

Bartels, Charlotte; König, Johannes; Schröder, Carsten

**Working Paper**

## Born in the Land of Milk and Honey: Hometown Growth and Individual Wealth Accumulation

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Email [office@cesifo.de](mailto:office@cesifo.de)  
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# Born in the land of milk and honey: Hometown growth and individual wealth accumulation \*

Charlotte Bartels   Johannes König   Carsten Schröder

July 23, 2025

## Abstract

How does economic growth affect individual wealth accumulation and, thereby, wealth inequality? Combining individual wealth from the Socio-Economic Panel (SOEP) and local GDP growth across 401 German counties, this paper documents a sizable *Hometown-Growth-Wealth Nexus*. We find that past variation in hometown growth across cohorts and regions contributes to high wealth inequality today. Individuals exposed to high growth during childhood save more and are more likely to be invested in housing. While this savings channel operates for heirs and non-heirs alike, heirs from the same hometown are richer. We validate the *Hometown-Growth-Wealth Nexus* and the savings channel for the UK.

*Keywords:* wealth distribution, regional inequality, intergenerational transmission

*JEL Classifications:* D31, D64, O47

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\*Bartels: University of Leipzig, DIW Berlin/SOEP, CEPR, CESifo, charlotte.bartels@uni-leipzig.de; König: BMF, jkoenig@diw.de; Schröder: DIW Berlin/SOEP & Freie Universität Berlin, schroeder@diw.de. Acknowledgements: We thank Thilo Albers, Sebastian Braun, Bertrand Garbinti, Edward Glaeser, Benny Goldman and Nathaniel Hendren for valuable suggestions and comments. Further, we are grateful for comments from the participants of the Berlin BSE Applied Micro Workshop 2021, ECINEQ 2021, Verein für Socialpolitik 2021, IIPF 2023 and seminar participants at ifo Center for Economics of Education, U Bayreuth, U Tübingen, MPIfG Köln, LMU Public Economics Seminar, Columbia Economic History Seminar, U Regensburg, U Roma Tre, ECONtribute Research Seminar Cologne and DICE Research Seminar. The authors acknowledge financial support from the German Federal Ministry of Labour and Social Affairs (BMAS) for the collection of the SOEP-P Sample, from the Hans Böckler foundation and from the Deutsche Forschungsgemeinschaft (DFG) (Project Nr. 430972113). We thank Hannah Eger, Marcelo Avila and Lotte Maaßen for outstanding research assistance.



# 1 Introduction

Increasing wealth inequality in many industrialized countries since the 1980s/1990s<sup>1</sup> has prompted growing interest in the mechanisms behind the accumulation and distribution of wealth. Intergenerational persistence of wealth has been identified as an important channel: wealthy parents have wealthy children.<sup>2</sup> Inequality of parental wealth and individual wealth might stem from spatial and intertemporal variation in productivity dynamics. In this paper, we investigate this channel looking at Germany that today features one of the most unequal wealth distributions in Europe and where productivity growth has varied greatly over the past decades across regions.<sup>3</sup>

What is the connection between local economic growth and individual wealth? Local economic growth increases labor income and, thereby, parents' ability to save and invest, for example, by buying a house (that is passed on to the children) or financially supporting children with a down payment. Individual experiences of national macroeconomic shocks (Malmendier and Nagel, 2011; Gargano et al., 2023; Malmendier and Wellsjo, 2024), peer-effects to *Keep Up With the Joneses*, and *learning from proximity* (Bailey et al., 2018; Banerjee et al., 2013; Bayer et al., 2021; Brown et al., 2008; Fehr and Reichlin, 2025) have been shown to affect savings and financial investment decisions. Local economic growth also produces capital gains for homeowners because land prices tend to grow faster than incomes. Housing supply is less elastic than local labor supply, especially in flourishing regions (Hsieh and Moretti, 2019). In turn, rising living costs reduce the saving potential (Gyourko et al., 2010; Moretti, 2013; Diamond and Gaubert, 2022).

We show that variation of hometown growth across regions (401 German counties) and over time (cohorts since 1920) translates into unequal wealth in adulthood. A simple OLG model with varying returns on wealth accumulation (=growth) predicts individual wealth inequality

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<sup>1</sup>See the long-run wealth inequality series for France (Garbinti et al., 2021), Germany (Albers et al., 2024), Italy (Acciari et al., 2024), Sweden (Lundberg and Waldenström, 2018), the United States (Saez and Zucman, 2016) and the United Kingdom (Alvaredo et al., 2018). In contrast, wealth inequality has declined in Spain (Martínez-Toledano, 2020)

<sup>2</sup>This persistence is mostly due to wealth transfers (Adermon et al., 2018; Boserup et al., 2018) and family background (Fagereng et al., 2021). Studies on the intergenerational correlation of wealth distinguish between genetically inherited abilities and preferences (nature) and environmental factors like parents' actions (nurture). On the one hand, genetically inherited abilities and preferences generate intergenerational links in income, savings behavior or financial risk taking. On the other hand, parents' actions affect children's accumulation of wealth. The investigated channels include direct transfers of wealth (inter vivos or through inheritance), parental investment in children's human capital and earnings capacity, or learning of attitudes and traits that influence children's savings propensity or financial risk taking (Fagereng et al., 2021).

<sup>3</sup>For an introduction to the phenomenon of German hidden champions see Audretsch et al. (2018). What Berbee et al. (2025) coined as reversing fortunes – the decline of the former heavy-industry centers like the Ruhr area – shifted high growth rates from West to South Germany, subsequently changing the economic landscape of Germany over the post-war period.

between individuals from different hometowns in Germany in 2019. Hence, we find that childhood neighborhood effects do not only matter for long-run human capital and earnings (Chetty et al., 2016; Chyn, 2018; Chetty and Hendren, 2018; Nakamura et al., 2022),<sup>4</sup> but also for accumulation of physical capital (=wealth). We document that high intergenerational persistence of wealth because of inheritances and gifts (Adermon et al., 2018; Boserup et al., 2018) is related to regional variation of past economic growth, reflected by valuation of houses and firms.

To empirically estimate what we term the *Hometown-Growth-Wealth Nexus*, we combine individual-level wealth data with a long-run panel of regional growth rates from official statistics, which we harmonized geographically over time. The individual-level wealth data are from the German Socio-Economic Panel (SOEP) which includes detailed information on individual wealth,<sup>5</sup> current county of residence, birth county (NUTS-3), parental background, and intergenerational wealth transfers (inheritances and gifts) at the individual level broken down by major asset classes. Hence, by linking the birth county to the county’s GDP per capita growth we can examine how local economic conditions shape the accumulation of wealth. We use the 2019 wave of the SOEP, which includes a new subsample of top-wealth individuals (SOEP-P) (Schröder et al., 2020). The oversampling of the wealthy lends additional credence to the magnitude and statistical precision of our estimates. The SOEP also asks for risk preferences, patience and Big 5 personality traits, what extends the scope of potential channels to be explored in comparison to administrative data. To measure regional growth rates, we collected historical GDP pc from publications of the statistical office, which we harmonized geographically to 2019 county borders. Similar to what Rosés and Wolf (2018) document for European regions, and important for our analysis, German counties’ growth rates declined over the post-war period, but at different rates. Consequently, we can draw on substantial variation of hometown growth across 401 German counties and cohorts since 1920. For example, the cohort born 1940-1959 experienced an average annual growth rate of more than 14 percent if born in areas of South Germany, but less than 3 percent if born in the declining industrial Ruhr area.

Investigating the mechanism behind the *Hometown-Growth-Wealth Nexus*, we find that individuals exposed to high growth during childhood save more and are more likely to be invested in owner- and tenant-occupied housing. The savings channel is in line with the theoretical

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<sup>4</sup>Chetty et al. (2014) and Connora and Storper (2020) document (changing) geographic differences of social mobility in the United States.

<sup>5</sup>Our measure of net wealth includes business assets, housing and real estate wealth net of outstanding debt, financial assets, insurance assets, tangibles as well as debt due to consumer or educational loans.

prediction of a standard OLG model that we introduce in Section 3.1 and with empirical studies highlighting peer-effects to *Keep Up With the Joneses*, and *learning from proximity* (Bailey et al., 2018; Banerjee et al., 2013; Bayer et al., 2021; Brown et al., 2008; Fehr and Reichlin, 2025). We find that willingness to take *financial* risks increases significantly with hometown growth for non-heirs (not for heirs), while general willingness to take risks or patience does not systematically vary with hometown growth. We validate the *Hometown-Growth-Wealth Nexus* and the savings channel for the United Kingdom using UKHLS wealth records and GDP growth across 10 regions (NUTS2).<sup>6</sup> Hence, variation in past growth rates contributed to high wealth inequality in Germany today.

Although the savings channel operates independently of the receipt of inter-vivos gift or an inheritance, such intergenerational transfers play an important role for the *Hometown-Growth-Wealth Nexus*. We follow Heckman and Pinto (2015) and Fagereng et al. (2021) and perform a mediation analysis. Three mediators – market income, years of schooling, and transfers (inheritances plus gifts) – explain 28 percent of the estimated growth coefficient. Remarkably, about 71 percent of this indirect effect is explained by inheritances and gifts, while the other mediators are of lesser importance. In turn, the impact of inheritances and gifts is driven by inherited real estate and firms, whose value is closely tied to hometown economic growth. Past growth has created large land price variation across German regions: Today, the price of a square meter of land is roughly 2,600 Euros in Munich – the capital of Bavaria in South Germany – as opposed to about 200 Euro in Recklinghausen, an urban center of the former industrial Ruhr area.

We find similar coefficients for East and West Germans, which may be surprising given the literature emphasizes differences in income, wealth, financial literacy and stock market participation between the two populations (Fuchs-Schündeln and Haliassos, 2021; Davoli and Hou, 2021; Bach et al., 2021; Albers et al., 2024). However, growth rates have been lower for those born in former East Germany (GDR) than for those born in former West Germany (FRG) throughout so that a similar coefficient predicts less accumulated wealth for East Germans.

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<sup>6</sup>A larger international comparison of the *Hometown-Growth-Wealth Nexus* faces two data challenges: First, birth region is rarely observed in combination with wealth records in international survey data. Second, to our knowledge, long-run regional GDP growth series only exist for Europe from Rosés and Wolf (2018). The US state income series available from wid.world is based on income tax data, i.e., fiscal income, which is subject to the large variation of income tax regimes across US states and over time. To study the geography of wealth accumulation in the US since the early 1800s, Dray et al. (2023) collect and refer to many data sources, but none for a regional, per capita GDP series. In order to study the US, smaller regional units than state-level for both growth series and birth regions are required. However, PSID and SIPP, which record household wealth, only record US state of birth. These challenges have made a reliable comparison with the US unfeasible.

To bypass endogeneity concerns such as regional sorting or a negative feedback loop of wealth on growth (Stiglitz, 1969, 2015), we pursue two independent IV strategies: 1) We use the distance to coal fields as an instrument for hometown growth, following Fernihough and O’Rourke (2021) and Berbée et al. (2025). 2) We construct a shift-share IV, where re-write county-level growth as the product of local sectoral shares and national shifts. Both strategies deliver congruent results and confirm a strong, positive, and statistically significant *Hometown-Growth-Wealth Nexus*. As a further check, we run panel regressions with the wealth survey years 2002, 2007, 2012, 2017, 2019 and individual fixed effects as well as regressions with birth-region fixed effects instead of birth GDP pc. Both checks reveal statistically significant coefficients, but less precisely estimated and lower than in our baseline specification ( $\approx 0.3$ - $0.4$ ). We also further investigate regional mobility: High-skilled parents in Germany might settle in more productive regions, so that economic growth and wealth accumulation are endogenous to these location decisions. Plotting net wealth against hometown growth using conditional binscatters reveals that both high- and low-skilled individuals similarly populate high- and low-growth hometowns. This applies to both parents and children. We view this as reassuring evidence that high-skilled parents or children are not concentrated in high-growth regions.

Our study speaks to the growing literature documenting the intergenerational correlations in wealth across countries (see, e.g., Charles and Hurst, 2003; Boserup et al., 2018; Adermon et al., 2018) and the role of inherited wealth for wealth inequality (Boserup et al., 2016; Elinder et al., 2018; Nolan et al., 2020; Nekoei and Seim, 2023; Black et al., 2024). Similar to Carneiro et al. (2021), we demonstrate that the intergenerational relationship between families’ resources and children’s outcomes is not stable, but that the timing matters. We view our study as a bridge between the intergenerational wealth correlation literature and the literature highlighting (childhood) neighborhood effects on long-run economic and educational outcomes (Chetty et al., 2016; Chyn, 2018; Chetty and Hendren, 2018; Nakamura et al., 2022).<sup>7</sup> Further, our study is related to the literature examining demographic milestones and wealth. Several studies show that homeownership significantly increases long-run wealth, while divorce, health shocks, and disability carry long-run reductions in wealth (Goda and Streeter, 2021; Di et al., 2007; Killewald and Bryan, 2016).

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<sup>7</sup>Chetty et al. (2014) and Connora and Storper (2020) document (changing) geographic differences of social mobility in the United States.

Our results also relate to [Malmendier and Nagel \(2011\)](#) who document that individual experiences of national macroeconomic shocks affect financial investment decisions such as stock market participation. We exploit regional variation of experienced macroeconomic volatility and add real estate investments to the analysis. Finally, we connect to [Schwandt and von Wachter \(2019\)](#) who highlight the persisting disadvantage of being born during a recession by demonstrating a persisting advantage of being born in locations with favorable economic conditions.

This paper is structured as follows. In Section [3.1](#), we theoretically establish the *Hometown-Growth-Wealth Nexus* with an OLG model. Section [2](#) introduces our data sources for individual wealth and regional growth and describes our estimation sample. Section [3](#) presents our main results based on OLS and IV estimations as well as robustness checks. We also present and discuss heterogeneity of economic growth across German regions and over cohorts born between 1920 and 1999. In Section [4](#), we investigate the mechanisms behind the *Hometown-Growth-Wealth Nexus*. We start with a mediation analysis deriving the direct and indirect effect of growth on individual net wealth and then explore several channels. We also compare the *Hometown-Growth-Wealth Nexus* and the savings channel between Germany and the United Kingdom, what reveals strikingly similar patterns. In Section [5](#), we evaluate the relevance of the *Hometown-Growth-Wealth Nexus* for wealth inequality in Germany today by constructing counterfactual wealth distributions. Section [6](#) concludes.

## 2 Data

### 2.1 Individual Wealth Data

We use individual wealth recorded in the Socio-Economic Panel (SOEP), which is a large random sample of German households ([Goebel et al., 2019](#); [Schröder et al., 2020](#)). Along with information on socio-demographics, education, labor market status, it contains a module about individual and household wealth every five years since 2002, as well as inheritances and gifts received by the individuals. The SOEP also collects the individual’s birth county (*Kreis*) since 2012, current county of residence, and information on the parents when the individual was 15 years old. Our main analysis uses the survey year 2019 (v36), which, for the very first time, included a subsample oversampling rich households. As a robustness check, we also exploit the panel dimension using all survey years with a wealth module: 2002, 2007, 2012, 2017 and 2019.

**Top-Wealth Sample** In 2019, the SOEP has added a new top-wealth sample (SOEP-P), which improves the coverage of the top of the wealth distribution known to be underrepresented in survey data (see [Schröder et al., 2020](#)). High wealth individuals were sampled using administrative business register data from the ORBIS database. Ranking ORBIS shareholders based in Germany by the value of their total shareholdings, a random sample of top shareholders was interviewed. SOEP-P is built on the same interviewing method and the same questionnaire as SOEP and, thus, is a fully integrated subsample of the SOEP. SOEP-P encompasses 1,956 individuals out of which 817 hold an individual net worth of at least one million Euro.

**Focal Variables** 1. *Net Wealth*: Surveyed assets include the primary residence, other real estate, financial assets, building-loan contracts, life and private pension insurance, tangible assets, vehicles, and, unincorporated businesses. The respondents are asked about their individual share if a house or a firm is owned by multiple individuals. The survey also collects liabilities: outstanding debt on the primary residence, outstanding debt on other real estate, consumer debt, and education debt.

2. *Transfers*: The SOEP individual questionnaires in 2001, 2017, and 2019 include questions on individual inheritances and gifts.<sup>8</sup> Individuals were asked to record, retrospectively over the lifecourse, the year, the value, type (inheritance/ gift), and asset type (real estate, securities/bonds/shares, cash/deposits, business, other) of at most three inheritances or gifts. To make inheritances and gifts received in different years comparable in the cross-section of 2019, we capitalize the inheritances and gifts recorded in the questionnaires in 2001, 2017, and 2019 using CPI-adjusted bond-rates for Germany provided by [Jordà et al. \(2019\)](#). Our measure of individual inheritances and gifts is the sum of all capitalized inheritances and gifts ever received by the individual.<sup>9</sup> For our regression analyses we winsorize this variable at the first and 99th percentile.

Figure 1 shows the share of heirs in the SOEP base population across age groups (left-hand graph) and the average individual inheritance/gift conditional on having received one (right-hand graph). The probability to receive an inheritance or gift increases with age and is about 30

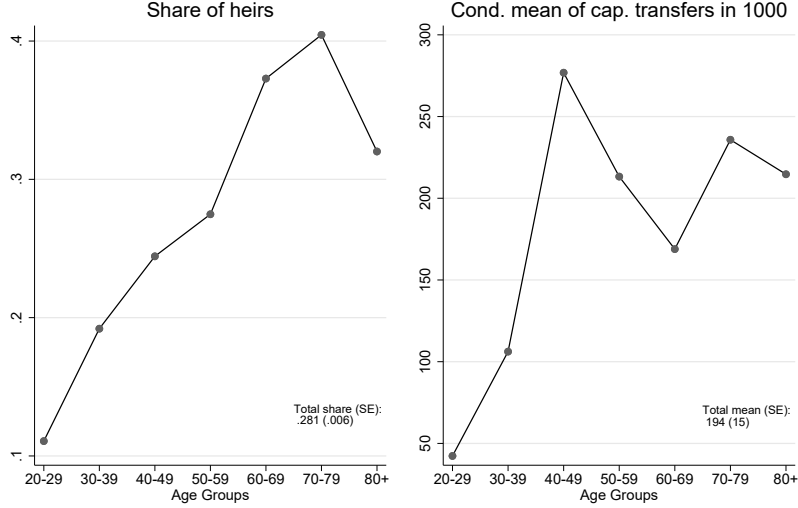
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<sup>8</sup>Since 2000, the SOEP *household* questionnaire asks for inheritances and gifts received by the household in the past year. The value of the inheritance/gift is asked if exceeding 2,500 Euro between 2000 and 2003 and if exceeding 500 Euro since 2004. Since this data is on the household level, we do not make further use of this information for our individual-level analysis.

<sup>9</sup>The time horizon for which inheritances/gifts are recorded varies across the questionnaires: in 2001 and 2019, it is asked for inheritances/gifts *ever* received; in 2017, it is asked for inheritances/gifts received in the past 15 years, i.e., since 2002. We combine all three questionnaires and remove double entries from the data. See Appendix Figures A.22-A.24 for the relevant parts of the questionnaires.

percent, on average. While younger age groups who received a transfer below age 40 typically received 100,000 Euros or less, older age groups have received a total sum of about 200,000 Euros.

