is shown in Panel 8 in the appendix.

[6] To avoid losing observations where the sum of inheritances/gifts is 0 and its logarithm is not defined, we add 1 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.

Based on the estimated production functions, we predict the counterfactual distributions in net wealth and gross labor earnings, calculate the Gini for each distribution in each year and plot the IOp ratio (Gini coefficient of the counterfactual distribution divided by the Gini coefficient of the empirical distribution). Figure 1a and 1b display the results. In both figures, the blue bars display the Gini for the complete distribution and the orange bars display the Gini for the counterfactual distribution. We apply bootstrapping to report 95% confidence intervals, using 500 bootstrap replications.

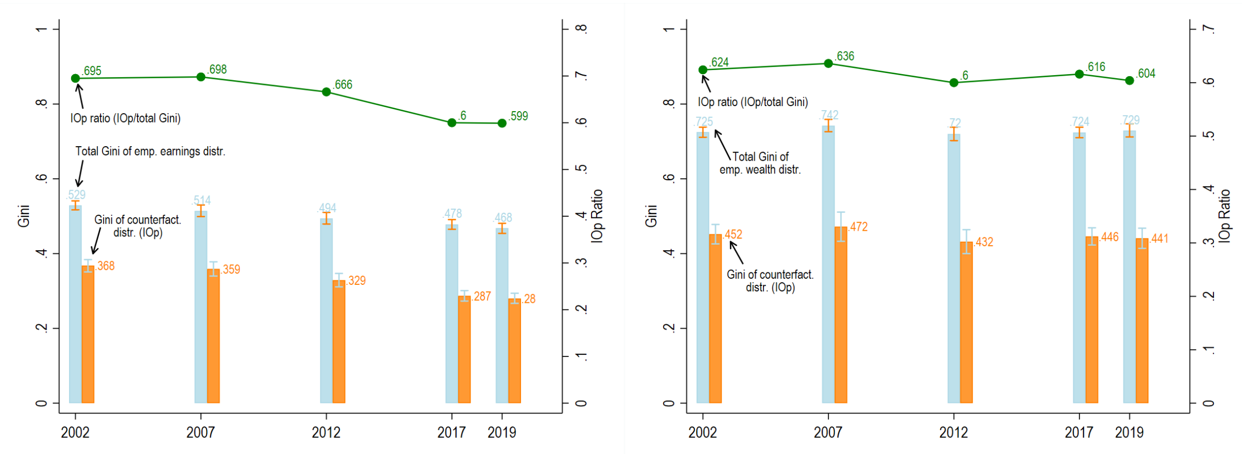
Total inequality in gross labor earnings is lower than for net wealth. Figure 1a shows that the Gini for the gross labor earnings, displayed by the blue bars, lies around 0.5 for the years 2002 to 2019. In contrast, for net wealth the Gini ranges around 0.7 for the same interval. Inequality in gross labor earnings declined between 2002 and 2019, while it remained at roughly the same level for net wealth. Figure 1a shows that total inequality in gross labor earnings declined from roughly 0.53 in 2002 to close to 0.47 in 2019. In Figure 1b, the total inequality is very stable at values close to 0.72 from 2002 and 2019.

Inequality of opportunity, i.e. the counterfactual Gini coefficient, is larger for net wealth than for gross labor earnings. Comparing the orange bars in Figure 1b and 1a, we observe that for all years, the absolute inequality of opportunity is larger for net wealth than for gross labor earnings. While the Gini values for absolute inequality of opportunity in gross labor earnings range from .28 to .37 between 2002 and 2019, the values for net wealth in the same time period range from 0.43 to 0.47. Moreover, while the absolute inequality of opportunity declined for gross labor earnings, we cannot observe a statistically significant decline in absolute inequality of opportunity for net wealth.

Turning to our statistic of interest, we see that the evolution of total and absolute inequality of opportunity result in a decline in relative inequality of opportunity in gross labor earnings, while relative inequality of opportunity in net wealth remains stable. In 2002, the IOp ratio was approximately 0.70 for gross labor earnings declining steadily to about 0.60 in 2017 and 2019. For net wealth, the relative inequality of opportunity was approximately 0.62 in 2002 and remains around 60% in every year that we observe[7].

[7]Specifying the logarithm of the total sum of inheritances/gifts instead of a dummy variable for having received any kind of transfer hardly changes the results, as can be seen in the appendix, Figure 9a

Figure 1: Inequality of opportunity



(a) Gross labor earnings

(b) Net wealth

Note: 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 confidence intervals drawn from 500 bootstrap iterations. 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 confidence intervals from 500 bootstrap iterations 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.

4.2 Decomposing inequality of opportunity

In order to disentangle the influence of various circumstances on gross labor earnings and net wealth inequality, we particularly focus on the role of gender, individuals' own school education, and whether they have received an inheritance or gift. We group the remaining circumstances into three categories: demographics (migration background, year of birth, body height); childhood and parental background (parents' education, parents' occupation, number of siblings, and whether and individual was (partially) raised in a single parent household); and place effects (federal state where the individual was born and degree of urbanization of the place of upbringing).

Comparing the contributions of circumstances on gross labor earnings and net wealth, we find considerable differences. For instance, as Figures 2a and 2b show, gender contributes substantially to inequality of opportunity in gross labor earnings, accounting for about 40% of relative inequality of opportunity in 2002. This contribution declines to about a third in 2017/2019. In contrast, gender does not contribute meaningfully to inequality of opportunity in net wealth in all years of our time series.

Demographics, and particularly the year of birth, appear to be crucial for inequality of opportunity in net wealth (accounting for 39-52% of IOp), but less so for gross labor earnings (24-33%)). For net wealth, age, captured partially by the year of birth, reflects differences in life-cycle savings and insurance motives. Accordingly, the contribution due to the year of birth also reflects a deterministic component stemming from the different positions individuals take along the course of their life.

Individuals' education matters more for inequality of opportunity in gross labor earnings than for net wealth. For gross labor earnings, one's own education accounts for approximately 19% in 2002 and increases to 26% in 2019. The same figures for net wealth are 3% and 12%, respectively. This is intuitive, as income is more tightly linked to human capital (Heckman et al., 2006). Note, however, that for both income and wealth education becomes are more important circumstance over time.

Other important differences include place effects, i.e. the region of birth and degree of urbanization of the place where an individual spent most of their childhood. We observe that place effects matter strongly for net wealth but less so for gross labor earnings. For net wealth, the contribution of place effects is 15% in 2002 and declines to 11% in 2019. For gross labor earnings, the contribution is about 4-8% throughout the years.

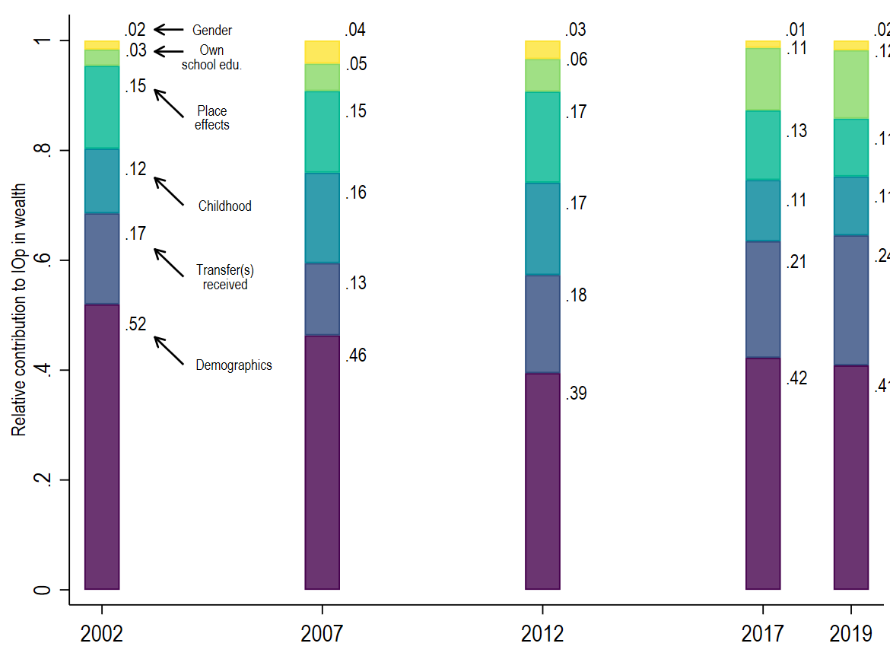
Childhood and parental background include parents' education, parents' occupation, number of siblings, and whether and individual was (partially) raised in a single parent household as circumstance variables. Here, we observe a similar pattern as for place effects – while their contribution to inequality of opportunity in gross labor earnings only amounts to 3-7% for all survey years, they explain up to 17% of inequality of opportunity in net wealth.

Turning to inheritances, we find that inheritances play an important role in explaining relative inequality of opportunity in net wealth. The explanatory power of inheritances increases from about 17% in 2002 to 24% in 2019[8]. For internal consistency, we include inheritances also for our model for gross labor earnings and, unsurprisingly, it explains fairly little.

[8]Specifying the logarithm of the total sum of inheritances/gifts instead of a dummy variable for having received any kind of transfer leads to a more pronounced increase from 12% in 2002 to 28% in 2019 (see Figure 9b)

Figure 2: Circumstances' contribution to IOp

(a) Gross labor earnings



(b) Net wealth

Note: Stacked bar charts of the share of inequality of opportunity (Gini coefficient of the counterfactual distribution) that is accounted for by respective circumstance in each survey year. The category 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 and individual was (partially) raised in a single parent household. The circumstances federal state in which one was born and degree of urbanization of the place of one's upbringing are grouped into the category place effects.

4.3 Life-cycle trends in cross-sectional IOp estimates

Figure 2 illustrates that the year of birth is one of the most relevant circumstances in explaining inequality of opportunity both in gross labor earnings and in net wealth. Between 33% and up to 42% of IOp in net wealth is accounted for by the year of birth alone, while this share ranges between 15% and 21% for IOp in gross labor earnings.

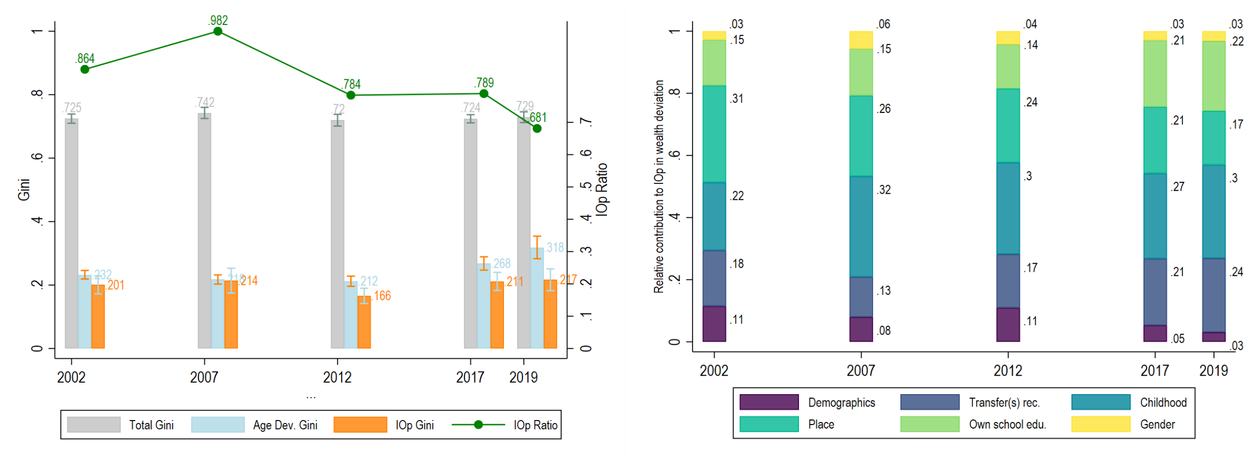
Arguably, an individual cannot be held responsible for the year that they were born in. Accordingly, we define year of birth as a circumstance. However, the year of birth included in our regression analyses most certainly captures both age, i.e. life-cycle effects, in addition to cohort effects. Thus, inequality between types also arises from the fact that we compare individuals of different ages (within the working age population). These differences can arise even in a setting with no inequality in life-time resources.

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 from all years and then regressing net wealth on age and age square. 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 3. As illustrated in Figure 3a, 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 the inequality of opportunity ratio. However, the estimates also vary to a larger degree across survey years, with estimates ranging between 68% and 98%.

Turning to Figure 3b, it is not surprising that demographics (migration background, body height, and remaining effects of year of birth, notably cohort effects) are now less relevant for inequality of opportunity, contributing between 3% and 11% to inequality of opportunity. In contrast, childhood variables and place effects are significantly more important, both individually accounting for up to 30% of inequality of opportunity depending on the year. Individuals' own school education is also notably more relevant, with its contribution ranging from 15% to 22%. Importantly, our finding that transfers explain up to a fourth of inequality

Figure 3: Inequality of opportunity in net wealth, net of age trend



(a) Inequality of opportunity estimates

(b) Circumstances' contribution to IOp

Note: Figure (a) shows inequality of opportunity 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 teal confidence intervals drawn from 500 bootstrap iterations. The blue bars depict the Gini coefficient of the distribution of deviations in net wealth from predicted wealth levels, given individuals' age, with orange 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 confidence intervals. The green connected dots show the IOp ratio, i.e. 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 Lerman and Yitzhaki (1985) decomposition of inequality of opportunity in the age deviation distribution into the standard set of circumstances.