Figure 1. Heirs and Transfers (Inheritances+Gifts) by Age Group



Notes. The figure shows the population-weighted fraction of heirs recorded in the SOEP 2019 (v36) and the mean of the inheritances/gifts in 1,000 EUR capitalized to 2019 using CPI-adjusted bond rates by age group conditional on having received a transfer.

3. *Biographical information:* Respondents are asked about a large set of biographical characteristics including 1) the place of birth recorded at the county-level (*Kreis* or NUTS-3), 3) education categorized by ISCED (2=lower secondary, 3-5=upper secondary,  $\geq 6$  tertiary) 2) the education of the father and mother coded into three categories (primary, lower, and upper secondary school completion), and 4) the profession of father and mother coded into five categories (no job, blue-collar worker, white-collar worker, self-employed, civil servant).

4. *Education and market income:* We use years of schooling and market income from labor as mediators in our mediation analysis. Years of schooling are the number of years required to complete the highest level of education that is recorded for the respondent (SOEP Group, 2021). Market income is annual individual gross labor income plus private and public pensions in Euro. Individual gross labor income and pensions are provided in the SOEP's equivalence file (Grabka, 2021). Individual labor income is the sum of all earnings from all employment types including training, primary and secondary jobs, and self-employment, as well as irregular compensation like bonuses.

**Estimation Sample** The SOEP base population with information on wealth in 2019 encompasses 25,831 individuals (excl. refugee samples M3-5 and individuals younger than 20).<sup>10</sup> We drop individuals born outside of Germany, because we are unable to compute hometown GDP growth for this group (3,818 obs.). We also have to drop individuals for whom information on birth-place, parental background and other characteristics is missing (8,909 obs.).<sup>11</sup> Further, due to our log-log specification, we exclude 1,873 observation with missing, zero, or negative wealth; however, we include these observations in a robustness check. This reduces our sample from 25,831 to 11,231 observations.

Table 1 presents summary statistics of the SOEP base population and our estimation sample. We can further split our estimation sample into the top-wealth sample SOEP-P vs. SOEP (excl. SOEP-P) as well as the subsample of heirs. 9,473 individuals are part of the existing SOEP samples and 1,758 individuals are part of the new top-wealth SOEP-P-sample. 3,171 individuals record transfers (inheritances or gifts). Comparing the SOEP base population to our full estimation sample shows that our estimation sample is, on average, more educated and richer, which is mostly due to the exclusion of the, on average, poorer and less-educated foreign-born population. Comparing SOEP-P to SOEP (excl. SOEP-P), shows that the SOEP-P sample consists of more men, is older, has more years of schooling and is more likely to be employed. Market income of the top-wealth sample is roughly three times higher, net wealth is about 10 times higher and inheritances and gifts are roughly three times higher. Hence, the SOEP-P sample substantially increases data coverage at the top of the wealth distribution compared to the traditional SOEP samples. We also demonstrate this in Figure 2, which plots the kernel densities of net wealth for the observations from our estimation sample for the SOEP observations and SOEP-P observations. The figure shows that even in the multi-million Euro range, SOEP-P adds valuable coverage, which SOEP did not have.

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<sup>10</sup>The three refugee samples (M3-5) that were not asked about wealth. By excluding the M3-5 refugee samples, we drop 3,899 observations. This population also has no home-town-growth as the places of birth are not in Germany.

<sup>11</sup>For example, birth-place is missing for 4,424 observations, father's education for 778 and father's job for 749.

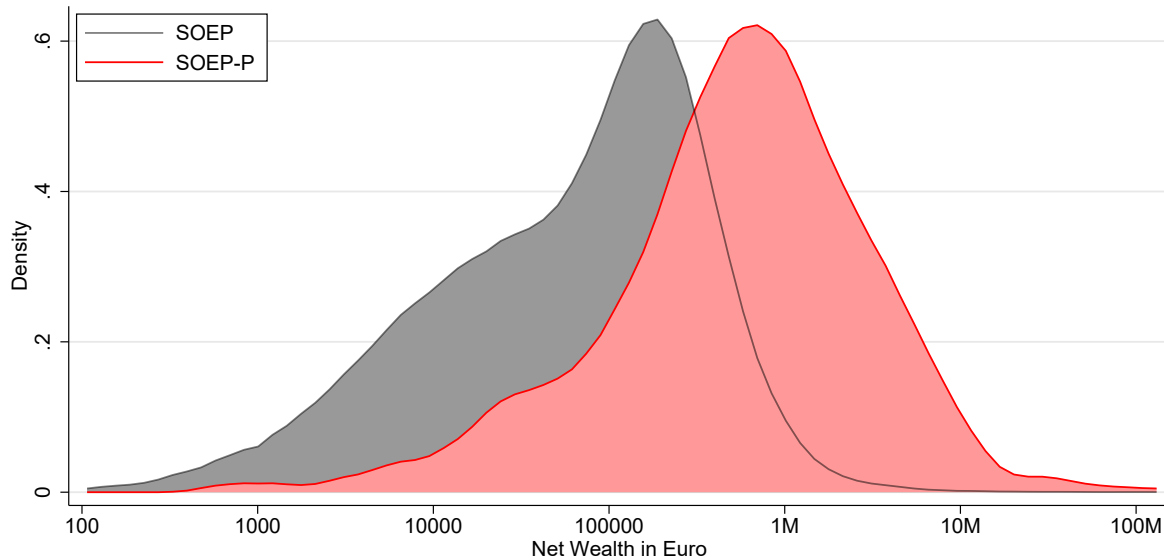


Table 1. Summary Statistics

		Estimation Sample				
		Full SOEP	Full Sample	SOEP	SOEP-P	Heirs
Female	Mean	.52	.49	.51	.36	.5
	SE	.003	.005	.005	.011	.009
Age	Mean	50.04	54.31	54.24	54.68	57.74
	SE	.108	.152	.173	.272	.252
Yrs Of School	Mean	12.65	13.35	13.17	14.27	13.95
	SE	.018	.027	.029	.067	.052
Employed	Mean	.67	.69	.65	.9	.66
	SE	.003	.004	.005	.007	.008
Market Inc	Mean	34318	43719	34180	95117	50579
	SE	333	617	388	3064	1394
Net Wealth in 1,000 Euro	Mean	287	466	195	1931	733
	SE	12	26	12	153	67
Transfers in 1,000 Euro	Mean	275	340	261	698	340
	SE	41	66	71	179	66
<i>N</i>		25831	11231	9473	1758	3171

Notes. Unweighted averages and standard errors for SOEP 2019 (v36). Our estimation sample includes German natives older than 19 years, for whom information on individual net wealth, birth-place and parental background is available. Market income is annual individual labor income plus private and public pensions in Euro. Net wealth is measured in 1,000 Euro. Transfers include all inheritances and gifts ever received capitalized using CPI-adjusted bond rates, measured in 1,000 Euro.

Figure 2. Kernel Density of Net Wealth for SOEP and SOEP-P



Notes. Kernel densities on a logarithmic net wealth scale for the SOEP without sample P (SOEP) and sample P (SOEP-P) for SOEP 2019 (v36) (unweighted). Only observations with more than 100 Euro net wealth used for calculations.

## 2.2 Regional Economic Growth Series

To measure economic growth, we use GDP per capita series at three different levels of aggregation: districts (NUTS-2), commuting zones (CZ) and counties (NUTS-3). Our preferred and finest level of aggregation comprises 401 counties in Germany in 2019.

The district-level series are from the Rosés-Wolf database version 6 (2020) spanning 12 benchmark years between 1900 and 2015 (Rosés and Wolf, 2018), which comprises 38 districts in Germany. From 1900-1950, they use regional variation in employment and wages to estimate GDP by region. Since 1960, their series is based on national accounts from the federal statistical office like our county-level series.

The county-level GDP per capita is our own data collection product. We collected GDP and population data from various publications of the German federal statistical office since the 1950s. These publications represent a collective effort of the statistical offices of the federal states. State-level GDP follows national GDP and closely builds on turnover tax statistics (*Umsatzsteuerstatistik*) which is then proportionately assigned to the counties of each federal state according to their employees and establishments by sector (Statistische Landesämter, 1964, pp.VIII). As a robustness check, we follow the economic history literature and compute growth of population density as a proxy for economic growth.

We have to harmonize county-level GDP geographically over time because county borders were frequently redefined. Even though some county reforms simply merged together two or more counties, other reforms split counties or merged parts of counties with (parts of) neighbouring counties. For the spatial harmonization, we fixed county borders at year 2019, computed the county area overlap between 2019 and historical borders and then reweighted GDP and population within the historical borders using the area share that is still part of the 2019 borders (see Brockmann et al. (2023) for a detailed exposition of this reweighting procedure). We extrapolate county-level GDP for German counties before 1950 as well as East German counties before 1990 as well using the district-level growth-rates from Rosés and Wolf (2018) leading up to 1990. We collapse our county-level series into 141 commuting zones defined by Kosfeld and Werner (2012).

Appendix Figures A.15 to A.21 compare our county-level GDP per capita series with the Rosés-Wolf GDP per capita series by district from 1960 to 2019. First, the figures confirm the general trend found in the Rosés-Wolf database for the NUTS-2 level. Second, our county-level

series add important variation of both levels and trends within districts, which allows us to more precisely identify the association with growth (as we will see in our regression results).

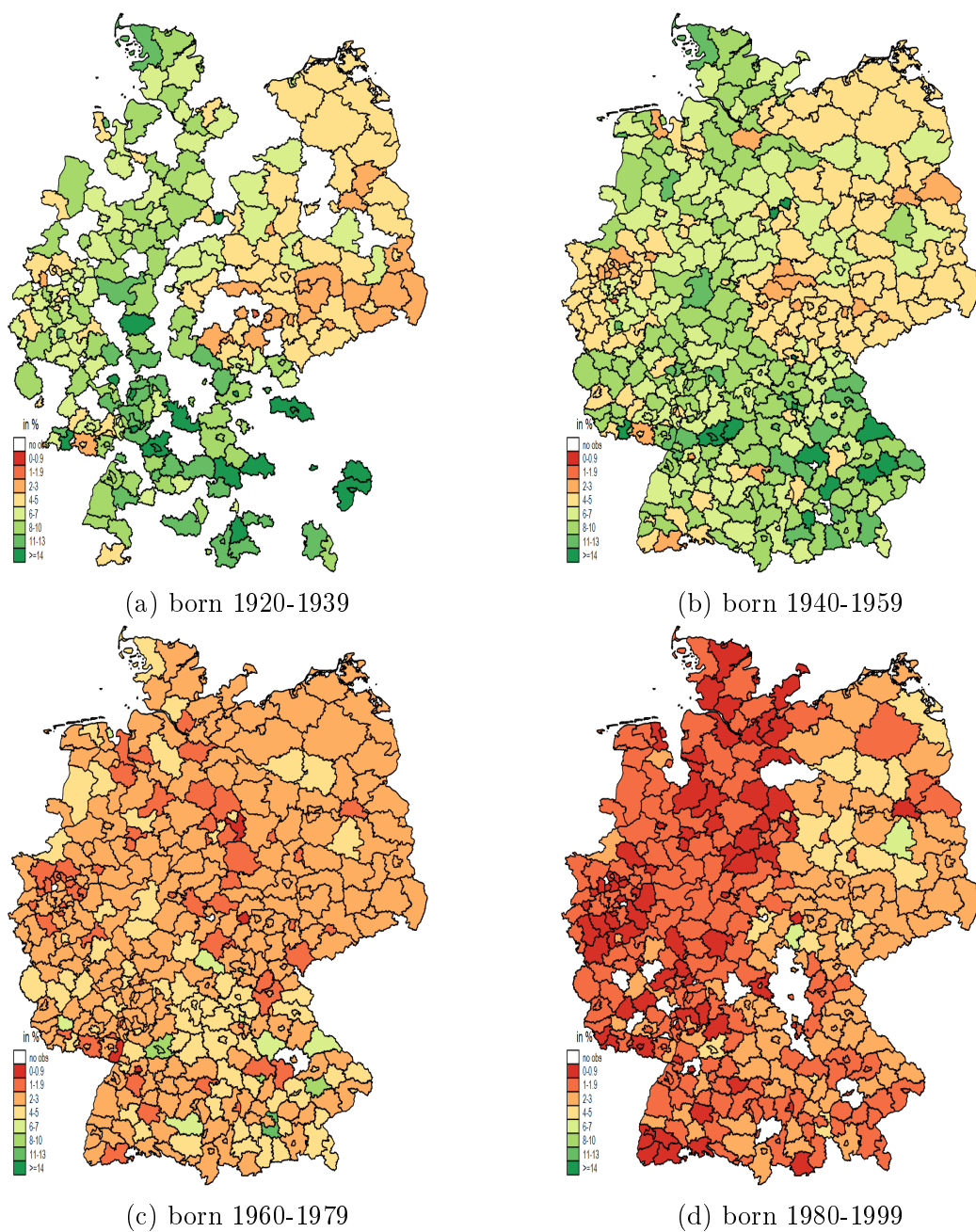
We construct a cumulative growth factor from birth year  $b$  up to our survey year  $t$  for each individual. As described in Section 3.1, the cumulative growth rate  $G$  of individual  $i$  is given by

$$G_i = 1 + \left( \frac{y_{t,r} - y_{b,r}}{y_{b,r}} \right) \quad (1)$$

where  $y_{t,r}$  denotes real GDP per capita region  $r$  in year  $t = 2019$  and  $y_{b,r}$  is real GDP per capita in the year of birth  $b$ . Birth region  $r$  is either defined as district (NUTS-2), commuting zone (CZ) or county (NUTS-3).

Figure 3 displays average annual growth rates by county and birth cohort (i.e.,  $G_i/(t - b_i)$ ). Note that some counties are in white because there are no according county-birth cohort observations in SOEP 2019 (v36). The areas around Frankfurt in West Germany, around Munich in South Germany and Hamburg in North Germany show strong economic growth in the immediate post-war period. Economic growth is also highly heterogeneous across generations as growth rates declined and converged over the post-war period. Older cohorts experienced substantially higher growth rates than younger cohorts. For example, individuals born in Oberbayern (south of Bavaria) between 1940 and 1959 (Figure 3b) experienced an average annual growth rate of 15 percent, whereas individuals born in Oberbayern in 1980 experienced less than 4 percent annual growth, on average (Figure 3d). Appendix Figure A.1 shows the density of log GDP pc growth across the four cohorts. Heirs experience slightly higher average growth than non-heirs as illustrated by Appendix Figure A.3, but the overall distribution is similar.

Figure 3. Average Annual Growth Rates since Birth by Cohort



Notes. Average annual real GDP per capita growth in birth county since birth until survey year 2019. Counties are in white if there are no according county-birth cohort observations in SOEP 2019 (v36).

### 3 The Hometown-Growth-Wealth Nexus

#### 3.1 A simple OLG model

How can we think theoretically about the mechanism behind a *Hometown-Growth-Wealth Nexus*? We will introduce a simple OLG model in the spirit of [Diamond \(1965\)](#) or [Acemoglu \(2009\)](#), where we create  $r \in R$  regions with different growth rates across regions and cohorts. For the simulation of this simple model, we will assume that these regions are small and factors are immobile and that individuals stay in their region of birth (no mobility) and regions do not interact with each other.<sup>12</sup> Production depends on two factors, labor and capital. In this model, growth rates translate into savings so that higher regional growth leads to higher wealth in that region via higher returns on savings. In [Section 3.2](#), we will see that the simulation using the OLG model predicts a very similar *Hometown-Growth-Wealth Nexus* as the empirical estimation using individual wealth data recorded in the SOEP. Hence, we are able to align our empirical results with a theory of how different growth rates in Germany across cohorts and regions contribute to high wealth inequality in Germany today via inequality in return on capital and savings.

**Production** The production function takes the form  $Y_{t,r} = A_{t,r}K_{t,r}^{1-\alpha}L_{t,r}^\alpha$ . The parameter  $0 < \alpha < 1$  denotes the output elasticity of labor, while  $A_{r,t}$  is total factor productivity, which varies across regions and time. Below, we calibrate  $A_{r,t}$  to match initially high and then declining regional growth rates in Germany. Each cohort size is normalized to 1 and labor supply is fixed, which implies that  $L_{t,r} = 1$ . Production factors are compensated according to their marginal products.

**Demographics** Two generations populate each regional unit: the young and the old. Within one unit of time  $t$ , the two generations complete different stages of their life-cycle. The young supply a fixed amount of labor and decide how much to consume and how much to save. The old rent out their wealth as capital and receive capital income. They die at the end of the period.

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<sup>12</sup>While these assumptions are extreme, they correspond to a limiting case of reality that lets us focus on the important mechanism at play. In the real world, regions possess different production technologies while labor and capital are imperfectly mobile between regions. Thus, some rewards from more productive technologies only accrue to the current residents of a more productive region. Note that, in our sample, half of the individuals stay in their county of birth. We empirically investigate regional mobility and sorting in [Subsection 3.4](#).

In each cohort, there are two types of individuals: heirs and non-heirs.<sup>13</sup> Non-heirs consume all their terminal wealth. Heirs receive a bequest  $b_1$  in the first period and bequeath  $b_2$  to their children in the second period. The share of heirs in the cohort  $h$  is constant.

**Consumption and Saving** Heirs ( $H$ ) and non-heirs ( $NH$ ) have perfect foresight. Here, we suppress region-specific and calendar-time-specific subscripts for ease of exposition. Non-heirs maximize the isoelastic utility,

$$\begin{aligned} & \max \frac{c_{1,NH}^{1-\eta}}{1-\eta} + \beta \left( \frac{c_{2,NH}^{1-\eta}}{1-\eta} \right) \\ & \text{s.t. } (1-h)v_1 = c_{1,NH} + w_{NH}, \quad c_{2,NH} = w_{NH}(1+r_2). \end{aligned} \quad (2)$$

Heirs maximize

$$\begin{aligned} & \max \frac{c_{1,H}^{1-\eta}}{1-\eta} + \beta \left( \frac{c_{2,H}^{1-\eta}}{1-\eta} + \chi \frac{b_2^{1-\eta}}{1-\eta} \right) \\ & \text{s.t. } hv_1 + b_1 = c_{1,H} + w_H, \quad c_{2,H} + b_2 = w_H(1+r_2). \end{aligned} \quad (3)$$

where  $v_1$  is labor market earnings during the working phase,  $h$  is the share of heirs in the population,  $w$  is wealth accumulation and  $r_2$  is the rate of return on wealth during retirement.  $c$  denotes consumption. The inverse of  $\eta \geq 0$  ( $\eta \neq 1$ ) is the intertemporal elasticity of substitution,  $\beta > 0$  is the discount factor (=patience) and  $\chi > 0$  captures the warm glow from leaving a bequest to the children.<sup>14</sup>

**Solution** The individual level solution for optimal wealth accumulation  $w$  for non-heirs is

$$w_{NH}^* = \frac{c_2^*}{1+r_2} = \frac{(1-h)v_1(\beta(1+r_2))^{1/\eta}}{1+r_2 + (\beta(1+r_2))^{1/\eta}} \quad (4)$$

For heirs it is

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<sup>13</sup>This model feature is motivated by the well-known importance of inheritances and bequests for intergenerational persistence of wealth and its distribution. Our central finding theoretical finding from the model, that is, the positive relationship between hometown growth and wealth also holds when only one type of individuals exists.