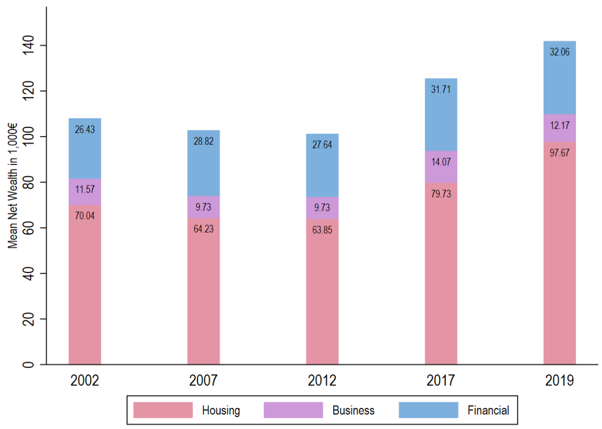
of opportunity and that their contribution to IOp is increasing over time remains robust to this alternative model specification.

4.4 Decomposition of wealth inequality by portfolio components

To understand whether inequality of opportunity 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 housing net wealth, i.e. financial assets (stocks, bonds, etc.), building-loan contracts, life and private pension insurance, tangible assets, and consumer debts.

Figure 4 shows the shares of the asset-specific contributions to the total net wealth Gini

Figure 4: 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.

coefficient, obtained by the Lerman and Yitzhaki (1985) decomposition. By far the most important wealth asset is housing: housing net wealth inequality accounts for around 73-76% of overall net wealth inequality in the years 2002 to 2017. This share increases even further to 78% in 2019. Business and financial wealth are nearly equally important, explaining between 11 to 15% and 11 to 16% of total net wealth inequality, respectively.

We compare total inequality in each of the three wealth assets to their respective relative inequality of opportunity estimates. Figure 5a 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. Total inequality of opportunity in housing wealth hovers around Gini estimates of 0.44-0.47 for survey years 2002-2019. Hence, similar to our results for total net wealth, relative inequality of opportunity amounts to around 60% for housing wealth.

We observe very similar results for financial wealth (see Figure 5b). Total inequality in financial wealth is measured at Gini coefficient levels of around .75. Total inequality of opportunity peaks at 0.47 in 2007, with relative inequality varying between 58% and 62%

For business wealth, we find results that are completely divergent from those for the previous two components. As illustrated in Figure 5c, total business wealth inequality remains steady at Gini levels of 0.99 form 2002 to 2019, a score of near-perfect inequality, since the maximum possible value the Gini coefficient can take on is 1[9]. The mechanism relevant to these findings is the extensive margin, because most respondents do not own any business wealth. Total inequality of opportunity in business wealth peaks in 2007 at a Gini estimate of 0.68, and then slightly declines until 2017, where we measure a Gini level of 0.59. Relative inequality of opportunity varies around values of 60-69% in all survey years.

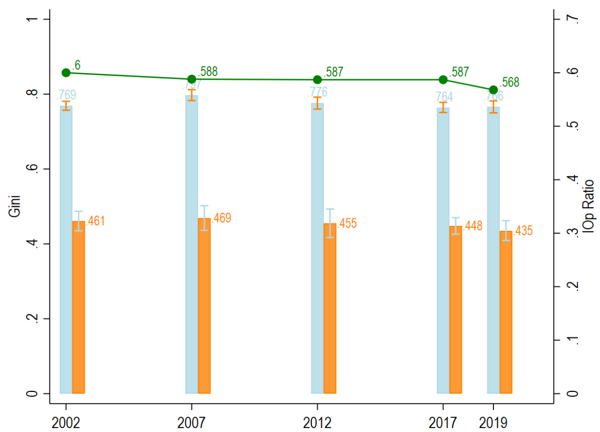
Finally, we decompose each of the three wealth assets' inequality of opportunity into single circumstances, to assess their respective influence. Again, we distinguish between six (groups of) circumstances: gender, individuals' own school education, having received an inheritance or gift, demographics (migration background, year of birth, body height), childhood and parental background (parents' education, parents' occupation, number of siblings, and whether and individual was (partially) raised in a single parent household), and place effects (federal state where the individual was born and degree of urbanization of the place of upbringing). The results are shown in Figures 6a, 6b, and 6c.

First, demographics do not matter equally for the different wealth assets. While around half (46-56%) of inequality of opportunity in net housing wealth is explained by individuals' demographics, this figure amounts to around 30% for business wealth in most survey years. It seems clear that the year of birth plays an important role for net housing wealth, since in a typical life-cycle trajectory, an individual purchases or inherits a house after completing their education and pursuing a more stable professional life. In the absence of large capital endowments, the house will be paid for with a mortgage that is continuously paid off over time, leading to higher net wealth. Alternatively, if a house is inherited, this typically happens when the parents die, i.e. rather later in life. The role of year of birth for business wealth, in contrast, is much less straightforward. When it comes to financial wealth, the share of inequality of opportunity explained by demographics decreases from 48% in 2002 to 37% in 2019.

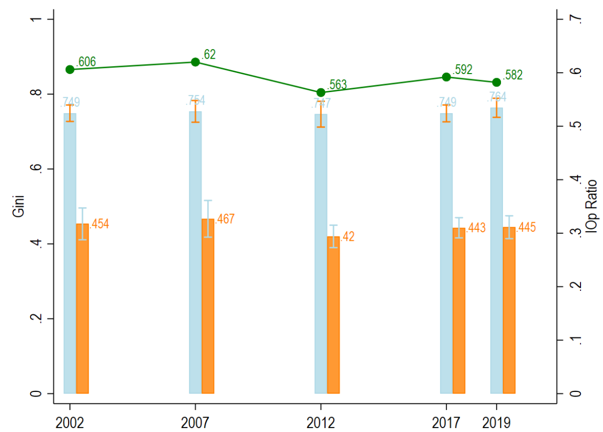
Second, we find that inheritances are most important for housing wealth. Between 15%

[9]As mentioned in section 2, we normalized the Gini coefficient to ensure it lies in the interval $[0, 1]$ in spite of negative values in the empirical wealth distribution.