<sup>14</sup>The mechanics of the model also hold in the limiting case where  $h = 1$  and  $b_1 \geq 0$  and  $\chi \geq 0$ .

$$w_H^* = \frac{(1 + \chi^{1/\eta})(hv_1 + b_1)(\beta(1 + r_2))^{1/\eta}}{1 + r_2 + (1 + \chi^{1/\eta})(\beta(1 + r_2))^{1/\eta}} \quad (5)$$

Note that the bequest motive acts as a positive multiplier of the optimal savings for heirs compared to the solution for non-heirs. The sum of  $w_{NH}^*$  and  $w_H^*$  is total wealth and thus total capital in the next period ( $K_2^*$ ). For both types, optimal wealth accumulation equals the discounted optimal period 2 consumption. The latter depends on the individual's optimally chosen lifetime income, composed of the unconsumed labor income in period 1 and the return on these savings. Note that optimal savings crucially depend on  $r_2$ , which itself depends on production in the next period.

Therefore, to close the model,  $r_2^*$  needs to equal capital's marginal factor product in period 2. Thus,

$$r_{2,r}^* = (1 - \alpha) A_{2,r} \underbrace{(w_{H,r}^*(r_{2,r}^*) + w_{NH,r}^*(r_{2,r}^*))}_{K_{2,r}^*}^{-\alpha}. \quad (6)$$

We solve this equation numerically using bisection ([Boyd and Vandenberghe, 2004](#)). We can then back out the savings of both groups, which are our variables of interest. Log individual wealth is the log of  $w_{H,r}^*$  and  $w_{NH,r}^*$  divided by their respective population shares.

**Parametrization and Calibration** For a quantitative simulation of the model, we calibrate two core parameters: The share of heirs  $h$  and total factor productivity  $A_{r,t}$ . The other free parameters are set to standard values from the related literature and summarized in Table C.8. The share of heirs in the model,  $h = 0.3$ , is set to roughly match the proportion in Germany. See Figure 1 for reference. The output elasticity of capital is set to 0.3 (see, e.g., [Douglas, 1976](#); [Kaymak and Poschke, 2016](#)). The evolution of total factor productivity over time is given by  $A_{t,r} = \exp(c_A + g_r \cdot t - d \cdot t^2)$ .

Thus, total factor productivity grows at the rate  $\frac{\dot{A}}{A} = g_r - 2d \cdot t$ , which fits the empirically observed pattern that growth rates are first high and vary greatly across regions, while they decline and converge in later years. The parameter  $d$  determines how the growth rate decays

over time, which we fix at 0.02.<sup>15</sup> Finally,  $c_A$  is a constant to roughly match wealth levels to those reported in the data.<sup>16</sup>

The remaining parameters concern the individuals' utility functions. For the intertemporal elasticity of substitution numerous estimates exist in the literature, but fortunately a meta-analysis by Havránek (2015) has collected these and gives a credible range of values for calibration between 0.3 and 0.4. We choose 0.4, which implies a value of 2.5 for the inverse of this elasticity,  $\eta$ . For the bequest motive, we choose  $\chi$  equal to 6, which implies that the optimal bequest is roughly 2 times the size of retirement period consumption (period 2).<sup>17</sup> Finally, we set  $\beta$ , the parameter for time preference, to 0.98 following previous literature, which traditionally assumes that individuals weigh the two periods almost equally with  $\beta$  usually varying between 0.95 and 0.99 (see, e.g., De Nardi, 2004; Heathcote et al., 2017; Hubmer et al., 2021).

**Simulation** With the solved and calibrated model in hand, we can back out the static comparison of regions with respect to their aggregate wealth and their GDP growth. This is the analogue of the empirical For this comparison, we need to define growth. The cumulative growth factor  $G$  from birth year  $b$  up to year  $t$  in region  $r$  is given by

$$G_{t,b,r}^* = 1 + \left( \frac{y_{t,r}^* - y_{b,r}^*}{y_{b,r}^*} \right) \quad (7)$$

where  $y_{t,r}^*$  denotes optimal output per capita in region  $r$  in year  $t$  and  $y_{b,r}^*$  is optimal output per capita in birth year  $b$ . Wealth  $w_{r,t}^*$  is equal to total capital in region  $r$  in year  $t$ .

We will plot the simulated against the empirically estimated *Hometown-Growth-Wealth Nexus* in the next Section 3.

### 3.2 Empirical estimation

Our empirical specification to quantify the *Hometown-Growth-Wealth Nexus* is motivated by the simulation of our OLG model. The simulation of our OLG model in Section 3.1 indicated a linear relationship between the log of hometown growth  $G$  and the log of wealth  $w$ , which suggests an OLS specification of the form:

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<sup>15</sup>Fixing  $d$  at 0.02 implies that  $\frac{\dot{A}}{A}$  declines at a rate of roughly 0.04, which matches the decline in the average growth for Germany.

<sup>16</sup>All important qualitative findings from the model hold even when setting  $c_A$  to zero.

<sup>17</sup>This calibration is derived by expressing the optimal bequest in terms of period 2 consumption for heirs.



$$\log(w_i) = \alpha + \beta_1 \log(G_i) + \beta_2 \log(y_{b,r}) + \mathbf{X}_i \gamma + \mathbf{P}_i \delta + \epsilon_i, \quad (8)$$

where the outcome variable  $\log(w_i)$  denotes log of individual net wealth (sum of financial assets, business assets and real estate minus debt) surveyed in the year 2019. Our coefficient of interest,  $\beta_1$ , measures the elasticity of wealth with respect to hometown GDP growth  $G_i$  (cumulative real GDP per capita growth in birth region since birth) on net wealth, that is, the percentage change of wealth given a percentage change in hometown growth. We include  $\ln(y_{b,r})$ , that is, log GDP per capita in the birth region at the time of birth (GDP per capita, CPI-adjusted to 2015 prices) as a control.<sup>18</sup> Further individual control variables  $\mathbf{X}_i$  include birth-year fixed effects, gender, indirect migration background,<sup>19</sup> and marital status. Parental background variables  $\mathbf{P}_i$  are father's and mother's school education as well as father's profession.<sup>20</sup>

Figure 4 comes back to our initial question of the relationship between hometown growth and wealth. It shows the wealth and growth combinations implied by the OLG model shown in the Figure 4a). Every point indicates one region with regions being identical except for their implied TFP growth path. The relationship is linear in logs as well as positive. In our empirical investigation, we have therefore estimated a log-log model. Our empirical results based on SOEP wealth records and cumulative log GDP pc growth across counties is shown in Figure 4b) (binscatters and linear fits of the relationship between hometown growth and wealth for heirs and non-heirs conditional on the individual and parental background variables used for Table 2). Both the OLG model and our empirical results reveal a positive slope of similar size for both heirs and non-heirs and a wealth difference between heirs and non-heirs.<sup>21</sup>

Table 2 shows the results from estimating Eq. (8) by OLS using counties as geographical unit (NUTS-3) for hometown growth. Column (1) displays the regression coefficients for the growth factor, GDP per capita at birth and individual controls and column (2) adds parental control variables. A one percent increase in growth since birth is associated with about 0.9 percent more individual net wealth. Among parental background variables in column (2), self-employment of the father reveals the largest coefficient. Results estimated at the district-level (NUTS-2) and

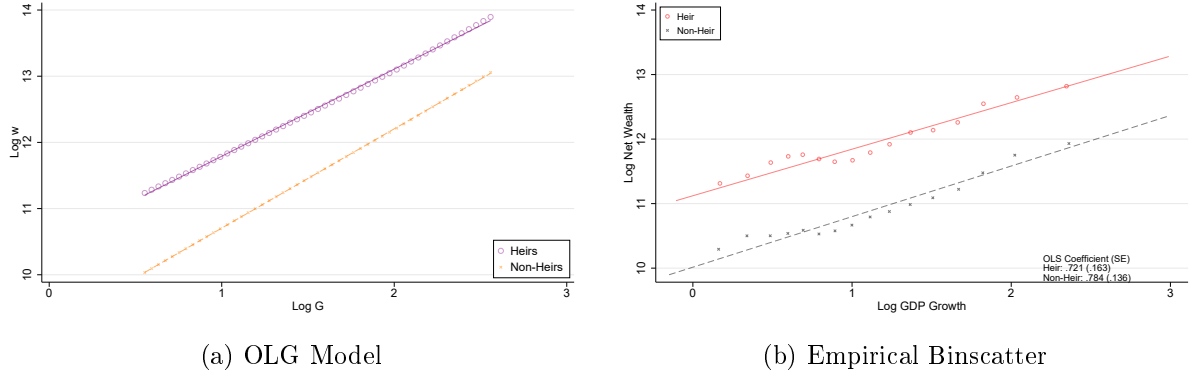
<sup>18</sup>In Table A.5, we exclude GDP at birth and control for birth-region and birth-year fixed effects instead. The results are very similar although the estimates lose some precision.

<sup>19</sup>Note that we exclude individuals with direct migration background because we cannot observe economic growth in their birth place.

<sup>20</sup>Information on the mother's profession is often missing because German mothers were less likely to participate in the labor market. Hence, we do not use this variable in our analysis.

<sup>21</sup>Spillover of growth effects between neighbouring regions may flatten the empirical slope compared to the simulated slope from the OLG model.

Figure 4. Hometown-Growth-Wealth Nexus - OLG model simulation vs. empirical estimation



Notes. Panel (a) shows a scatter and linear fit for the OLG model of the log of  $w_H^*$  (wealth of the heirs) and  $w_{NH}^*$  (wealth of the non-heirs) for different log output growth determined by total factor productivity growth. We compute output growth over 3 periods, which roughly covers three generations as in our analysis sample. Panel (b) shows binscatters and linear fits of the relationship between log hometown GDP growth and log net wealth for heirs and non-heirs. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2. Data. SOEP 2019 (v36).

commuting-zone-level are displayed in Appendix Tables A.1 and A.2. The Hometown-Growth-Wealth Nexus increases with the level of aggregation moving from county ( $\approx 1$ ) to commuting zone ( $\approx 1.5$ ) and district-level ( $\approx 1.3$ ). Growth factor coefficients are significant at the 1 percent level for all levels of aggregation, while most precisely estimated on the county-level. As a robustness check, we compute growth of population density, which is regularly used as a proxy for economic growth in economic history studies. Appendix Table A.4 shows that results are quantitatively and qualitatively very similar estimated coefficients exceeding the GDP growth coefficients by .2.

Using the estimate from our baseline reported in column (2) of Table 2, we can now predict wealth gains for different cohorts from different hometowns. We first predict wealth levels setting hometown growth to zero, and then predict wealth levels setting hometown growth to the sample average of a given cohort-hometown combination. The difference between the two predicted wealth levels gives the wealth estimates shown in Table 3.

We pick Recklinghausen and Munich to illustrate the strongly divergent growth paths that Bavaria and the West-German coal regions took after the end of World War II. The table shows that the oldest cohorts have experienced the largest GDP growth over time and, thus, have the largest gains from the *Hometown-Growth-Wealth Nexus*. On average, a person born between 1920 and 1939 gained wealth of about 836,000 Euro from hometown growth. However, especially the regional disparities shown in the third and fourth column are of note: A person from the

Table 2. Hometown-Growth-Wealth Nexus - Baseline

	OLS	
	(1)	(2)
	Base	+Parental Vars
Log GDP Growth	1.063*** (0.148)	0.881*** (0.146)
Log GDP At Birth	0.513*** (0.111)	0.326*** (0.100)
Female	-0.488*** (0.029)	-0.476*** (0.029)
Ind. Mig. Backgr.	0.018 (0.086)	0.161* (0.081)
Married	0.557*** (0.050)	0.561*** (0.049)
F:MS		0.391*** (0.102)
F:HS		0.726*** (0.118)
M:MS		0.276*** (0.094)
M:HS		0.458*** (0.122)
F:Worker		-0.133* (0.069)
F:Selfemp		0.884*** (0.095)
F:Wht. Collar		0.230** (0.086)
F:Civ Serv		0.399*** (0.092)
Constant	6.837*** (0.446)	6.433*** (0.424)
<i>N</i>	11231	11231
<i>R</i> <sup>2</sup>	0.206	0.253
Cohort FE	✓	✓

Notes. The table shows OLS coefficients for log individual net wealth and log GDP per capita growth, log GDP per capita at birth, individual characteristics and parental background variables based on Eq. 8 estimated at the county-level. *F:HS* is a dummy for the father having at most a high school education, *F:MS* is the analogous dummy for middle school. *M:HS* and *M:MS* are the analogous coefficients for the mother. *F:Worker.*, *F:Selfemp.*, *F:Wht. Collar* and *F:Civ.Serv.* are dummies for the father being a laborer, self-employed, white collar employee, or a civil servant, respectively. Standard errors clustered at the NUTS2-level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Data. SOEP 2019 (v36).

1920-1939 cohort born in Recklinghausen gained about 582,000 Euro, while this increases to about 1.4 million Euro for a person born in Munich. Hence, the wealth gain from growth is about 2.4 times larger for Munich than for Recklinghausen. This regional gap is found for all cohorts. Note, however, that, in agreement with Figure 3, regional disparities in growth are most pronounced for the cohort born during and immediately after the World War II (1940-1959) and decline for younger cohorts.

Table 3. Predicted Wealth Gain by Region and Cohort in 1,000 Euro

Cohort	Average	Recklinghausen	Munich City	M/R
1920-1939	836	582	1389	2.4
1940-1959	673	367	975	2.7
1960-1979	229	166	306	1.8
1980-1999	85	55	66	1.2

Notes. The table shows the implied growth gain in 1,000 Euros using the estimates from column (2) of Table 2. We first predict wealth levels setting hometown growth to zero ( $\hat{W}_i^{\text{base}} = \exp(\hat{\alpha} + \hat{\beta}_2 \log(y_{b,r}) + \mathbf{X}_i \hat{\gamma} + \mathbf{P}_i \hat{\delta} + \frac{\hat{\sigma}_\epsilon^2}{2})$ ), and then predict wealth levels setting hometown growth to the sample average of a given cohort-hometown combination ( $\hat{W}_i^{\text{cfac.}} = \exp(\hat{\alpha} + \hat{\beta}_1 \log(G_{\text{cfac.}}) + \hat{\beta}_2 \log(y_{b,r}) + \mathbf{X}_i \hat{\gamma} + \mathbf{P}_i \hat{\delta} + \frac{\hat{\sigma}_\epsilon^2}{2})$ ) (Rainey, 2017). The difference between the averages of the two predicted wealth levels gives the effects ( $\overline{\hat{W}_i^{\text{cfac.}}} - \overline{\hat{W}_i^{\text{base}}}$ ). For the average in the cohort, we compute mean growth in the cohort. For Recklinghausen, we compute the cohort-specific growth values within the county of Recklinghausen and we calculate analogous growth values for Munich City. In the column labeled  $M/R$  we divide the predicted Munich gain by the predicted Recklinghausen gain.

### 3.3 Instrumenting hometown growth

We use the distance to coal fields and a shift-share instrument to bypass endogeneity concerns. First, economic growth and wealth accumulation might be endogenous to location decisions, if high-skilled parents in Germany settle in more productive places.<sup>22</sup> Although we control for several parental characteristics that relate to the parents' skill-level, one may still be concerned that our estimates are contaminated by the effect of skilled parents' unobserved ability on children's wealth. Second, if higher wealth affects growth, our OLS regression may suffer from reverse causality. Stiglitz (2015) argues that the scarcity of land leads to an increase in land prices so that wealth increases, but productive capital does not.

<sup>22</sup>Regional productivity gaps might arise (1) from sorting of high-skilled people to preferred places, (2) from the concentration of productive industries, (3) from endogenous factors like population density or human capital or (4) from exogenous factors like geography or climate (Glaeser and Gottlieb, 2009; Card et al., 2025). While the sorting-based explanation implies that mobility has no effect on movers' incomes, theories based on industry composition or place-based factors imply that productivity and incomes rise when people move to more productive places. For example, evidence for knowledge spillover is provided by Dauth et al. (2022) who demonstrate that high-quality workers and high-quality firms more easily match in large cities (in Germany). A larger local share of entrepreneurs spurs long-run economic growth (Bartels et al., 2024).

Coal strata were formed millions of years ago and have been shown to have favored the emergence of heavy industries and, hence, been used as an instrument for industrialization (Fernihough and O’Rourke, 2021) and for the decline of heavy industry regions since the coal crisis in 1957 (Berbée et al., 2025). Appendix Figure A.13 illustrates the geography of coalfields in Germany based on the map from Fernihough and O’Rourke (2021).

To construct the shift-share instrument, we re-write the county-level growth as the product of local sectoral shares and shifts and then replace the county-level shifts by national-level shifts. The identification strategy is valid if national shifts in GDP affect individual wealth accumulation either via county-level shifts in GDP per capita or via the shares. Here, we claim that exogenous variation comes from the shifts (Borusyak et al., 2022), not from the shares (Goldsmith-Pinkham et al., 2020).

We also explored the possibility to use mass layoffs as exogenous shocks to local growth paths following Gathmann et al. (2018). However, obtaining county-level indicators of mass layoffs from the IAB’s historical establishment panel (BHP) is likely not representative and potentially biased because the data only cover 50% of establishments and indicators are only released to researchers for further analysis if based on more than 20 observations, i.e., in our case, more than 20 establishments with more than 500 employees to be laid off in a county.

Both IV estimates are positive, statistically significant, and of congruent magnitudes. While the coal field IV estimates are somewhat larger than the OLS estimates, the shift-share IV estimates are of fairly similar size to the OLS estimates. Table 4 shows the IV results. First-stage results are displayed in Appendix Table A.3. A candidate explanation for larger effect sizes in the coal IV specification is a negative feedback loop of wealth on growth generating a downward bias for our OLS coefficient. IV estimators may also, in absolute terms, be upward biased. In our setting, this may be the case if, for example, counties far away from coal fields grew more and generated more income and wealth after the war than counties nearer to coal fields. The standard errors are large enough that even at these much larger point estimates the 99 percent confidence interval of the shift-share IV encloses the OLS estimates. Overall, the IV estimates are indicative of a causal relationship between hometown growth and individual wealth accumulation.

Table 4. Hometown-Growth-Wealth Nexus - IV Estimates

	Coal IV		Shift-Share IV	
	(1) Base	(2) +Parental Vars	(3) Base	(4) +Parental Vars
GDP Growth	2.165*** (0.442)	1.821*** (0.410)	1.364*** (0.142)	1.126*** (0.151)
$N$	11231	11231	7153	7153
$R^2$	0.190	0.242	0.274	0.322
Cohort FE	✓	✓	✓	✓
Eff-F	20.763	20.467	71.685	69.001

Notes. The table shows TSLS-IV coefficients using distance to coal and a shift-share as instruments for hometown growth. The coal instrumental variables are the centroid distance of the county to a carboniferous area and its square based on the data provided by [Fernihough and O'Rourke \(2021\)](#). The shift-share instrument is constructed from initial shares of industry-specific local GDP contributions and the national growth rate of these industries. Initial shares correspond to the year of birth of the individual. F-statistic (Eff-F) is given by weak-instrument test based on [Olea and Pflueger \(2013\)](#). First-stage results are displayed in Appendix Table A.3. Standard errors clustered at the NUTS2-level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Data. SOEP 2019 (v36).