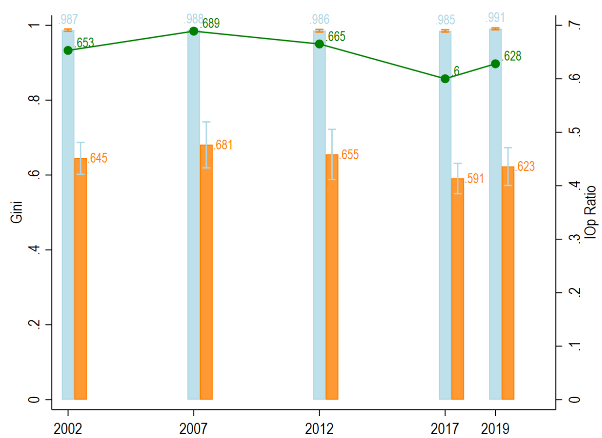
Figure 5: IOp in Wealth Assets



(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 confidence intervals drawn from 500 bootstrap iterations. The orange bars depict the Gini coefficient of the respective counterfactual distribution, where differences in respective wealth levels are due to circumstances alone. Blue confidence intervals from 500 bootstrap iterations 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.

and 24% of inequality of opportunity in housing is attributed to having received an inheritance or gift. For business wealth, this share amounts to 11% in 2002 and steadily rises to 20% in 2019. This increase in the role of transfers for inequality of opportunity is even more pronounced for financial wealth, with only 7% of IOp explained by inheritances in 2002, as opposed to 19% in 2019.

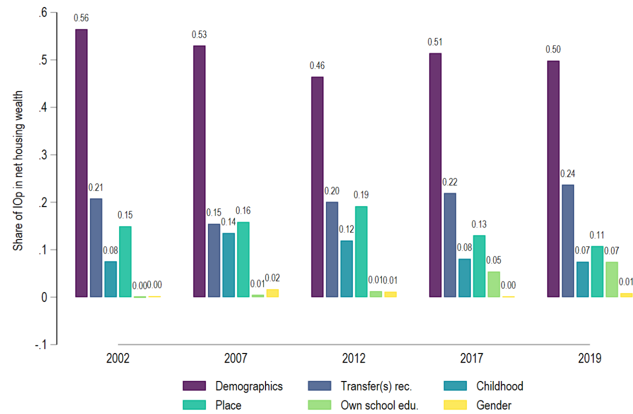
Third, the role of childhood and parental background in explaining inequality of opportunity also varies significantly across wealth assets. While between 7% to 16% of inequality of opportunity in both housing and financial wealth are explained by childhood circumstances, this share ranges between more than 22% and 35% for business wealth. This finding suggests that, beyond inheritances or gifts received from parents, their education and occupational status might influence the children's human capital as well as cultural norms and values, leading to markedly different business wealth accumulation.

When it comes to place effects, i.e. the federal state where an individual was born, as well as the degree of urbanization of the main place of upbringing, we observe a contribution of between 11% to 19% to inequality of opportunity in housing net wealth. The influence on IOp in financial wealth is a bit lower, with shares ranging from 7% to 14%. The higher influence of place effects on IOp in housing wealth can be explained by the distinct role of the urbanization variable. In regression analyses not shown here, we can observe that being brought up in the countryside (as opposed to small or medium cities) is significantly associated with much higher housing wealth, while we do not see any significant effects of the degree of urbanization on financial wealth. For business wealth, however, place effects are hard to grasp. Figure 6c shows that in 2019, place effects account for 17% of inequality of opportunity in business wealth, whereas they are an equalizing factor in the years 2002, i.e. the share of its contribution to inequality of opportunity is negative.

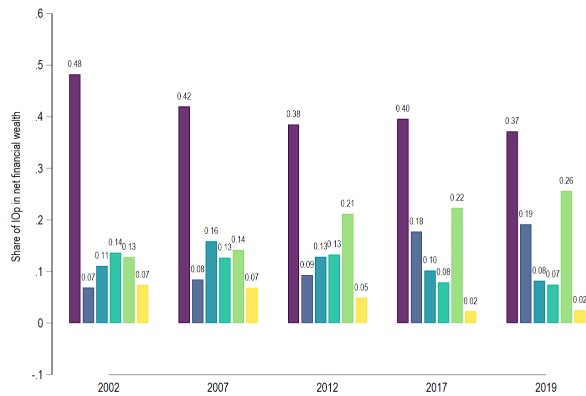
Individuals' own education hardly matters for inequality of opportunity in net housing and business wealth. Since housing wealth is often the result of life-cycle accumulation or inheritance, this result appears intuitive. Education accounts for 13% to 26% of inequality of opportunity in financial wealth, however, with its contribution rising over time. This is also intuitive, because participation and success with respect to financial investment are correlated with cognitive ability (Guiso and Sodini, 2013).

Gender contributes nearly nothing to inequality of opportunity in net housing wealth. This is likely due to the fact that couples in Germany most often adhere to an equal sharing rule when it comes to housing wealth, i.e. each partner owns 50% of the commonly owned and inhabited real estate. For instance, Sierminska et al. (2018) show that in 2012, men are more likely to own their house than women, but only by about four percentage points (40% of men lived in owner-occupied property, while this share amounts to 36% for women). In contrast, gender plays a moderately important role for financial wealth. As illustrated in Figure 6b, the share of inequality of opportunity in financial wealth explained by gender amounts to 7% in 2002 and 2007, but declines continuously to around 2% in 2017 and 2019. A possible explanation for this decline lies in changing gender norms and increasing financial literacy of women, but it would also be plausible that more intergenerational transfers take on the form of financial assets than used to be the case, and that these are inherited in equal parts by sons and daughters. Yet another pattern of gender emerges when analyzing inequality of opportunity in business wealth. Considering Figure 6c, it becomes evident that gender explains around 20% and more of inequality of opportunity in business wealth, in survey years 2007-2017.

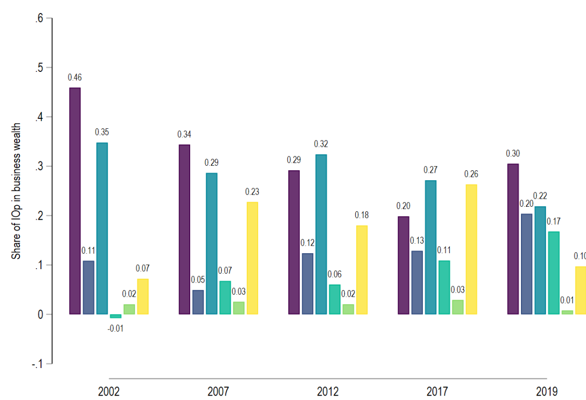
Figure 6: Circumstances' contribution to IOp in wealth assets



(a) Housing



(b) Financial



(c) Business

Note: Bar charts of the share of inequality of opportunity 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. Note that the contribution of individual circumstances to IOp can be negative, i.e. inequality reducing.

4.5 IOp measurements based on regression trees

Until now, we have estimated the counterfactual distribution of net wealth via parametric, linear OLS models, e.g., we impute the types' expected net wealth with the values predicted by the estimates of the OLS model. However, the correct model specification is not known. Potential interactions between our circumstances and non-linearities could be relevant in the correct model. In addition, the functional form could vary over the years. We estimate random forests to investigate whether misspecification is an important issue for our analysis (Brunori et al., 2018). The predictions from random forests are based on ensembles of decision trees. And decision trees allow to account for non-linearities and interactions between circumstances via successive partitioning. [10]

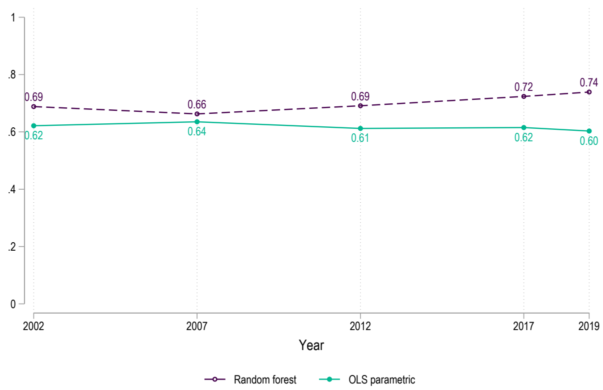
Our results show that potential misspecification does cause modest biases in our IOP estimations for net wealth. Figure 7a displays the time series for our Gini IOp ratio based on the OLS as well as the RF predictions. Throughout, the IOp ratio based on RF predictions lies above IOp ratio based on OLS predictions. Further, while the ratio based on the OLS model suggests no trend over time in net wealth IOp, the RF based estimates suggest a slight upward trend. Overall, the relative differences between OLS and random forest estimates range between -4.15% in 2007 and -18.41% in 2019, as Figure 7c shows.

For gross labor earnings, similar to the comparison for net wealth, we find that parametric OLS estimates systematically underestimate the true level of relative IOp by 10 to 15 percentage points. Figure 7b displays the time series for relative IOp in gross labor earnings based on the OLS and random forest prediction, respectively. The relative IOp in gross labor earnings based on the random forest predictions is consistently higher than the relative IOp estimate based on parametric OLS predictions. In addition, the downward trend in relative IOp is absent for the time series based on the random forest predictions, compared to the estimates based on the OLS predictions. Further, Figure 7d shows that the relative bias is ranges from -9.25% in 2007 to -20.51% in 2019, indicating modest bias in relative IOp estimates due to misspecification for gross labor earnings too.

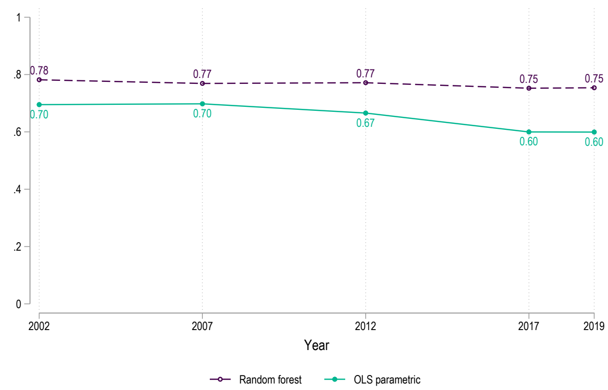
The relative importance plots in Figure 7e and 7f, which display the average reduction of the mean squared error at each split in which the circumstance is involved, confirm the

[10] For a short description of random forests, please refer to Section C in the appendix.

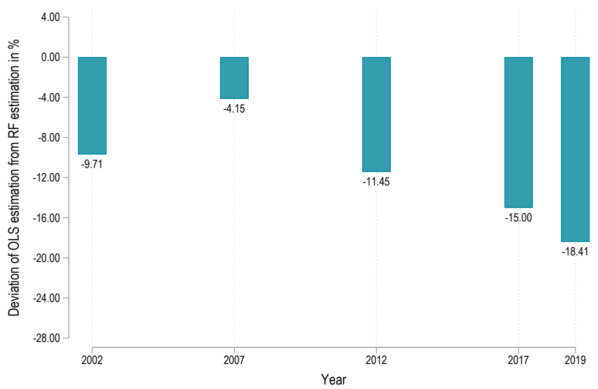
Figure 7: Comparison of OLS and random forest prediction



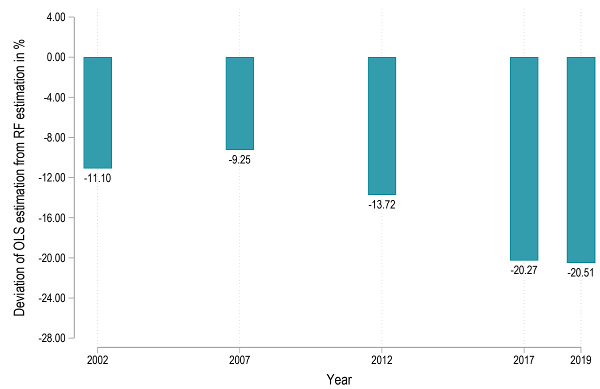
(a) Level estimates: Net wealth



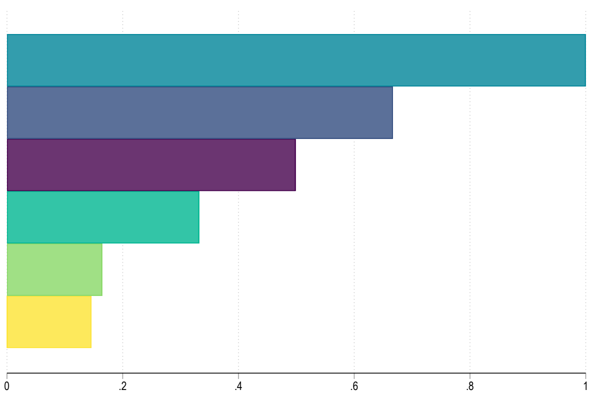
(b) Level estimates: Gross labor earnings



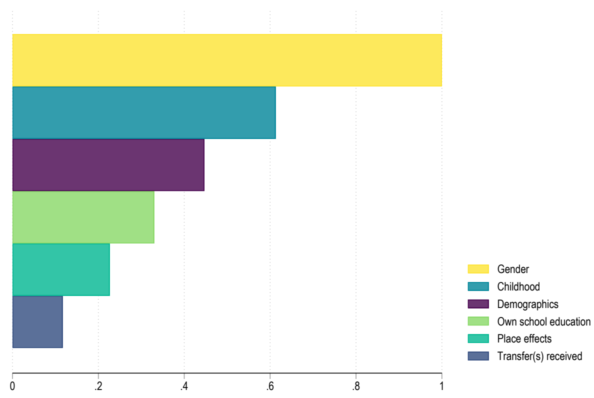
(c) Relative bias: Net wealth



(d) Relative bias: Gross labor earnings



(e) Relative importance: Net wealth



(f) Relative importance: Gross labor earnings

Note: Figure 7a and 7b display the time series for relative IOp of net wealth and gross labor earnings based on OLS and random forest predictions, respectively. Figure 7c and 7d display the relative deviation of the estimates based on OLS predictions from the random forest predictions for net wealth and gross labor earnings, respectively, in %. Figure 7e and 7f display the relative importance plots for net wealth and gross labor earnings, respectively.

results of our decomposition in Section 4.2. Furthermore, the rank correlation of the order of the circumstances in our relative importance analysis is 0.26, indicating a low correlation of the circumstances' ranks across the relative importance plots. In addition, we can not reject the hypothesis that the two rankings are independent with a p-value of 0.37.