### 3.4 Robustness

We now test several alternative specifications to further check the robustness of the *Hometown-Growth-Wealth Nexus*. As stated above, our results are robust to different levels of aggregation like counties, commuting zones or districts (Appendix Tables A.1 and A.2). Given the heavy tail of the wealth distribution, OLS results might be driven by a few very wealthy individuals. Hence, we estimate the *Hometown-Growth-Wealth Nexus* using different functional forms. We find that the baseline OLS coefficient is very similar to those estimated by the nonlinear Pseudo-Poisson maximum likelihood (PPML) estimator ([Silva and Tenreyro, 2006](#)) and when imputing a log of zero for everyone with non-positive wealth (Appendix Figure A.4). For the PPML specification the OLS estimate is contained in the 95 percent confidence interval.

As a further robustness check aiming to reduce unobserved heterogeneity, we run panel regressions with the wealth survey years 2002, 2007, 2012, 2017, 2019 and individual fixed effects (Table A.6). In another specification, we include birth-region fixed effects instead of controlling for birth region GDP (Table A.5). Both checks reveal positive and statistically significant coefficients, which are less precisely estimated and smaller than those in our baseline specification ( $\approx 0.3 - 0.4$ ). Two remarks are in order: First, county of birth is only asked in the SOEP since 2012, which leaves us with a smaller sample per year (ca. 5,800 in 2002, ca. 11,000 in 2019 and ca. 9,100 on average) than the 2019 cross-section (ca. 11,000). Notably, the

panel is balanced only for ca. 2,600 individuals. Second, the growth coefficient in the individual fixed effects estimation is identified through variation in growth rates between 2002 and 2019. Since this a time when variation in growth rates across regions had significantly declined, it is unsurprising that the coefficient is smaller and less precisely estimated compared to the main specification.

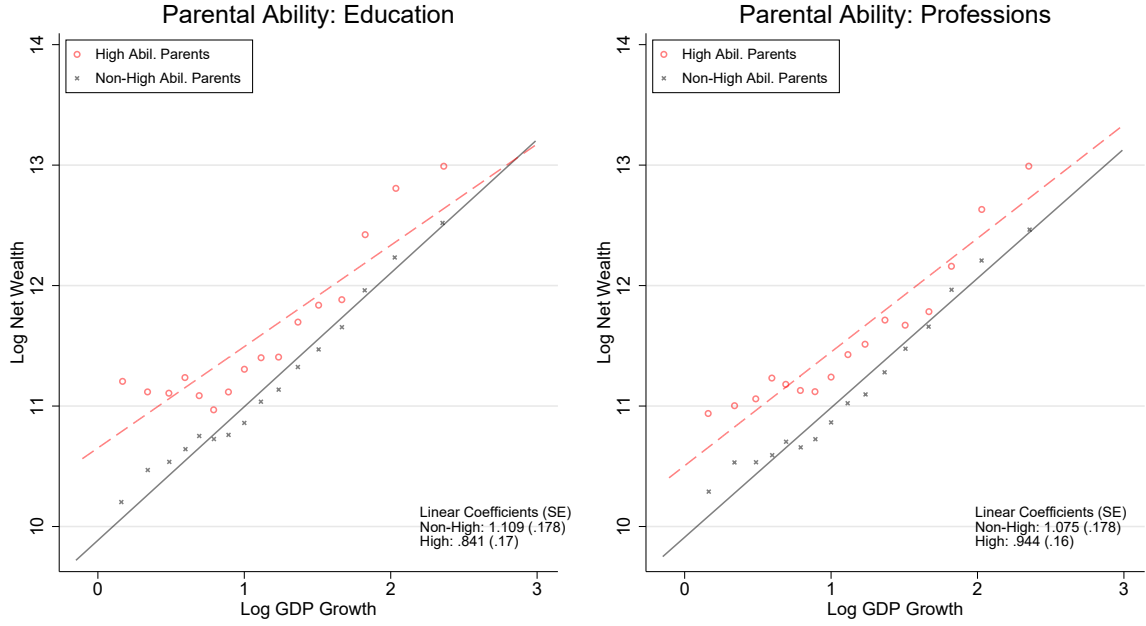
Next, we investigate regional mobility, which is an important confounding factor to our analysis as noted above. Let us start with some elaborations on residential mobility in Germany, which is low when put in an international comparison.<sup>23</sup> While the share of annual transactions in total dwellings is 3-5 percent in France, Sweden, the United Kingdom and the United States, this share is at 1.5 percent in Germany between 2010 and 2021 (see Appendix Figure A.12). This evidence for little residential mobility and house transactions in Germany chimes well with the observation that about half of our population sample stays in their county of birth (see Table 1). What is next, is the rather short time window for residential mobility: Half of the moving population is younger than 30 years, according to the German statistical office. Appendix Figure A.11 shows that the probability to move is 15 percent between 20 and 30 and drops to less than 5 percent after age 35. At the same time, homeownership rates sharply increase from ca. 15 percent at age 30 to ca. 40 percent at age 40 (see Appendix Figure A.11). Taken together, these statistics suggest that (1) the majority of (potential) parents does not move, i.e., does not sort, and (2) most parents in Germany have settled when founding a family, i.e., if they sort, they sort at the beginning of their working life.

Still, high ability parents might have sorted into more productive places *before* starting a family. Even though we cannot observe the true ability of parents', we can investigate several proxies. Figure 5 shows binscatters and third-order polynomial fits of the relationship between hometown growth and wealth by parents education (left-hand) and profession (right-hand). It shows that high- and low-skilled parents populate both high- and low-growth hometowns, i.e., they are not concentrated in high-growth regions. Also, the *Hometown-Growth-Wealth Nexus* is similar for both high- and low-skilled parents, yet children from low-skilled parents achieve lower wealth levels throughout.

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<sup>23</sup>Residential mobility is high in the Australia, Norway, Sweden, and the United States, where more than 20 percent of households changed residence within the last 2 years. This indicator is ca. 10 percent for Germany, ca. 15 percent for the United Kingdom and ca. 17 percent for France. Generally, residential mobility is higher in countries with lower transaction costs, greater access to credit, more responsive housing supply, lower rent controls and tenant protection (Caldera Sanchez and Andrews, 2011). Germany ranks high or low, respectively, in all the above categories.

Figure 5. Binscatter: Net Wealth by Parental Human Capital



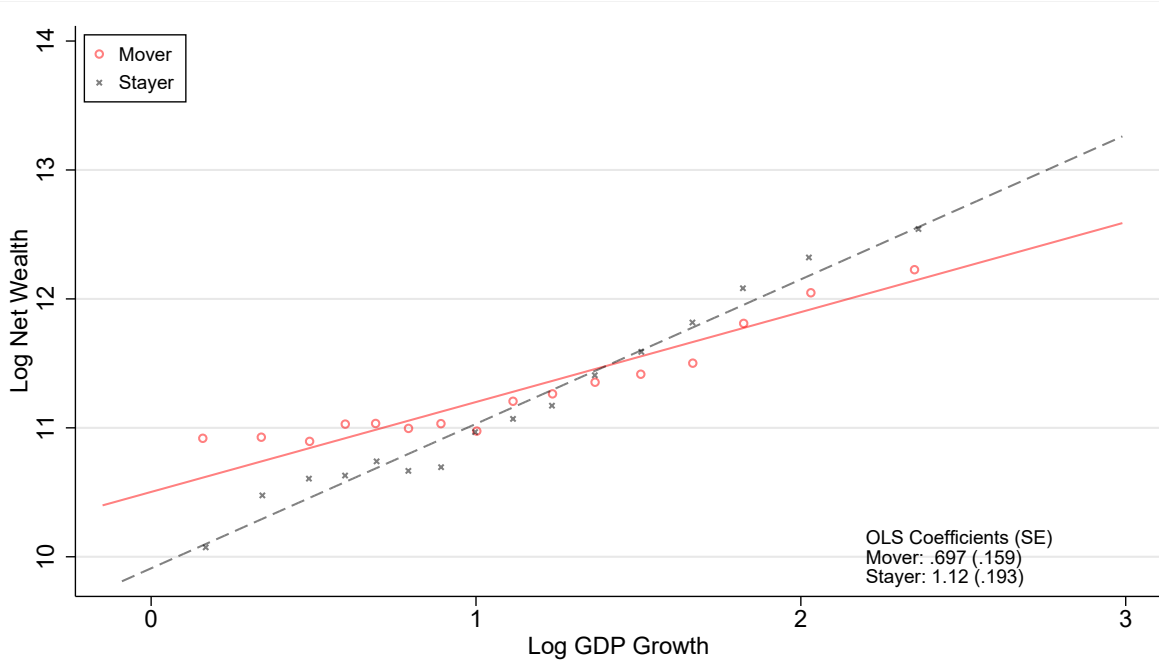
Notes. The figure shows binscatters and linear fits of the relationship between log hometown growth and log net wealth by parental education or profession group. High parental education is one if at least parent has a university or equivalent degree. High parental profession is one if at least one parent is 1) a master tradesman, 2) self-employed with several employees, 3) an employee with management duties, or 4) a high-level civil servant. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2. Data. SOEP 2019 (v36).

To uncover sorting patterns of the current generation, we can zoom into the group of movers – individuals who left their county of birth – which represents roughly half of our estimation sample. Appendix Figure A.5 shows binscatters and third-order polynomial fits of the relationship between hometown growth and relative growth difference (left-hand) and moving distance (right-hand) by individual skill group (tertiary vs. primary/secondary education). Several findings stand out. First, there is a negative relationship between hometown growth and the growth difference between birth and current county. Put differently, individuals from low-growth counties were more likely to move to counties that grew faster than their birth county. The growth difference achieved from moving is up to 100 percent, which is sizable given that the average cumulative growth rate is 260 percent. Second, we do not find differential sorting by skill. Neither growth difference nor moving distance reveals sizable differences between skill groups.

Figure 6 shows that the *Hometown-Growth-Wealth Nexus* is similar for movers and stayers, but the slope is higher for stayers. This means that stayers tend to benefit more from higher hometown growth.



Figure 6. Binscatter: Movers and Stayers



Notes. The figure shows binscatters and linear fits of the relationship between log hometown GDP growth and log net wealth for movers and stayers. Stayers are those who still live in their region of birth at the time of the survey. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2. Data. SOEP 2019 (v36).

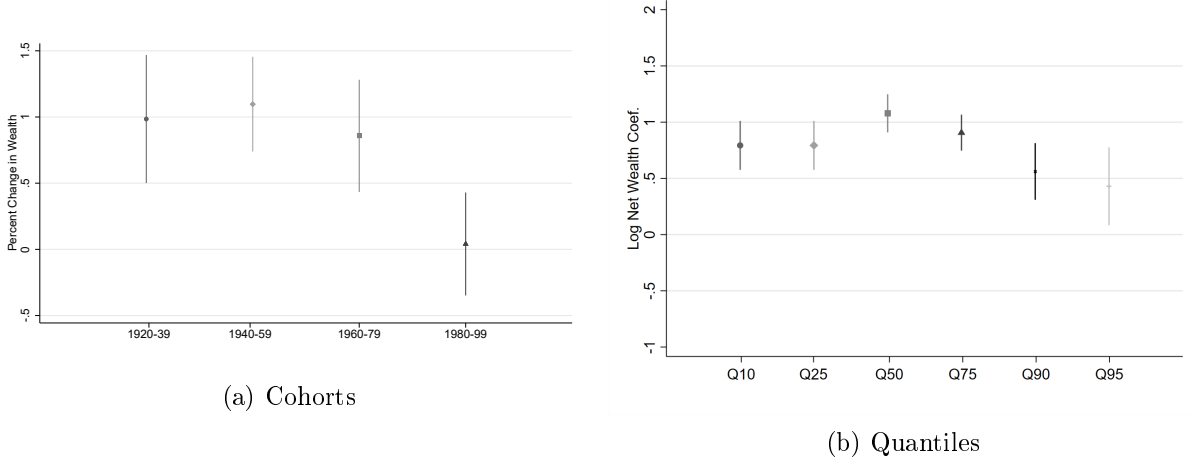
### 3.5 Heterogeneity

We now further investigate the heterogeneity of the *Hometown-Growth-Wealth Nexus*. We start by looking at different cohorts in Figure 7a). Using the same four cohort categories as in Figure 3 and Table 3, we run OLS regressions with separate intercepts and growth slopes for the respective cohorts. Figure 7a) reveals that the marginal growth coefficient is positive for all four cohorts and is significant at the 5 percent level up to the 1960-1979 cohort. The estimate is smaller and not significant for the cohort born 1980-1999. It is important to note, however, that the point estimate is positive for all four cohorts, lending credence to the idea that not only variation across cohorts, but also regional variation within cohorts drives our results.

Next, we investigate how the *Hometown-Growth-Wealth Nexus* changes with wealth. We show the results of unconditional quantile regressions following Firpo et al. (2009) for Q10, Q25, Q50 (median), Q75, Q90, and Q95 in Figure 7b). The growth coefficient from such a regression will be the marginal change of the unconditional quantile given a change in growth. The growth coefficients are all positive and significant at the 5 percent level. The coefficients are larger for the middle class than for the top of the individual wealth distribution. As we will see in Section

4, real estate investments play a significant role behind the *Hometown-Growth-Wealth Nexus* and real estate represents the dominant asset in (upper) middle class portfolios for which the coefficients are the largest.

Figure 7. Hometown-Growth-Wealth Nexus - Cohorts and Quantiles



Notes. The figure (a) shows the coefficients of log GDP per capita growth based on separate OLS regressions for several birth cohorts with individual and parental background controls for the county-level based on Eq. 8. In Figure A.2 we show boxplots for the sizes of cumulative growth, which rationalizes our partition of the cohorts as GDP growth varies non-linearly over the cohorts. The figure (b) shows coefficients of unconditional quantile regressions between current log net wealth and log GDP per capita growth for the county-level based on Eq. 8. 95 percent confidence intervals computed based on bootstrap standard errors from 200 replicates. The specifications included the main controls and parental background controls. Standard errors for the calculation of the 95 percent confidence intervals are clustered at the district-level. Data. SOEP 2019 (v36).

Table 5 shows that the *Hometown-Growth-Wealth nexus* operates quite similarly for men and women, East and West Germans and individuals with or without tertiary education. Similar coefficients for East and West Germans may surprise given the literature emphasizing differences in income, wealth, financial literacy and stock market participation between the two populations (Albers et al., 2024; Davoli and Hou, 2021; Fuchs-Schündeln and Haliassos, 2021). However, growth rates have been lower for those born in former East Germany (GDR) than for those born in former West Germany (FRG) throughout so that a similar coefficient predicts less accumulated wealth for East Germans. Note that there existed possibilities to accumulate wealth in the former GDR. While apartments were publicly owned, 25 percent of the population owned a single-family house. Also, savings and interest rates were quite high given the lack of consumption possibilities (Albers et al., 2024).

Finally, we check *when* growth matters over a life-cycle perspective. Is it important to experience high growth during childhood or in early adolescence when entering the labor and

Table 5. Hometown-Growth-Wealth Nexus - Subgroups

	Female		East		Tertiary Educ.	
	Yes	No	Yes	No	Yes	No
Log GDP Growth	0.964*** (0.163)	0.836*** (0.177)	0.616** (0.282)	0.672*** (0.127)	0.800*** (0.157)	0.970*** (0.166)
<i>N</i>	5457	5774	2560	8671	3877	7354
Ind. Controls	✓	✓	✓	✓	✓	✓
Parent Controls	✓	✓	✓	✓	✓	✓

Notes. The table shows the log GDP per capita growth coefficients for several subgroups based on OLS specifications with individual characteristics and parental background variables based on Eq. 8 estimated at the county-level. Standard errors clustered at the district-level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Data. SOEP 2019 (v36).

housing market? Table 6 shows the results from regressing individual net wealth on average growth rates experienced at different ages. The association is strong and statistically significant during childhood (0-9, 10-19) and then decreases in size. The finding that the relation between families' resources and children's outcomes is not stable, but that the timing matters relates to Carneiro et al. (2021) who document the time-varying influence of parental income.

Table 6. Hometown-Growth-Wealth Nexus - Lifecycle

	(1)	(2)	(3)	(4)	(5)
	0-9	10-19	20-29	30-39	40-49
Log GDP Growth	0.936*** (0.191)	0.744*** (0.145)	0.626*** (0.163)	0.416*** (0.131)	-0.252 (0.214)
Log GDP At Birth	0.105 (0.074)	0.075 (0.076)	0.075 (0.078)	0.024 (0.085)	-0.044 (0.078)
<i>N</i>	11231	11231	10369	9140	7480
$R^2$	0.247	0.246	0.166	0.130	0.117
Ind. Controls	✓	✓	✓	✓	✓
Parent Controls	✓	✓	✓	✓	✓

Notes. The table shows the OLS coefficients of log GDP per capita growth by age with individual characteristics and parental background variables based on Eq. 8 estimated at the county-level. In this specification, the growth rate is computed at different ages, e.g., average growth experienced between 0 and 9 years. Standard errors clustered at the NUTS2-level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Data. SOEP 2019 (v36).

In sum, exposure to growth during childhood seems to matter more than growth in early adolescence and for the house-owning middle-class. Taking these indications together, we will explore the mechanism behind the *Hometown-Growth-Wealth Nexus* in the next section.

## 4 Exploration of mechanisms

We now take the model presented in Section 3.1 to the data and empirically investigate the role of the model’s central parameters - transfers (inheritances+gifts) and wealth accumulation - with different empirical methods.

### 4.1 Transfers

Following up on the influential role of transfers for intergenerational persistence of wealth shown by previous literature, we conduct a mediation analysis as in Heckman and Pinto (2015) and Fagereng et al. (2021). Our measured mediators – market income from labor (labor income plus pensions), years of schooling, and transfers – are chosen to replicate Fagereng et al. (2021) and to reflect the dichotomy between transfers and human capital (see Appendix Section B for details on the implementation of the mediation analysis). Figure 8 shows the results of the mediation analysis.<sup>24</sup> The total effect consists of a direct effect of growth on wealth and an indirect effect through the mediators. The indirect effect is further decomposed into the contributions of transfers and the other mediators. The indirect effect through mediators explains 28 percent of the total effect and 71 percent of the indirect effect works through transfers.<sup>25</sup>

To further explore the transfer channel, we add transfers to our baseline specification (Eq. 8) in column 2 of Table 7. The first column of Table 7 repeats our baseline coefficient with parental controls (see second column of Table 2). Once transfers are included, the growth coefficient declines slightly from 0.9 to 0.74, which mirrors our mediation results. The coefficient for transfers is sizable, positive, and statistically significant at the 1 percent level.

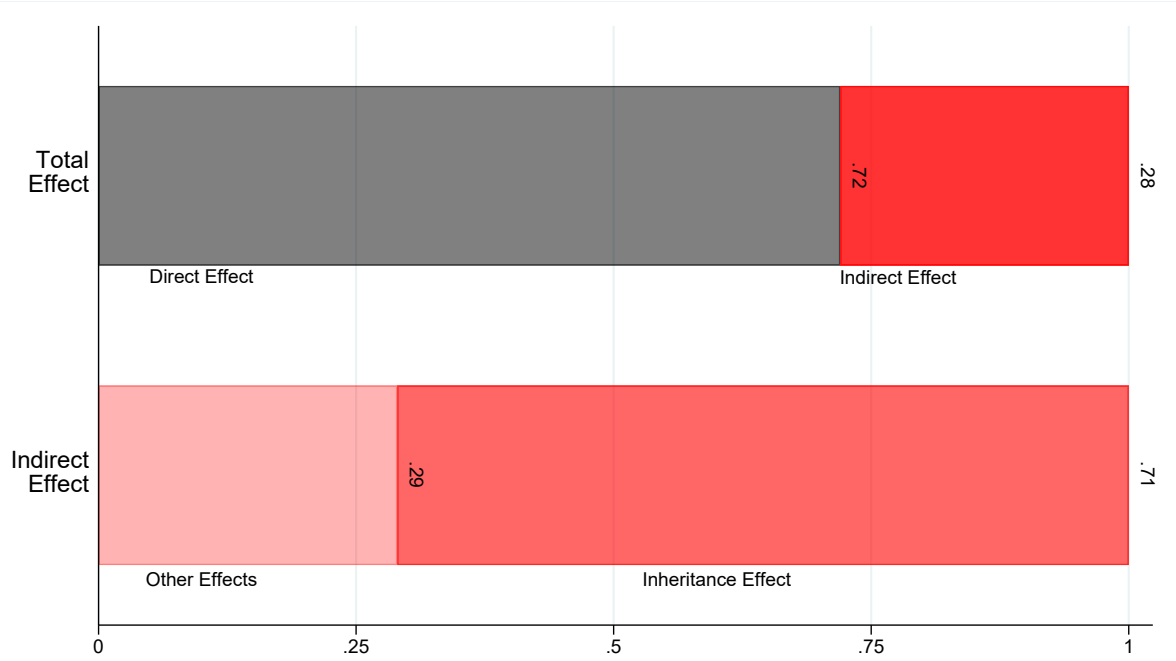
To isolate the link between transfers and hometown land prices, we restrict the sample to heirs having received a house or business transfer (col. 3 to 5). In column 3, we estimate the baseline specification for this sub-group. Adding transfers in column 4 almost halves the growth coefficient. To see whether indicators related to asset appreciation in the birth region are driving the effect, we control for the land price in the birth region in column 5. Note that we are controlling for the current price *level*, not the growth of land prices over time (for which no data are available). The fifth column shows that, when controlling for hometown land prices, the growth coefficient is no longer statistically significant, while land prices are highly statistically

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<sup>24</sup>To flexibly control for the mediators, we construct dummies for each level of years of schooling (16), 20 dummies for quantiles of intergenerational transfers, and 30 dummies for quantiles of market income.

<sup>25</sup>These results are both qualitatively and quantitatively in alignment with Fagereng et al. (2021), who measure the effect of parental wealth on the wealth of children.

Figure 8. Mediation Analysis



Notes. The figure shows the relative contributions in percent of the indirect and direct effects to the total effect as well as the relative contributions of the capitalized inheritance mediator and all others to the indirect effect in the sense of Eq. (B.5) estimated on the county-level.

Data. SOEP 2019 (v36).

significant. We view this evidence as being consistent with the mechanism suggested by the model above, where a combination of bequests and capital gains determine individual wealth in adulthood.<sup>26</sup>

So far, we have documented a substantial role for intergenerational transfers. Yet, only 30 percent of the population received an inheritance or gift.<sup>27</sup> This raises the question of how hometown growth is relevant for non-heirs.

<sup>26</sup>Appendix Figure A.10 illustrates a positive relationship between GDP pc growth and land prices (as a proxy for  $r$ ) for post-war Germany. Transfers, particularly the large ones, come in the form of houses or firms. Land prices tend to grow faster than incomes in an expanding local economy because labor is more mobile than capital, i.e., workers can commute and local housing supply is less elastic than local labor supply (Gyourko et al., 2010).

<sup>27</sup>Note that *recall bias* might lead to an underestimation of this population share in survey data like SOEP. We stress, however, that the SOEP is the best available datasource because inheritance and gift tax data only cover large inheritances and gifts that are tax-relevant and the allowance for children per parent is 400,000 Euro every ten years.

Table 7. Hometown-Growth-Wealth Nexus - Capital Transfers

	Full Sample		Heirs		
	(1) Base	(2) +Transfers	(3) Base	(4) +Transfers	(5) + Land Price
Log GDP Growth	0.881*** (0.146)	0.739*** (0.128)	0.773*** (0.187)	0.394*** (0.143)	0.218 (0.138)
Log GDP At Birth	0.326*** (0.100)	0.246*** (0.088)	0.561*** (0.121)	0.277*** (0.092)	-0.019 (0.122)
Log Transfers		0.080*** (0.004)		0.404*** (0.017)	0.398*** (0.017)
Log Land Price					0.122*** (0.035)
Constant	6.433*** (0.424)	6.751*** (0.383)	6.573*** (0.559)	4.285*** (0.410)	4.765*** (0.423)
$N$	11231	11231	3171	3171	3163
$R^2$	0.253	0.289	0.217	0.346	0.349
Ind. Controls	✓	✓	✓	✓	✓
Parent Controls	✓	✓	✓	✓	✓

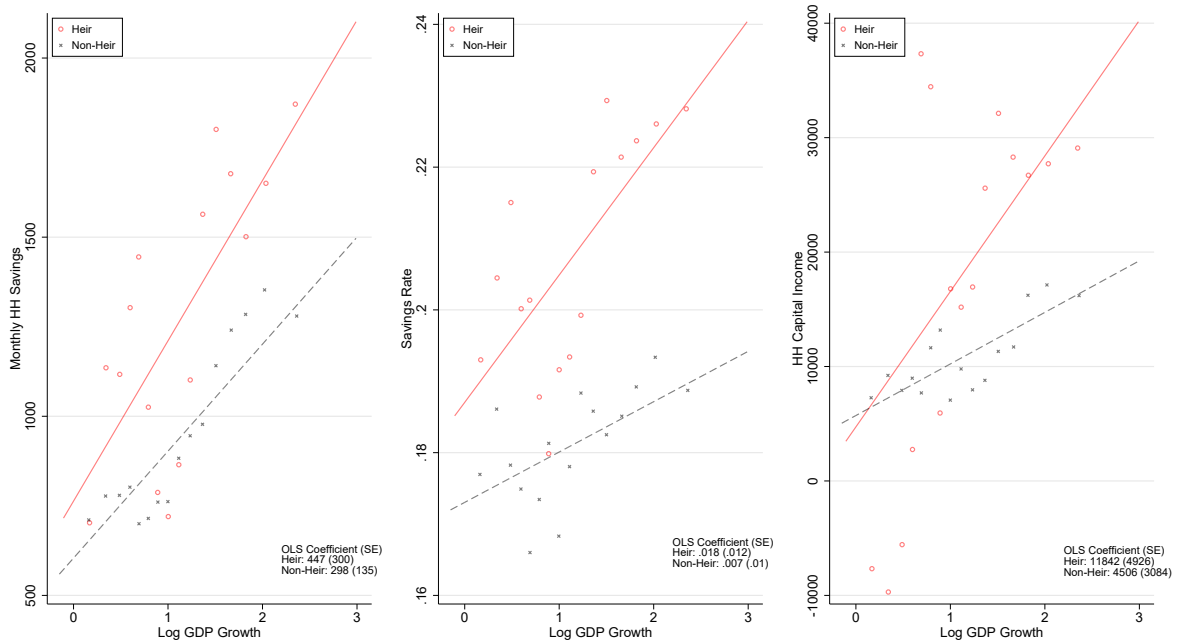
Notes. The table shows OLS coefficients for log GDP per capita growth, log GDP per capita at birth based on Eq. 8 estimated at the county-level. Intergenerational transfers are capitalized inheritances and gifts. In columns (2) and (4) we control for the log of transfers. In column (2) we set the log of transfers to zero for individuals with zero transfers. In column (5) we additionally include for log land prices. Land prices are per square meter in Euro in birth county. Standard errors clustered at the NUTS2-level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Data. SOEP 2019 (v36).

## 4.2 Wealth accumulation

The OLG model predicts that higher growth leads to higher wealth accumulation. We first look at monthly savings, savings rates and household's annual capital income,<sup>28</sup> all of which are recorded in the SOEP. Figure 9 reports a positive relationship between hometown growth and monthly savings, savings rates and capital income for both for non-heirs and heirs. As predicted by the model, both indicators turn out to be higher for individuals from high-growth hometowns. Where do the savings go and how does higher capital income come about? Appendix Figures A.6 and A.7 show that the likelihood to own, the value of and income from both tenant- and owner-occupied housing increase with hometown growth.

Figure 9. Binscatter: Saving and Capital Income



Notes. The figure shows binscatters and linear fits of the relationship between between log hometown GDP growth and yearly household capital income, monthly savings, and the monthly savings rate for heirs and non-heirs. Savings are the sum of savings out of monthly income and debt repayment. The savings rate is calculated as the ratio between savings and household disposable income. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2. Data. SOEP 2019 (v36).

Note that for both heirs and non-heirs, years of schooling or labor market experience fail to explain the *Hometown-Growth-Wealth Nexus*. Binscatters for these outcomes exhibit no clear gradient for the relationship between these outcomes and hometown growth. However, market

<sup>28</sup>Unfortunately, capital income is only asked on the household-level, not on the individual-level. The savings rate is calculated as the ratio between active savings as stated by the respondents and household disposable income.

income (labor income plus pensions) is positively related to hometown growth for non-heirs, but no clear pattern holds for heirs (see Appendix Figure A.9). Furthermore, we can exclude human capital investment of parents in extra-curricular activities like music and sports as driver of the *Hometown-Growth-Wealth Nexus*.<sup>29</sup>

The economic rationale to save more and then invest in real estate should be very salient in dynamic regions, even to children, when living in environments with rising housing costs: First, to escape rising rents, and, second, to benefit as a landlord. Empirical evidence, for example from the finance literature, backs this mechanism. Several studies highlight that individuals *learn from proximity* and emphasize peer-effects arguing that investments are a way to *Keeping Up With the Joneses* (Bailey et al., 2018; Banerjee et al., 2013; Bayer et al., 2021; Brown et al., 2008; Fehr and Reichlin, 2025).

The SOEP also asks for individual preferences and personality traits related to investment decisions. We find that Big 5 personality traits do not systematically vary with hometown growth (Appendix Figure A.8. General willingness to take risks or patience also fails to show a pattern (Figure 10). Only willingness to take *financial* risks increases significantly with hometown growth for non heirs (not for heirs) as illustrated by the center graph of Figure 10.

### 4.3 Validation for the United Kingdom

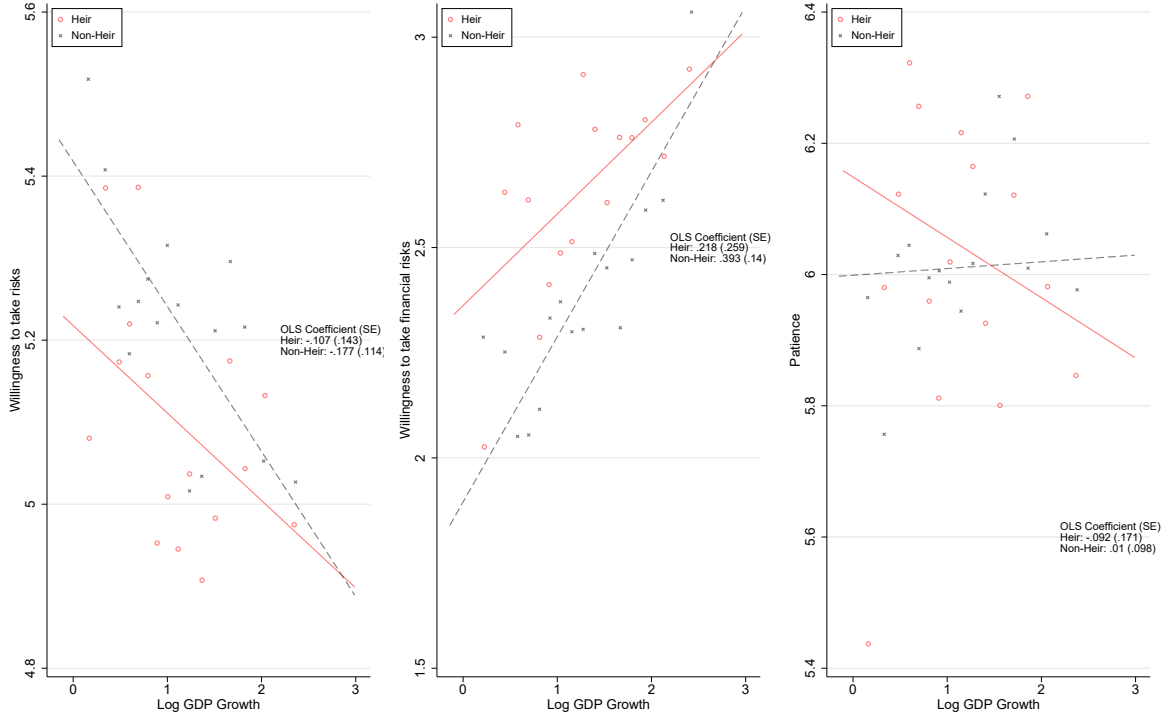
An international validation of the *Hometown-Growth-Wealth Nexus* faces two data challenges: First, birth region is rarely observed in combination with wealth records in international survey data. Second, to our knowledge, long-run regional GDP growth series only exist for Europe from Rosés and Wolf (2018). The United Kingdom Household Longitudinal Study (UKHLS) records both the region of birth and some household asset types. The survey records home ownership, individual income from renting and leasing so that we can construct an indicator for being a landlord and household financial assets. To estimate the *Hometown-Growth-Wealth Nexus* for the United Kingdom, we group the birth regions recorded in UKHLS into NUTS2-regions and

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<sup>29</sup>In Germany, parental investment into the human capital of young children in monetary terms is much lower than, for example, in the United States. Private schools and universities are rare and play much less of a role for top education than in the United States. In Appendix Table A.7, we include several additional control variables to our baseline specification that could be seen as a proxy for parental human capital investments in Germany. Mastering a musical instrument or having practiced sport during childhood (answer is yes/no) is likely to be incentivized and financially supported by the parents. While the signs of the coefficients are as expected (music and sports in childhood are related to higher adult wealth), only the base coefficients are statistically significant and not the interaction with the growth rate.



Figure 10. Binscatter: Risk preference and patience



Notes. The figure shows binscatters and linear fits of the relationship between between log hometown GDP growth and willingness to take risks, willingness to take financial risks and patience for heirs and non-heirs. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2. Data. SOEP 2019 (v36).

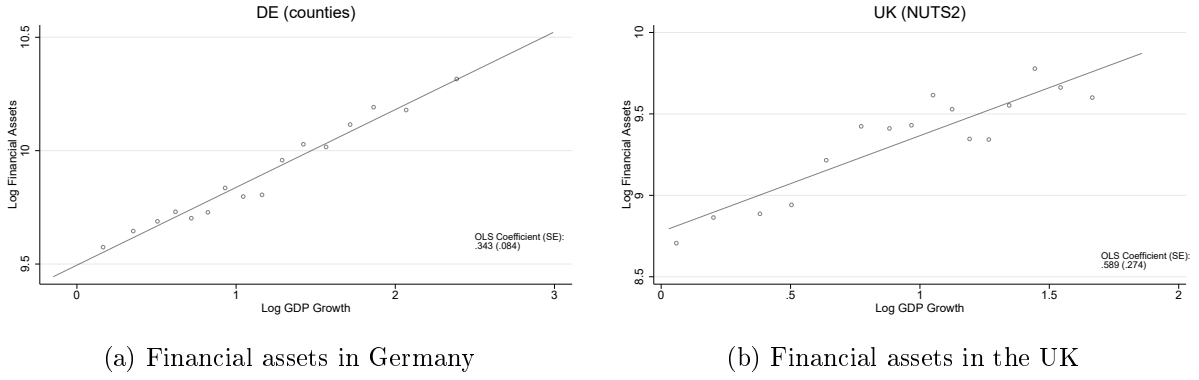
then link the NUTS2 birth region to the respective GDP pc growth rate from [Rosés and Wolf \(2018\)](#).

Figure 11 reveals that financial assets increase with hometown growth both in Germany and the United Kingdom. Figures 12 shows that this positive slope is also confirmed for the likelihood to be a landlord.

## 5 Implications for Wealth Inequality

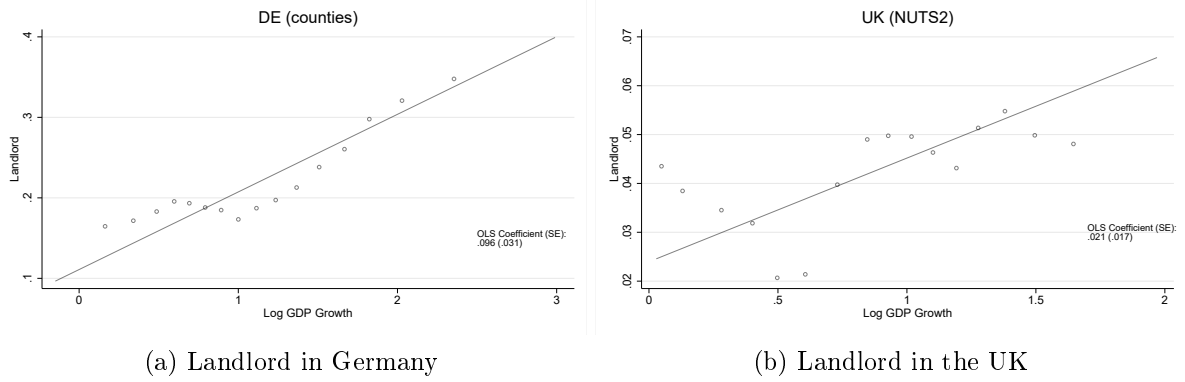
In the previous sections, we have established the *Hometown-Growth-Wealth Nexus* and the mechanisms underpinning it. Now we want to understand the broader implications of differential growth rates for the distribution of wealth. We will pursue a simple counterfactual exercise: we will endow each individual with the growth rates of 1) the 1940-1959 cohort, and 2) the growth rate for the 1940-1959 cohort born in Munich City. By contrasting these regional differences

Figure 11. Binscatter: Financial assets in Germany and the UK



Notes. The figure shows binscatters and linear fits of the relationship between between log hometown GDP growth and financial assets. In the SOEP, financial assets consist of savings accounts, bonds and shares. In the UKHLS, financial assets consist of national savings certificates, trusts, company stocks and shares, and other investments. Data. SOEP 2019 (v36) and UKHLS (SN 6931).