5 Discussion and conclusion

In this paper, we presented the first long-run time series for IOp in net wealth in Germany. Throughout, we contrasted our results with the IOp in gross labor earnings. We show that IOp in net wealth is at a similar level compared to gross labor earnings, where the ratio of the Gini coefficients of the counterfactual to the empirical distribution ranges around 60% for both outcomes. However, for gross labor earnings, we find a decline in both total and relative inequality of opportunity over time, with relative IOp dropping from around 70% to around 60% between 2002 and 2019.

Turning to the decomposition of IOp in net wealth and labor earnings, we find that gender contributes significantly to the overall IOp in gross labor earnings but not to the IOp in net wealth. This is potentially explained in the possibility that there exist more opportunities to discriminate on the basis of gender in labor markets (Blau and Kahn, 2017). In addition, there exists evidence that women tend to work less than men in order to adhere to specific gender norms (Bertrand et al., 2015). In contrast, couples are likely to adhere to an equal sharing rule when it comes to net wealth. This is most likely supported by the fact that housing wealth typically makes the lions' share on total wealth per individual. For instance, in our data, housing wealth accounts for 75% of IOp in net wealth. Lastly, we find that the age profile contributes more strongly to inequality of opportunity in wealth than for labor earnings, emphasizing the important role of the insurance motive for the cross-sectional inequality of net wealth.

Another stark difference is the role of individuals' own education. While it is an important contributor to relative inequality of opportunity in gross labor earnings, its role for inequality of opportunity in net wealth is much smaller and not straightforward. On the labor market, one's own formal education is either reflecting individuals' productivity or merely a screening device. For inequality of opportunity in net wealth, it appears as if those two channels are muted and other factors play a more important role.

Noteworthy, while the individuals' region of birth plays only a minor role for the inequality of opportunity in gross labor earnings, it is considerably more important for net wealth. This speaks to the literature on the role of place effects on intergenerational mobility (Chetty and Hendren, 2018a,b). In a separate analysis, not yet shown here, we check to which extent this might be driven by the former separation of Germany into the German Democratic Republic (GDR), a former state within current Germany's borders, and the Federal Republic of Germany (FDR). The GDR was a socialist state. As a consequence, individuals living in the former GDR might have had less opportunities to accumulate wealth since the unification of Germany. Other explanations might include adherence to different norms, i.e., lower importance attached to wealth property. A preliminary analysis confirms that the East-West divide appears to be driving region effects: Depending on the year of observation, about 50% to 75% of the inequality caused by the states can be explained by whether the state individuals are born in is on the ground of the former GDR.

In addition, inheritances play an important role in shaping the inequality of opportunity in net wealth. Depending on the year we consider, the estimates suggest that about 20% of the inequality of opportunity are accounted for by inheritances.

Further, we decompose net wealth into its main components: Housing wealth, financial wealth and business wealth. We find the relative inequality of opportunity in housing, financial, and business wealth are of a similar level. However, when it comes to business wealth, both the Gini coefficients for total inequality of the empirical distribution and absolute inequality of opportunity are much higher for business wealth than for the other two assets, probably due to the extensive margin (the majority of individuals owns no business wealth, resulting in large Gini estimates).

Turning to our decomposition of relative inequality of opportunity in net wealth, we find that the circumstances' contribution to inequality of opportunity varies considerably across wealth components. For housing wealth, the two most important circumstances are age and whether individuals received inheritances or gifts. Gender does not seem to matter for inequality of opportunity in housing wealth. For financial wealth, individuals' own education matters highly for inequality of opportunity. Contrary to the other two wealth assets, gender matters considerably for inequality of opportunity in business wealth. Moreover, we find that childhood variables (particularly, parental occupation) matter considerably more for business wealth than for housing and financial wealth.

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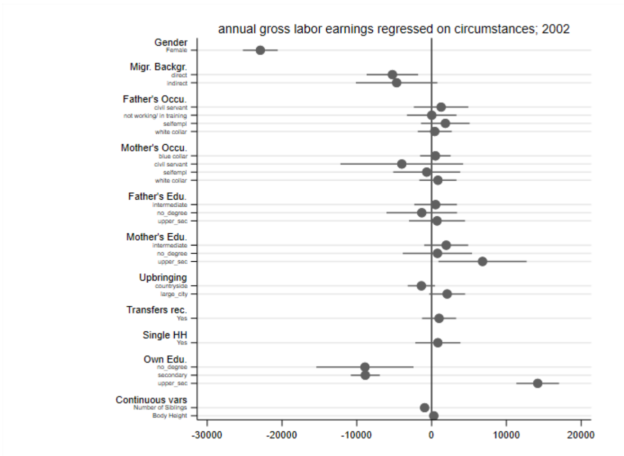
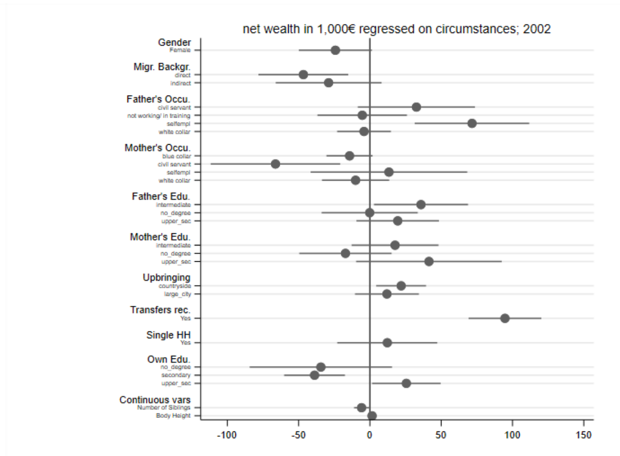
Appendix

A Figures

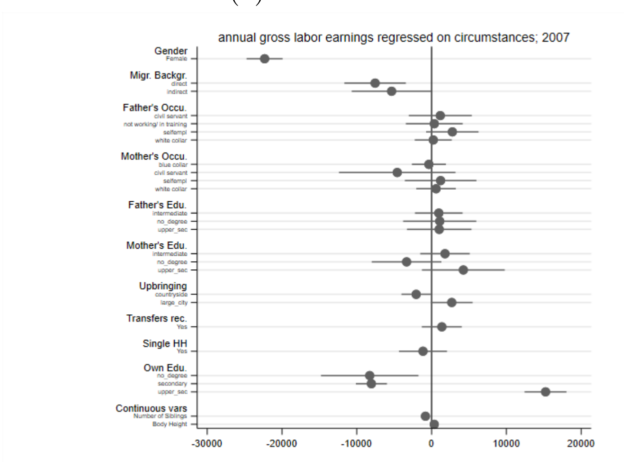
Figure 8: Coefficient plots of gross labor earnings and net wealth regressed on circumstances



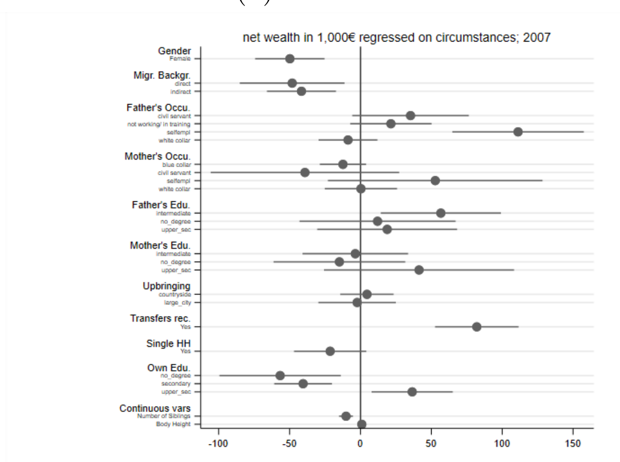
(a) GLE 2002



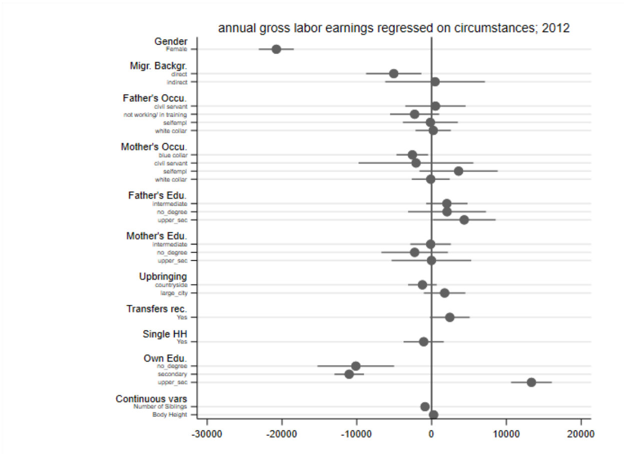
(b) NW 2002



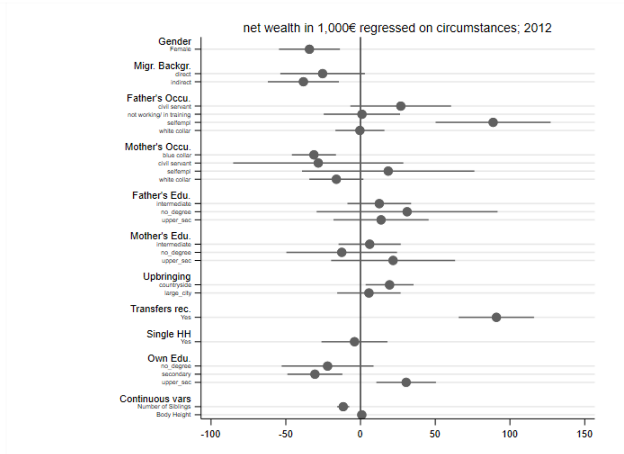
(c) GLE 2007



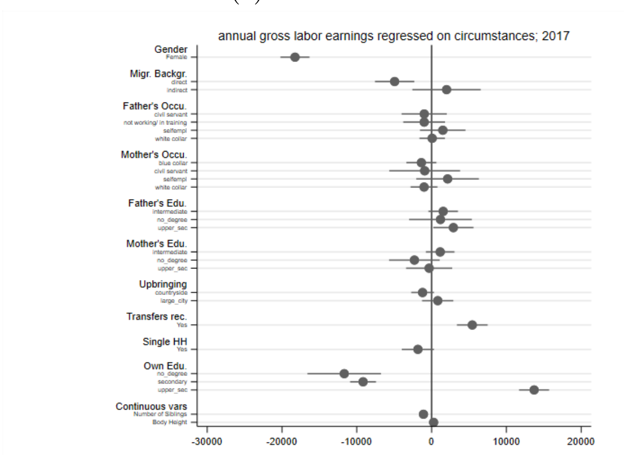
(d) NW 2007



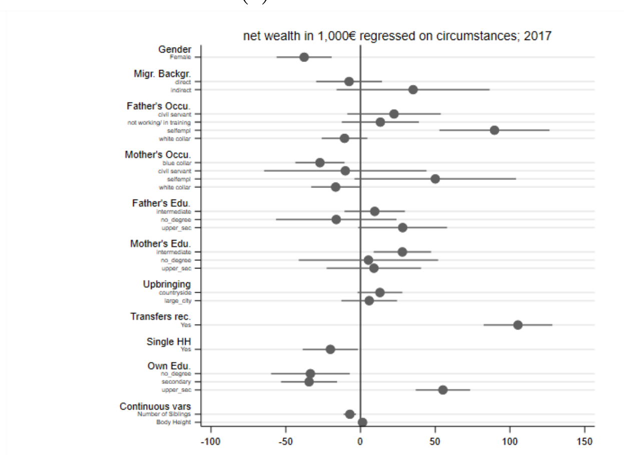
(e) GLE 2012



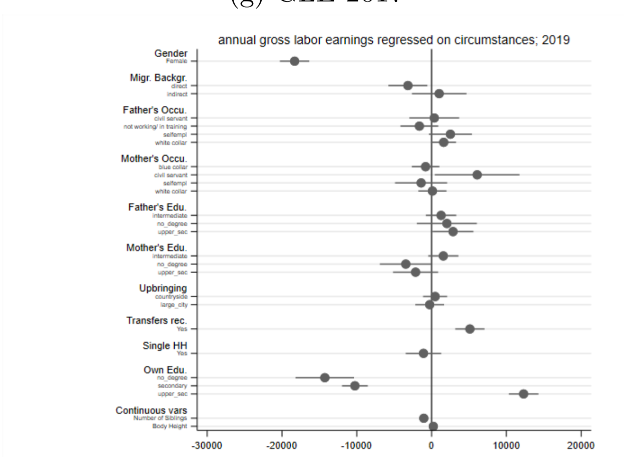
(f) NW 2012



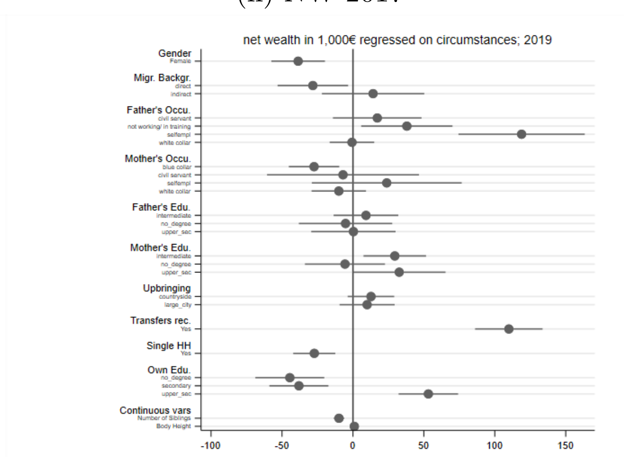
(g) GLE 2017



(h) NW 2017

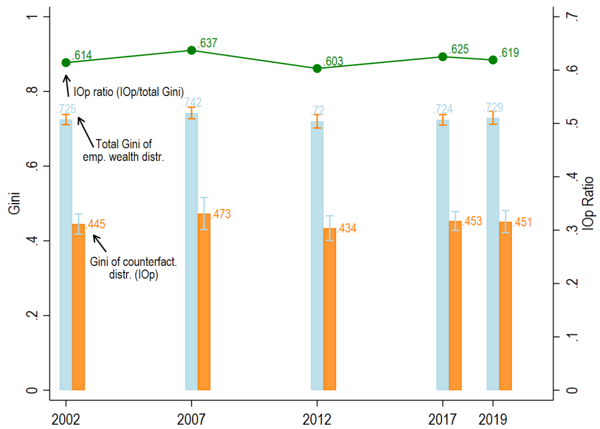


(i) GLE 2019

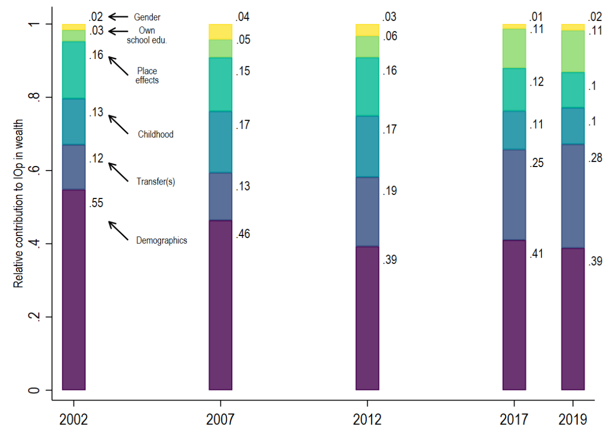


(j) NW 2019

Figure 9: IOp estimates considering amount 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)Lerman and Yitzhaki (1985) decomposition results based on model as specified in (a)

B Tables

Table 1: Descriptive Statistics of Pooled Sample

	mean	sd	min	max	count
indiv. annual gross labor earnings	32738.92	35390.92	0	382086	28442
net overall wealth	135963.07	313451.94	-214987	5226748	28442
Housing net wealth	87791.24	195192.82	-125886	5247313	28442
Business wealth	14325.89	152578.19	0	5000000	28442
Financial net wealth	33726.22	87209.60	-589500	2089282	28442
Gender: Female	0.53	0.50	0	1	28442
father's occu: blue collar	0.42	0.49	0	1	28442
father's occu: civil servant	0.09	0.29	0	1	28442
father's occu: not working/ in training	0.07	0.26	0	1	28442
father's occu: selfempl	0.12	0.33	0	1	28442
father's occu: white collar	0.29	0.46	0	1	28442
mother's occu: blue collar	0.20	0.40	0	1	28442
mother's occu: civil servant	0.03	0.16	0	1	28442
mother's occu: not working/ in training	0.40	0.49	0	1	28442
mother's occu: selfempl	0.06	0.24	0	1	28442
mother's occu: white collar	0.32	0.47	0	1	28442
father's edu: intermediate	0.20	0.40	0	1	28442
father's edu: no_degree	0.03	0.17	0	1	28442
father's edu: secondary	0.62	0.49	0	1	28442
father's edu: upper_sec	0.15	0.36	0	1	28442
mother's edu: intermediate	0.24	0.42	0	1	28442
mother's edu: no_degree	0.04	0.20	0	1	28442
mother's edu: secondary	0.63	0.48	0	1	28442
mother's edu: upper_sec	0.09	0.29	0	1	28442
migration background: no	0.85	0.35	0	1	28442
direct migration background	0.12	0.32	0	1	28442
indirect migration background	0.03	0.17	0	1	28442
not born in GER	0.12	0.32	0	1	28442
born in [1] Schleswig-Holstein	0.02	0.16	0	1	28442