Figure 12. Binscatter: Real estate investments in Germany and the UK



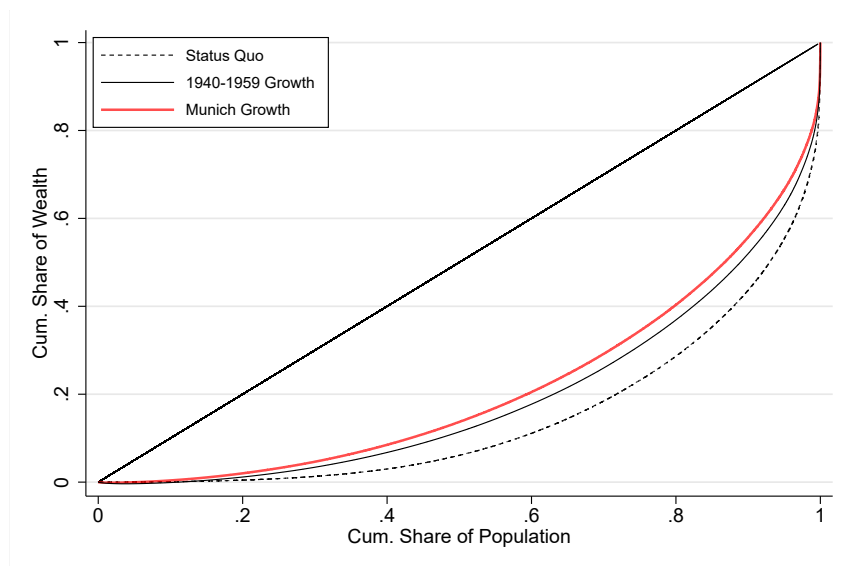
Notes. The figure shows binscatters and linear fits of the relationship between between log hometown GDP growth and the likelihood for being a landlord. Landlord is one if the individual receives rental income. Data. SOEP 2019 (v36) and UKHLS (SN 6931).

in growth rates, we can get a clearer picture of how the regional variation compares to the cohort-specific variation.

To construct the counterfactuals we use the baseline estimate of the Column (2) in Table 2: We predict the growth effect for every individual in our sample and subtract this predicted part from net wealth. We then predict the growth effect for everyone using the counterfactual growth rates and add these effects back into the distribution. Essentially, this is the same procedure as the one we follow to generate Table 3. We present our results in the form of a Lorenz curve shown in Figure 13 and Table 8, which gives several inequality measures.

Figure 13 shows that leveling the playing field in terms of the GDP growth has a strong equalizing effect, particularly on the middle of the wealth distribution.<sup>30</sup> The Lorenz curve for the 1940-1959 counterfactual almost Lorenz-dominates the status quo, while the Munich counterfactual does. Additionally, the Munich counterfactual is appreciably closer to the line of equality than the 1940-1959 cohort counterfactual.

Figure 13. Lorenz Curve of Net Wealth: Status Quo vs. Counterfactual Growth



Notes. The figure shows the Lorenz curve of net wealth for the status quo and the counterfactual scenario of everyone experiencing the average GDP per capita growth of the cohort born between 1950 and 1960 as well as the 1950-60 cohort from Munich and from Recklinghausen. Results are calculated using our estimation sample for our main specification and weighted using the individual weighting factors provided by the SOEP. The procedure to calculate the individual counterfactual wealth levels is described in the notes of Table 3. Data. SOEP 2019 (v36).

In Table 8 we compute several counterfactual distributional statistics: the Gini coefficient, and the bottom 50 percent, top 10 percent, top 5 percent, and top 1 percent wealth shares. The Gini coefficient drops considerably from 0.7 to either 0.61 for the cohort counterfactual or 0.57 for the Munich counterfactual. The Gini coefficient is particularly sensitive to changes around the mean of the distribution, so that top wealth shares can add another valuable perspective. The most striking finding is that in the case of the Munich counterfactual the bottom 50 percent gain almost seven percentage points of total wealth while the top 1 percent lose roughly eight percentage points.

<sup>30</sup>The equalizing effect arises from the unequal distribution of hometown growth: Appendix Figure A.14 shows that the top 10 percent of the wealth distribution experienced GDP growth of about 350 percent, while the bottom four deciles only experienced GDP growth of less than 240 percent.

Table 8. Distributional Statistics: Status Quo vs. Counterfactual Growth

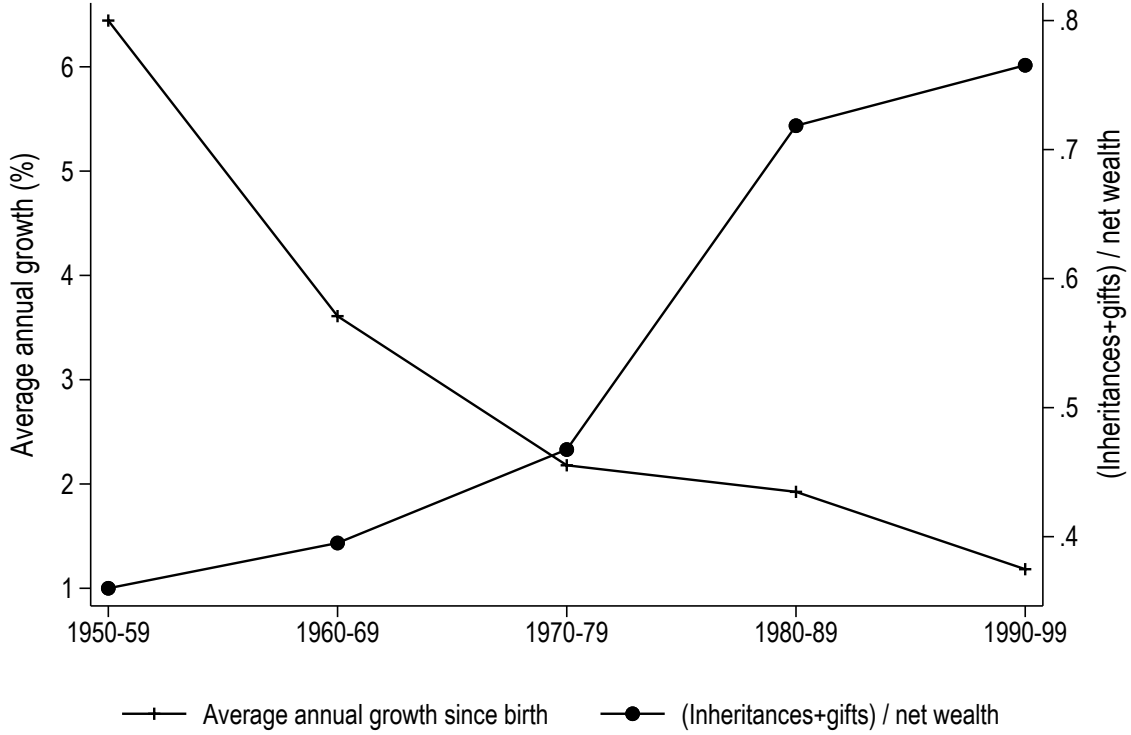
	Wealth Shares				
	Gini	Bottom 50%	Top 10%	Top 5%	Top 1%
Status Quo	0.71	6.11	56.26	44.51	26.61
1950-1960 Cohort	0.61	11.44	48.02	37.07	21.51
Munich City	0.57	13.70	44.29	33.46	18.87

Notes. The table shows several distributional statistics of net wealth for the status quo, the counterfactual scenario of everyone experiencing the average GDP per capita growth of the cohort born between 1950 and 1960, and the counterfactual scenario of everyone experiencing the average GDP per capita growth of that cohort from the county of Munich or the county of Recklinghausen. Results are calculated using our estimation sample for our main specification and weighted using the individual weighting factors provided by the SOEP. The procedure to calculate the individual counterfactual wealth levels is described in the notes of Table 3. The Gini index was renormalized to adjust for negative values according to the method in [Raffinetti et al. \(2017\)](#). Data. SOEP 2019 (v36).

What if high economic growth rates are a phenomenon of the past? As shown in our introduction, economic growth has declined in all major industrial economies. [Piketty \(2011\)](#) develops a model that illustrates how declining growth rates increase the importance of inheritances over savings from labor income. In periods of sizable growth, young workers earn a lot more than their parents. Accordingly, they may save more, which reduces the relative importance of inheritance. When growth declines, savings cannot contribute to young workers wealth stock and inheritances dominate ([Piketty, 2011](#), p.1113). Figure 14 shows suggestive evidence that the transfer-wealth-ratio in Germany has indeed increased over cohorts, while, at the same time, each 10-year cohort born in post-war Germany has experienced lower average growth than the previous cohort (see also Figure 3). For the figure, we calculated the share of inherited wealth in total net wealth for all individuals in our estimation sample who already received an inheritance or gift. The cohort born 1950-59 has seen an average annual growth rate of more than 6 percent and a transfer-wealth-ratio of less than 40 percent. The cohort born 1980-89 has seen an average annual growth rate of ca. 2 percent and a transfer-wealth-ratio of more than 70 percent.<sup>31</sup>

<sup>31</sup>Note that the transfer-wealth-ratio of the youngest cohort might still decline as they grow older and accumulate more wealth.

Figure 14. Transfer-Wealth-Ratio and Growth over Cohorts



Notes. The Figure shows the share of transfers (inheritances and gifts) in net wealth conditional on having received an inheritance or gift.

Data. SOEP 2019 (v36).

## 6 Conclusion

In this paper we have shown the importance of one's place of birth and its economic trajectory for wealth in adulthood, what we called the *Hometown-Growth-Wealth Nexus*. We found that a one percent increase in economic growth in a person's birth place since birth translates to 0.9 percent more wealth in adulthood. According to this estimate, a person born in flourishing Munich between 1940 and 1959 will have accumulated almost three times more than a person from the same cohort born in the declining industrial Ruhr area.

Inheritances and gifts, particularly houses and firms emerge as important determinants of the *Hometown-Growth-Wealth Nexus* via increased variation in land prices. Yet, wealth of non-heirs also increases with hometown growth via higher savings, investments and capital income. We validate the *Hometown-Growth-Wealth Nexus* and the savings channel for the United Kingdom using UKHLS wealth records and GDP growth across 10 regions (NUTS2).

Our paper adds a new perspective on how past growth and subsequent parental transfers shape wealth inequality of the next generation. Individuals from economically dynamic birth regions accumulated more wealth. We find that high economic growth has an overall equalizing impact on wealth inequality. In a context of declining growth rates and large regional variation in land prices (as a result of different growth rates in the past), we expect the importance of intergenerational transfers for wealth distributions to increase and wealth inequality with it.

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## A Internet Appendix

### A.1 Appendix Tables

Table A.1. Hometown-Growth-Wealth Nexus - District Level

	OLS		Coal IV		Shift-Share IV	
	(1) Base	(2) +Parental Vars	(3) Base	(4) +Parental Vars	(5) Base	(6) +Parental Vars
Log GDP Growth	1.483*** (0.259)	1.295*** (0.241)	3.472** (1.392)	3.041** (1.243)	7.993** (3.465)	7.106** (3.113)
Log GDP At Birth	1.233*** (0.202)	0.961*** (0.194)	1.638*** (0.402)	1.326*** (0.379)	2.404** (0.935)	2.061** (0.828)
Female	-0.479*** (0.029)	-0.469*** (0.029)	-0.465*** (0.028)	-0.458*** (0.029)	-0.526*** (0.037)	-0.511*** (0.037)
Ind. Mig. Backgr.	-0.084 (0.083)	0.070 (0.079)	-0.111 (0.095)	0.042 (0.090)	-0.199* (0.105)	-0.023 (0.092)
Married	0.543*** (0.050)	0.551*** (0.049)	0.542*** (0.048)	0.550*** (0.047)	0.557*** (0.069)	0.575*** (0.069)
F:MS		0.394*** (0.103)		0.371*** (0.105)		0.450*** (0.128)
F:HS		0.722*** (0.116)		0.711*** (0.115)		0.634*** (0.145)
M:MS		0.293*** (0.090)		0.307*** (0.086)		0.424*** (0.115)
M:HS		0.475*** (0.118)		0.495*** (0.117)		0.602*** (0.163)
F:Worker		-0.117* (0.067)		-0.091 (0.069)		0.001 (0.088)
F:Selfemp		0.872*** (0.093)		0.839*** (0.091)		0.973*** (0.088)
F:Wht. Collar		0.224** (0.084)		0.239*** (0.083)		0.317*** (0.103)
F:Civ Serv		0.381*** (0.088)		0.354*** (0.088)		0.397*** (0.106)
Constant	4.373*** (0.755)	4.204*** (0.712)	2.382 (1.656)	2.423 (1.543)	-1.593 (3.906)	-1.517 (3.495)
<i>N</i>	11231	11231	11231	11231	7153	7153
<i>R</i> <sup>2</sup>	0.212	0.257	0.192	0.242	0.105	0.191
Cohort FE	✓	✓	✓	✓	✓	✓
Eff-F			1.951	1.891	3.598	3.527

Notes. The table shows TSLS-IV coefficients for log GDP per capita growth, log GDP per capita at birth, individual characteristics and parental background variables based on Eq. 8 estimated at the district-level with log individual net wealth as the dependent variable. *F:HS* is a dummy for the father having at most a high school education, *F:MS* is the analogous dummy for middle school. *M:HS* and *M:MS* are the analogous coefficients for the mother. *F:Worker.*, *F:Selfemp.*, *F:Wht. Collar* and *F:Civ.Serv.* are dummies for the father being a laborer, self-employed, white collar employee, or a civil servant, respectively. The coal IV refers to the centroid distance of the commuting zone to a carboniferous area and its square based on the data provided by [Fernihough and O'Rourke \(2021\)](#). The shift-share IV is constructed from initial shares of industry-specific local GDP contributions and the national growth rate of these industries. Initial shares correspond to the year of birth of the individual. F-statistic (Eff-F) is given by weak-instrument test based on [Olea and Pflueger \(2013\)](#). Standard errors clustered at the NUTS2-level are in parentheses \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Data. SOEP 2019 (v36).

Table A.2. Hometown-Growth-Wealth Nexus - Commuting Zone Level

	OLS		Coal IV		Shift-Share IV	
	(1) Base	(2) +Parental Vars	(3) Base	(4) +Parental Vars	(5) Base	(6) +Parental Vars
Log GDP Growth	1.769*** (0.202)	1.524*** (0.180)	2.771*** (0.444)	2.301*** (0.359)	3.311*** (0.659)	2.843*** (0.579)
Log GDP At Birth	1.368*** (0.212)	1.121*** (0.173)	1.951*** (0.278)	1.575*** (0.214)	1.975*** (0.405)	1.650*** (0.347)
Female	-0.486*** (0.029)	-0.474*** (0.029)	-0.482*** (0.029)	-0.472*** (0.029)	-0.526*** (0.039)	-0.510*** (0.038)
Ind. Mig. Backgr.	-0.023 (0.085)	0.113 (0.078)	-0.050 (0.083)	0.089 (0.078)	-0.096 (0.084)	0.065 (0.078)
Married	0.545*** (0.051)	0.552*** (0.049)	0.541*** (0.049)	0.550*** (0.048)	0.566*** (0.065)	0.584*** (0.066)
F:MS		0.384*** (0.104)		0.374*** (0.102)		0.492*** (0.112)
F:HS		0.729*** (0.119)		0.725*** (0.118)		0.710*** (0.131)
M:MS		0.264*** (0.093)		0.256*** (0.092)		0.298*** (0.101)
M:HS		0.469*** (0.125)		0.473*** (0.124)		0.492*** (0.148)
F:Worker		-0.128* (0.068)		-0.116* (0.069)		-0.059 (0.077)
F:Selfemp		0.856*** (0.096)		0.822*** (0.091)		0.944*** (0.095)
F:Wht. Collar		0.232** (0.089)		0.235*** (0.088)		0.283*** (0.093)
F:Civ Serv		0.386*** (0.091)		0.364*** (0.089)		0.415*** (0.101)
Constant	3.803*** (0.771)	3.619*** (0.650)	1.590 (1.017)	1.909** (0.833)	1.423 (1.492)	1.400 (1.334)
<i>N</i>	11197	11197	11197	11197	7126	7126
<i>R</i> <sup>2</sup>	0.213	0.259	0.206	0.255	0.252	0.307
Cohort FE	✓	✓	✓	✓	✓	✓
Eff-F			13.931	13.605	13.307	13.262

Notes. The table shows TSLS-IV coefficients for log GDP per capita growth, log GDP per capita at birth, individual characteristics and parental background variables based on Eq. 8 estimated at the level of commuting zones with log individual net wealth as the dependent variable. *F:HS* is a dummy for the father having at most a high school education, *F:MS* is the analogous dummy for middle school. *M:HS* and *M:MS* are the analogous coefficients for the mother. *F:Worker*., *F:Selfemp*., *F:Wht. Collar* and *F:Civ.Serv.* are dummies for the father being a laborer, self-employed, white collar employee, or a civil servant, respectively. The coal IV refers to the centroid distance of the commuting zone to a carboniferous area and its square based on the data provided by Fernihough and O'Rourke (2021). The shift-share IV is constructed from initial shares of industry-specific local GDP contributions and the national growth rate of these industries. Initial shares correspond to the year of birth of the individual. F-statistic (Eff-F) is given by weak-instrument test based on Olea and Pflueger (2013). Standard errors clustered at the NUTS2-level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Data. SOEP 2019 (v36).

Table A.3. First Stages of IV Specifications

	Coal IV		Shift-Share IV	
	(1) Base	(2) +Parental Vars	(3) Base	(4) +Parental Vars
Distance to Carbon	0.003*** (0.001)	0.003*** (0.001)		
Sq. of Distance to Carbon	-0.000*** (0.000)	-0.000*** (0.000)		
Shift-Share IV			-0.258*** (0.030)	-0.257*** (0.031)
constant	1.201*** (0.144)	1.208*** (0.136)	1.287*** (0.110)	1.286*** (0.103)
$N$	11231	11231	7153	7153
$R^2$	0.881	0.882	0.853	0.854
Ind. Controls	✓	✓	✓	✓
Parent Controls		✓		✓
Cohort FE	✓	✓	✓	✓

Notes. The table shows OLS coefficients of the different IV specifications include two different sets of controls. As growth rates declined over time, cohort fixed effects are large and increase substantially with age, turning the coefficient of the Shift-Share IV negative. Standard errors clustered at the NUTS2-level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Data. SOEP 2019 (v36).