born in [2] Hamburg	0.02	0.13	0	1	28442
born in [3] Niedersachsen	0.09	0.28	0	1	28442

born in [4] Bremen	0.01	0.09	0	1	28442
born in [5] Nordrhein-Westfalen	0.18	0.38	0	1	28442
born in [6] Hessen	0.06	0.24	0	1	28442
born in [7] Rheinland-Pfalz,Saarland	0.04	0.19	0	1	28442
born in [8] Baden-Wuerttemberg	0.09	0.29	0	1	28442
born in [9] Bayern	0.12	0.33	0	1	28442
born in [10] Saarland	0.01	0.11	0	1	28442
born in [11] Berlin	0.03	0.16	0	1	28442
born in [12] Brandenburg	0.04	0.20	0	1	28442
born in [13] Mecklenburg-Vorpommern	0.02	0.15	0	1	28442
born in [14] Sachsen	0.07	0.26	0	1	28442
born in [15] Sachsen-Anhalt	0.04	0.20	0	1	28442
born in [16] Thueringen	0.04	0.19	0	1	28442
childhood in countryside	0.36	0.48	0	1	28442
childhood in large_city	0.23	0.42	0	1	28442
childhood in sm_city	0.41	0.49	0	1	28442
raised in single-parent HH	0.11	0.31	0	1	28442
school degree: intermediate	0.49	0.50	0	1	28442
school degree: no_degree	0.01	0.10	0	1	28442
school degree: secondary	0.23	0.42	0	1	28442
school degree: upper_sec	0.27	0.44	0	1	28442
body height	172.34	9.41	120	210	28442
year of birth (indicator)	-	-	1937	1994	28442
number of siblings	1.96	1.66	0	17	28442
received transfer	0.21	0.41	0	1	28442

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 dissimilar as possibles across nodes. The prediction is than determined as the mean within the respective nodes. Formally, for every step k, the data D is 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:

$$D_{k,L} = \{x|x_j < \gamma(k,j)\}; D_{k,R} = \{x|x_j \geq \gamma(k,j)\}. \tag{8}$$

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

$$\min_{\forall\ x_j \in x \text{ and } \gamma(k,j) \in R_{x_j}} SSE_{k,L} + SSE_{k,R}, \tag{9}$$

where $SSE_{k,m} = \sum_i^{N_m} (y_i - \hat{y}_i)^2$. The resulting nodes than enter the algorithm as input again. 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 typically reduces the variance of the out-of sample predictions. However, this comes at costs of increased bias.

To avoid this trade-off, researchers typically 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 have to 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 it's argument.