Table A.4. Hometown-Growth-Wealth Nexus - Growth of Population Density

	OLS	
	(1) Base	(2) +Parental Vars
Log Pop Density Growth	1.216*** (0.112)	1.000*** (0.111)
Log Pop Density At Birth	0.043 (0.027)	0.001 (0.023)
Female	-0.526*** (0.029)	-0.513*** (0.029)
Ind. Mig. Backgr.	-0.045 (0.084)	0.122 (0.075)
Married	0.627*** (0.060)	0.632*** (0.058)
F:MS		0.405*** (0.113)
F:HS		0.704*** (0.127)
M:MS		0.351*** (0.084)
M:HS		0.535*** (0.116)
F:Worker		-0.053 (0.075)
F:Selfemp		0.984*** (0.101)
F:Wht. Collar		0.333*** (0.093)
F:Civ Serv		0.446*** (0.098)
Constant	8.918*** (0.113)	7.624*** (0.182)
<i>N</i>	9194	9194
<i>R</i> <sup>2</sup>	0.246	0.294
Cohort FE	✓	✓

Notes. The table shows OLS coefficients for log individual net wealth and log population density growth, log population density at birth, individual characteristics and parental background variables based on Eq. 8 estimated at the county-level. The sample size is slightly smaller than in the baseline regression in Table 2 as population data are only available since 1950. *F:HS* is a dummy for the father having at most a high school education, *F:MS* is the analogous dummy for middle school. *M:HS* and *M:MS* are the analogous coefficients for the mother. *F:Worker.*, *F:Selfemp.*, *F:Wht. Collar* and *F:Civ.Serv.* are dummies for the father being a laborer, self-employed, white collar employee, or a civil servant, respectively. Standard errors clustered at the NUTS2-level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Data. SOEP 2019 (v36).

Table A.5. GDP Growth on Individual Wealth - Birth-region FE (instead of GDP at birth)

	(1)	(2)
	Base	+Parental Vars
Log GDP Growth	0.257** (0.117)	0.274** (0.115)
Female	-0.457*** (0.028)	-0.457*** (0.031)
Ind. Mig. Backgr.	-0.132 (0.083)	-0.020 (0.081)
Married	0.545*** (0.051)	0.554*** (0.048)
F:MS		0.352*** (0.107)
F:HS		0.873*** (0.116)
M:MS		0.320*** (0.088)
M:HS		0.621*** (0.118)
Constant	10.823*** (0.142)	10.022*** (0.165)
$N$	11228	11228
$R^2$	0.262	0.282
Cohort FE	✓	✓
birth-region FE	✓	✓

Notes. The table shows OLS coefficients for log GDP per capita growth, individual characteristics, and parental background variables based on Eq. 8 estimated at the county-level with log individual net wealth as the dependent variable. As an alternative control for starting conditions we drop GDP per capita at birth and absorb birth-county and birth-year fixed effects. Standard errors clustered at the NUTS2-level are in parentheses \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Data. SOEP 2019 (v36).

Table A.6. GDP Growth on Individual Wealth - Panel

	OLS		Fixed Effects	
	(1) Base	(2) +Parental Vars	(3) Fixed Effects	(4) +Parental Vars
Log GDP Growth	1.092*** (0.042)	0.982*** (0.043)	0.365*** (0.106)	0.376*** (0.112)
Log GDP At Birth	0.467*** (0.030)	0.371*** (0.031)		
Constant	4.803*** (0.463)	4.709*** (0.454)	7.448*** (0.315)	7.466*** (0.316)
Obs.	50071	46152	50071	46152
$R^2$	0.264	0.298	0.153	0.158
N	20320	18595	20320	18595

Notes. The table shows OLS coefficients for log GDP per capita growth from a panel regression based on Eq. 8 estimated at the county-level. Years included in the panel estimation are 2002, 2007, 2012, 2017, 2019. The table shows OLS coefficients for log GDP per capita at birth and log GDP per capita growth. Columns (3) and (4) show estimates after controlling for individual fixed effects. Obs. denotes the total number of observations, while  $N$  is the number of individuals observed for at least two consecutive wealth survey years (2002, 2007; 2007, 2012; 2012, 2017; 2017, 2019). Standard errors clustered at the NUTS2-level are in parentheses \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Data. SOEP 2019 (v36).

Table A.7. Hometown-Growth-Wealth Nexus - Human Capital

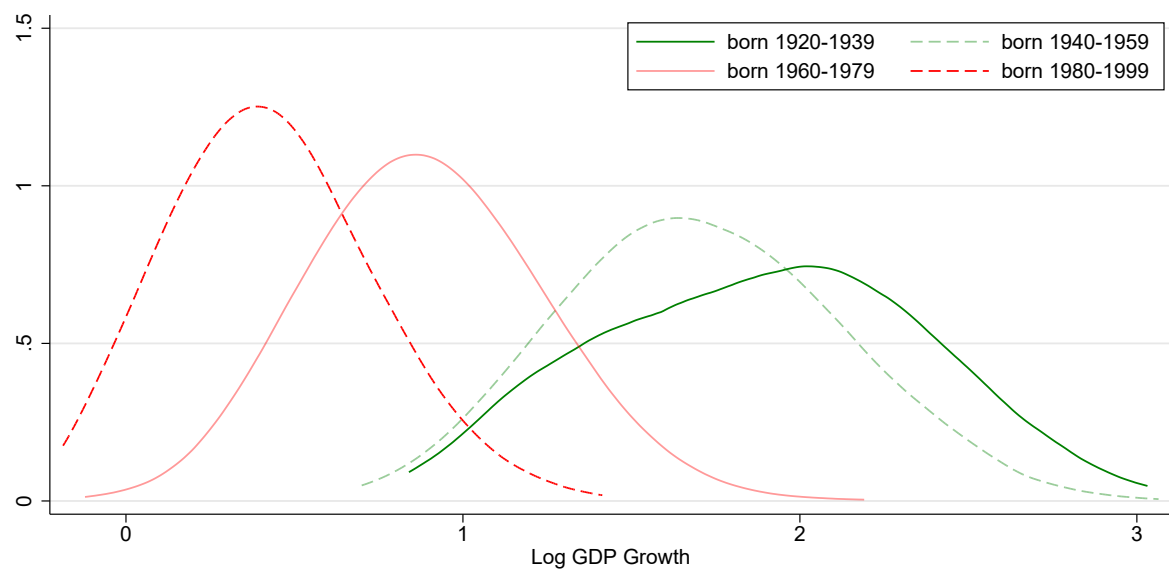
	(1)	(2)	(3)	(4)
Log GDP Growth	0.816*** (0.140)	0.924*** (0.140)	1.023*** (0.166)	0.892*** (0.180)
Growth $\times$ Music	0.029 (0.051)			
Mastering Musical Instrument	0.174** (0.068)			
Growth $\times$ Sport		-0.125 (0.080)		
Practicing Sports		0.356*** (0.125)		
Growth $\times$ Comp.			-0.280*** (0.078)	
Competing in Sports			0.311*** (0.066)	
Growth $\times$ Math				-0.002 (0.038)
Math Grade				-0.189*** (0.054)
<i>N</i>	8775	8785	5819	8527
<i>R</i> <sup>2</sup>	0.232	0.232	0.256	0.238
Ind. Controls	✓	✓	✓	✓
Parent Controls	✓	✓	✓	✓

Notes. The table shows marginal effects of GDP per capita growth controlling for different activities during childhood which are likely proxys for human capital transfers from parents to children. Standard errors clustered at the NUTS2-level are in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Data. SOEP 2019 (v36).

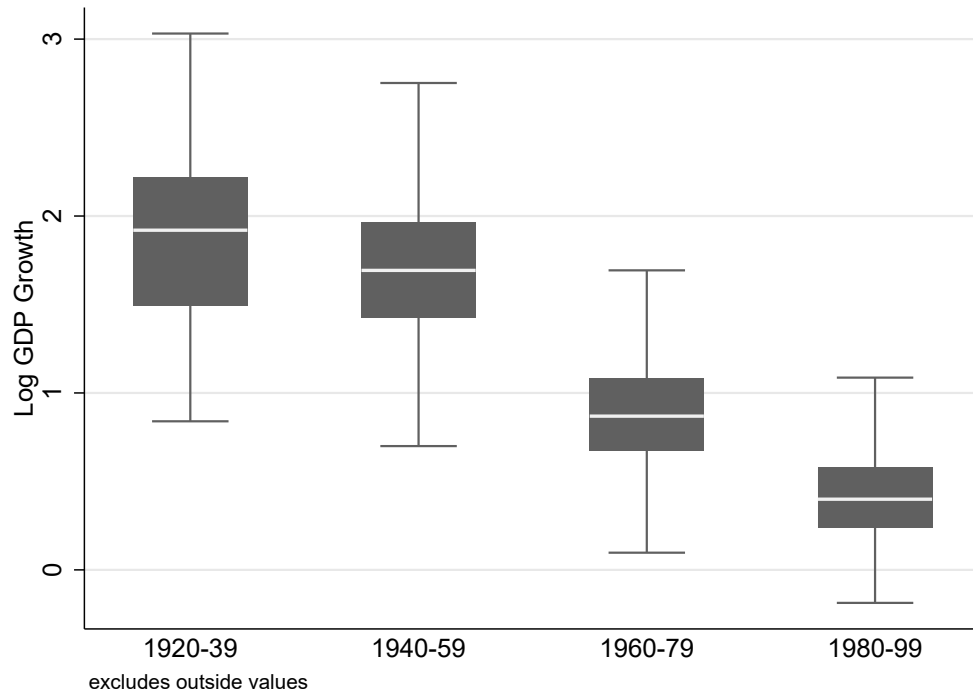
## A.2 Appendix Figures

Figure A.1. Kernel Density of Log GDP Growth by Cohort



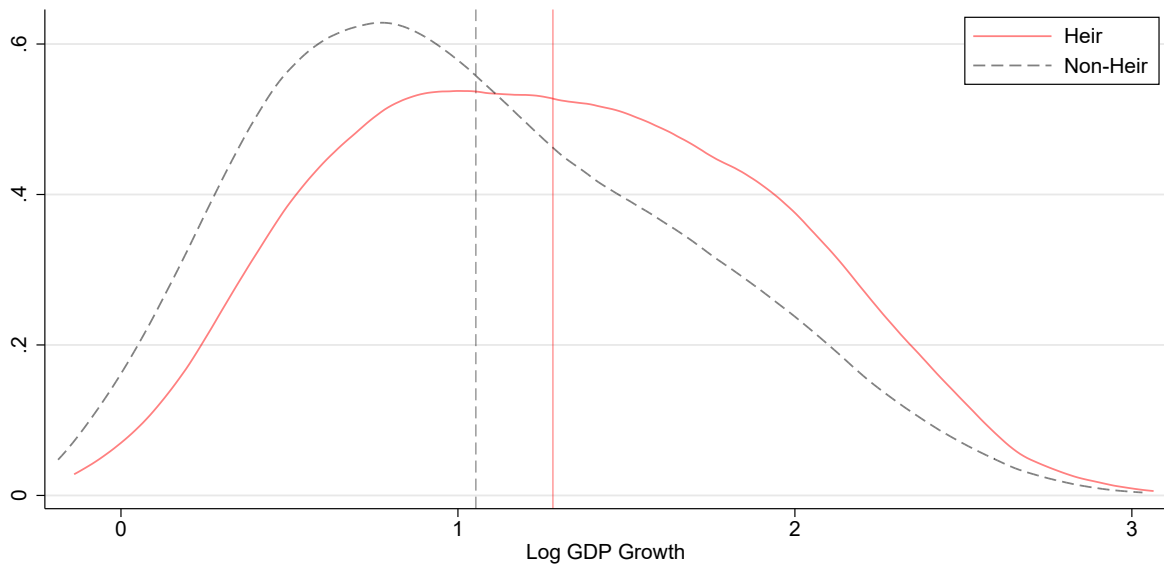
Notes. Kernel densities of log real GDP per capita growth in birth county since birth until survey year 2019 for four different birth cohorts. Data. SOEP 2019 (v36).

Figure A.2. Boxplots - GDP Growth of Cohorts



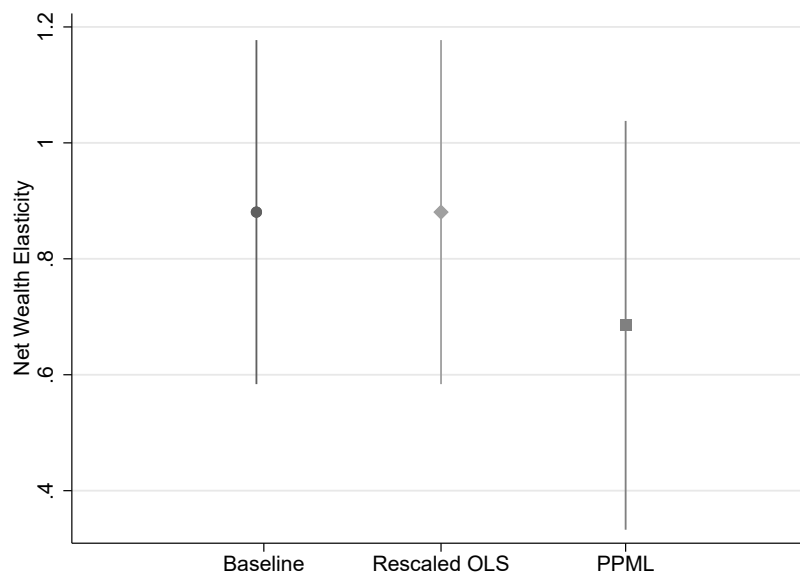
Notes. The figure shows boxplots for the sizes of cumulative hometown GDP growth for different cohorts.  
Data. SOEP 2019 (v36).

Figure A.3. Kernel Density of Log GDP Growth for Heirs and Non-Heirs



Notes. Kernel densities of log real GDP per capita growth in birth county since birth until survey year 2019 for heirs and non-heirs. Data. SOEP 2019 (v36).

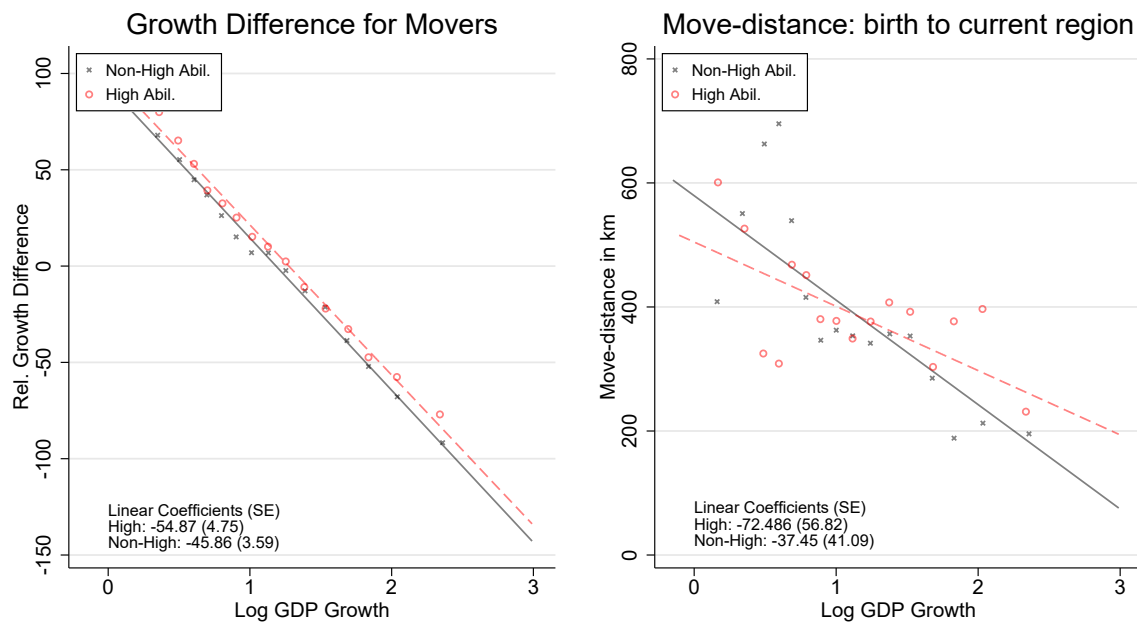
Figure A.4. Hometown-Growth-Wealth Nexus - Functional Forms



Notes. The figure shows the estimated elasticities of net wealth with respect to GDP per capita growth for several functional forms for the county-level. *Baseline* is equivalent to the coefficient in Table 2 col. 2, *Rescaled OLS* is the coefficient resulting when we impute zeros for log net wealth when net wealth equals zero or less, *PPML* is the Poisson pseudo maximum likelihood estimate of the net wealth elasticity estimated based on net wealth in levels (Silva and Tenreyro, 2006). Standard errors for the calculation of the 95% confidence intervals are clustered at the NUTS2-level.

Data. SOEP 2019 (v36).

Figure A.5. Binscatter: Net Wealth by Moving Decision and Human Capital

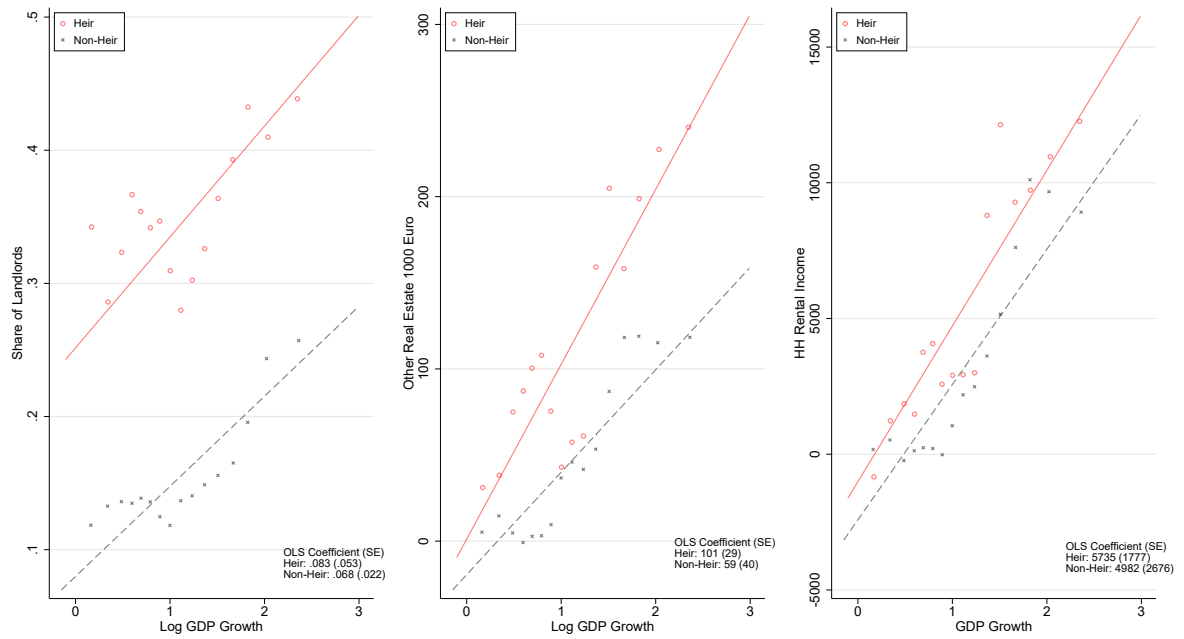


Notes. The figure shows binscatters and linear fits of the relationship between log hometown growth and the relative growth difference (right-hand) and moving distance (left-hand) by high and non-high parental ability. High individual education indicates a university or equivalent degree. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2.

Data. SOEP 2019 (v36).

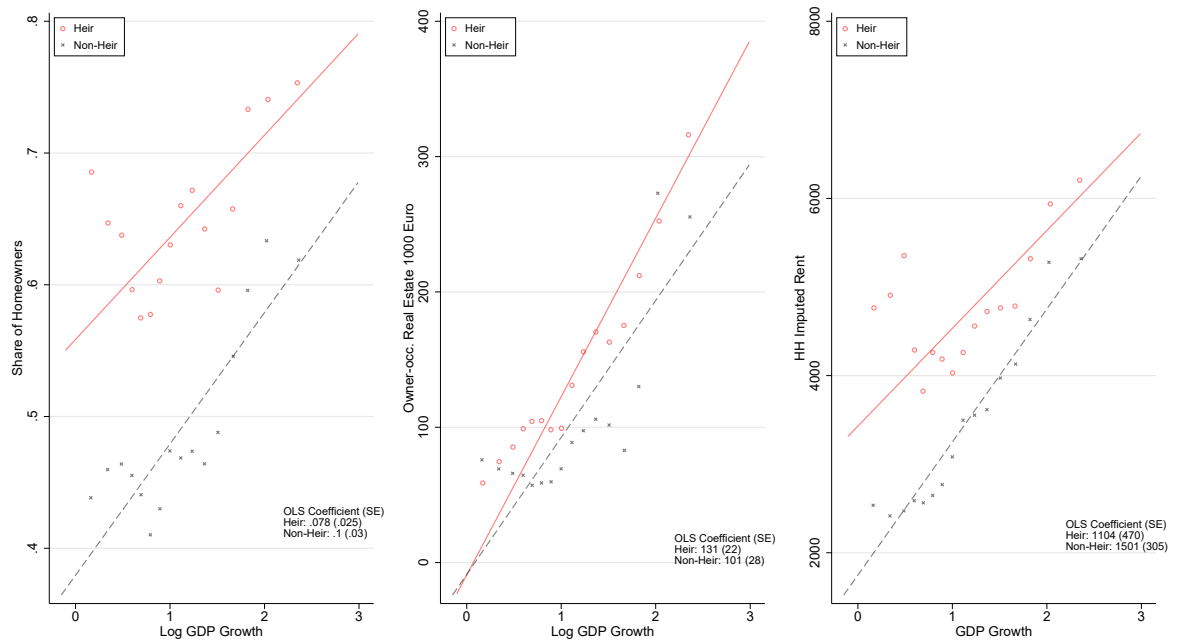


Figure A.6. Binscatter: Non-owner-occupied Real Estate



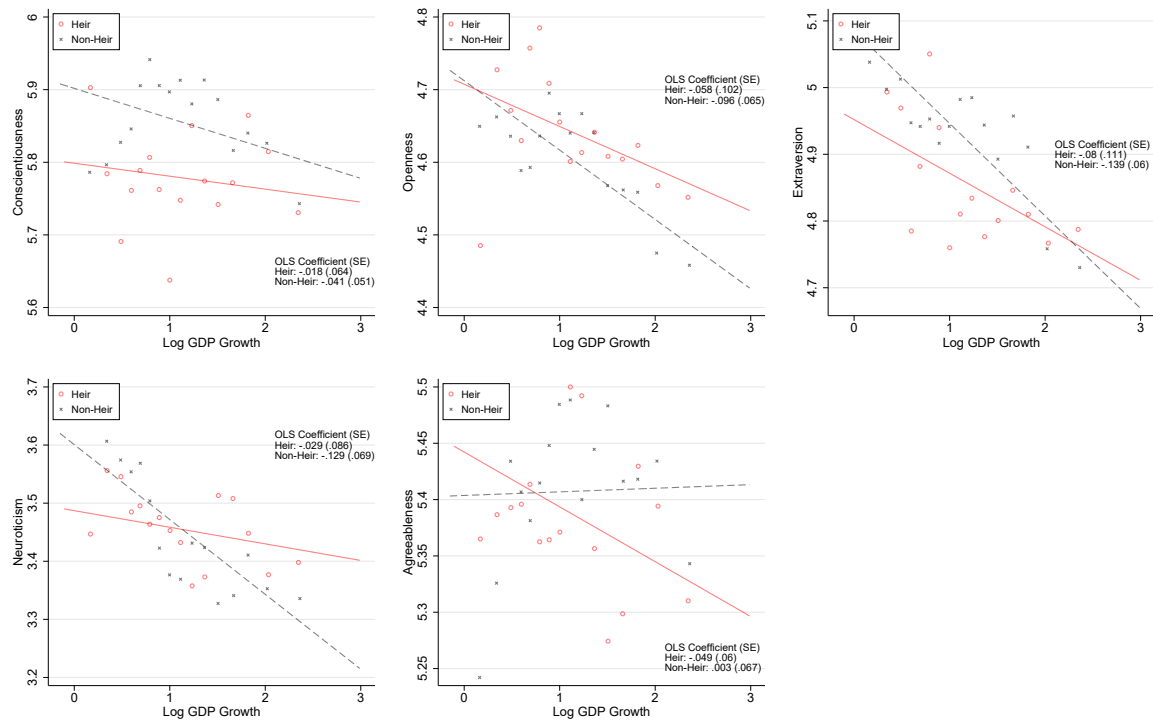
Notes. The figure shows binscatters and linear fits of the relationship between between log hometown GDP growth and the share of landlords, that is, owners of non-owner-occupied real estate, the value of these assets, and household income from renting and leasing for heirs and non-heirs. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2. Data: SOEP 2019 (v36).

Figure A.7. Binscatter: Owner-occupied Real Estate



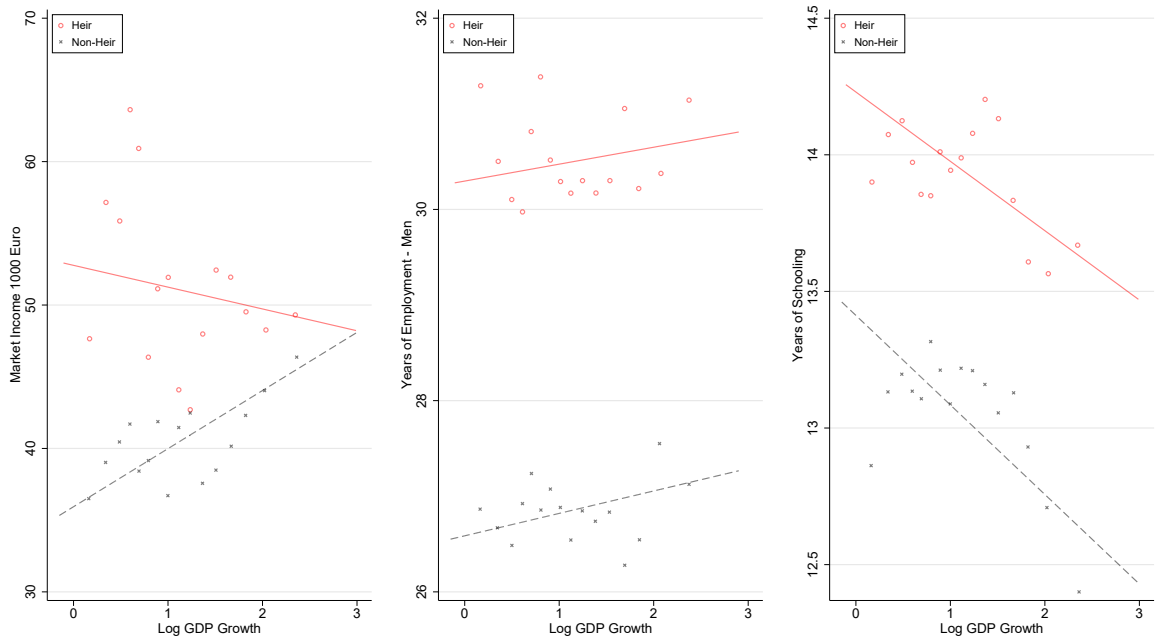
Notes. The figure shows binscatters and linear fits of the relationship between between log hometown GDP growth and the share of homeowners, that is, owners of owner-occupied real estate, the value of these assets, and the household's imputed rent for heirs and non-heirs. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2. Data. SOEP 2019 (v36).

Figure A.8. Binscatter: Big 5 personality traits



Notes. The figure shows binscatters and linear fits of the relationship between between log hometown GDP growth and Big 5 characteristics. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2. Data. SOEP 2019 (v36).

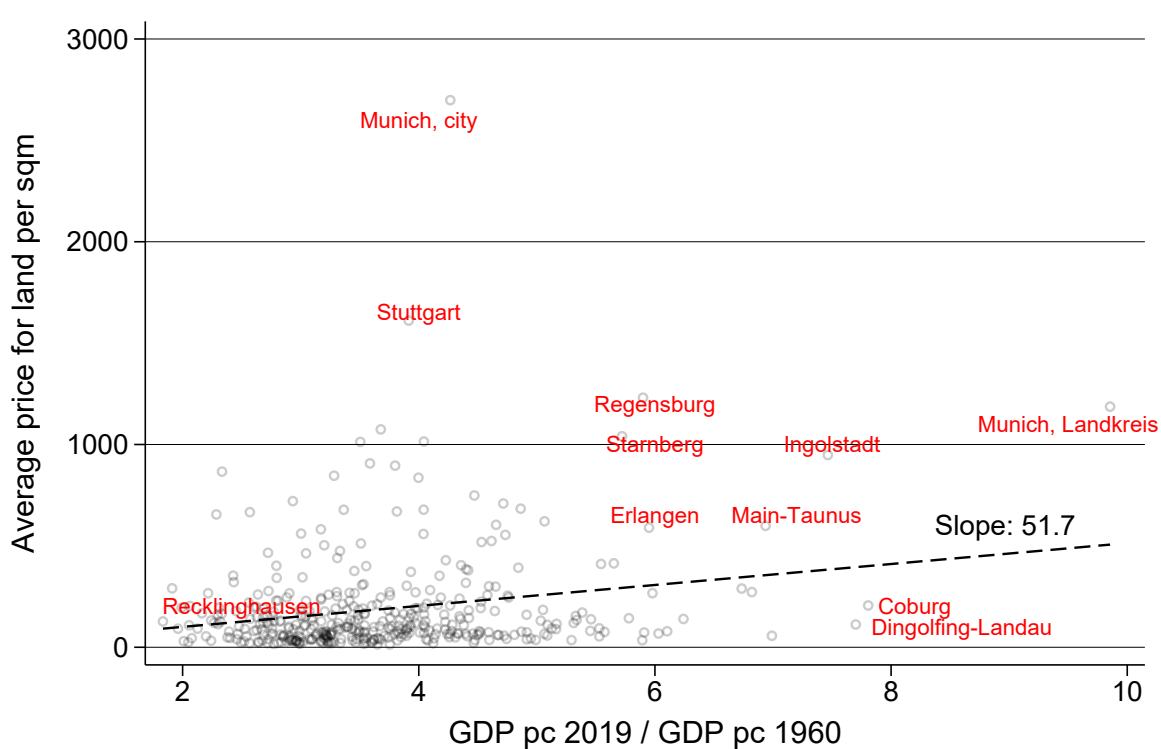
Figure A.9. Binscatter: Human Capital Factors



Notes. The figure shows binscatters and linear fits of the relationship between hometown growth and market income (labor income plus pensions), years of schooling, and employment experience for men split for heirs and non-heirs. The figure also displays the OLS coefficients for log GDP growth and their standard errors. Both the binscatters and linear fits are conditional on the set of individual and parental background variables in Table 2.

Data. SOEP 2019 (v36).

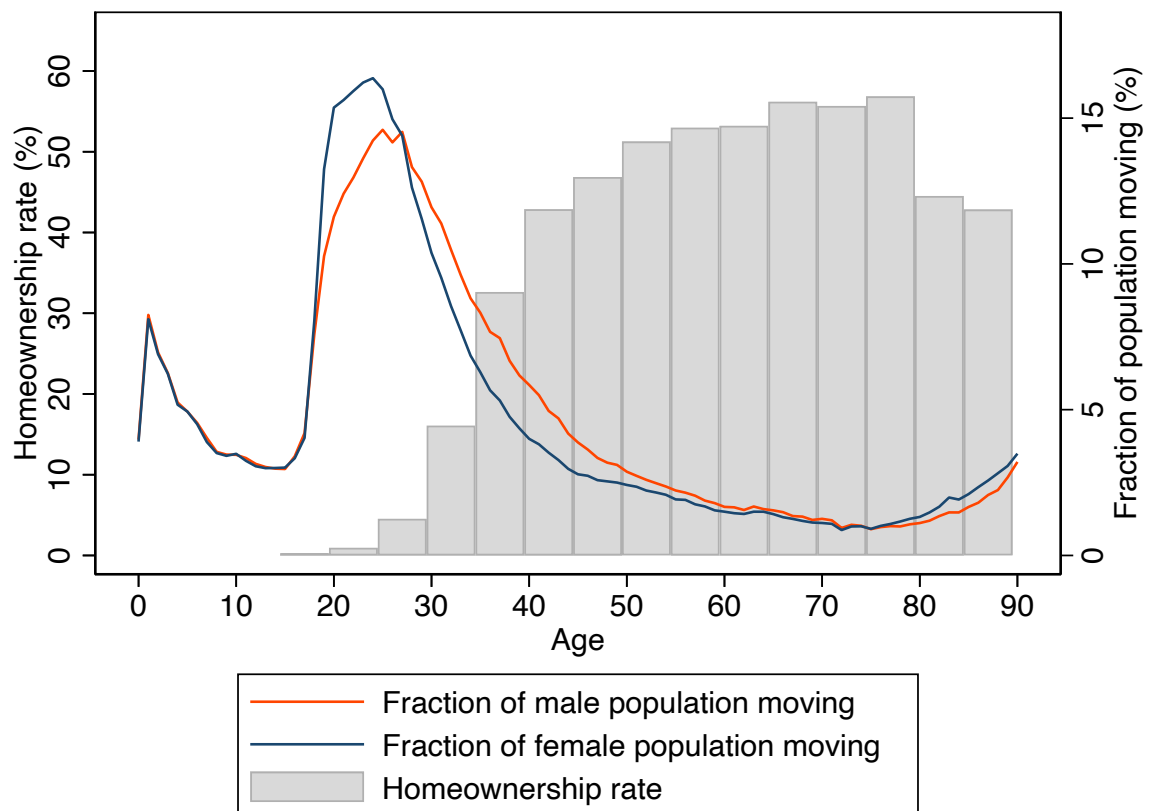
Figure A.10. Growth and land prices



Notes. The figure shows the correlation between GDP per capita growth measured by the ratio of GDP per capita 2019 and 1960 and the average price for building land per square meter in 2020.

Data. County-level GDP per capita see Section 2.2. Land price data from Destatis.

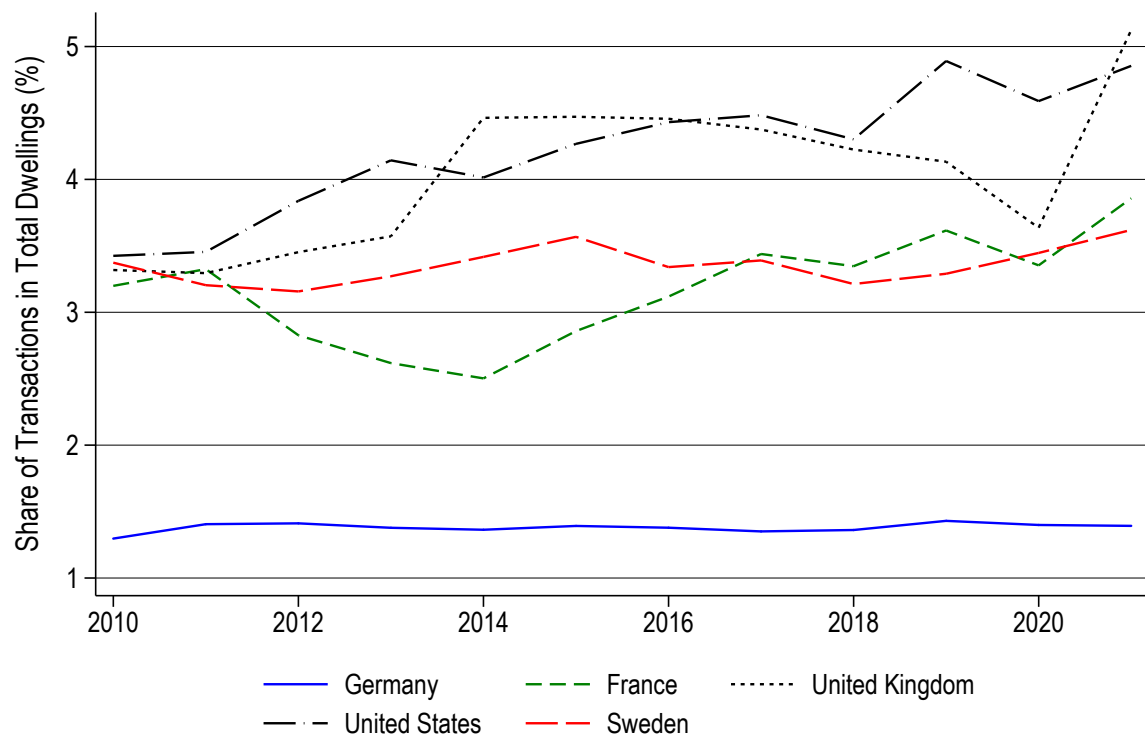
Figure A.11. Homeownership rate and moving population by age



Notes. The left axis displays the share of homeowners by age group in 2017. The right axis shows the population share by age moving from one German municipality to another in 2017.

Data. Moving population from Bundesinstitut für Bevölkerungsforschung (BiB). Homeownership rates are own calculations based on SOEP.

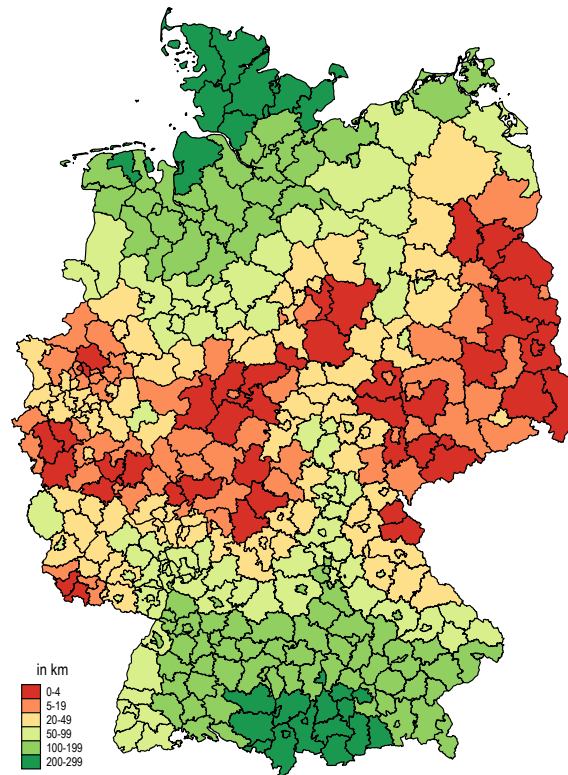
Figure A.12. Share of Transactions in Total Dwellings



Notes. The graph depicts the number of transactions divided by the total number of dwellings.

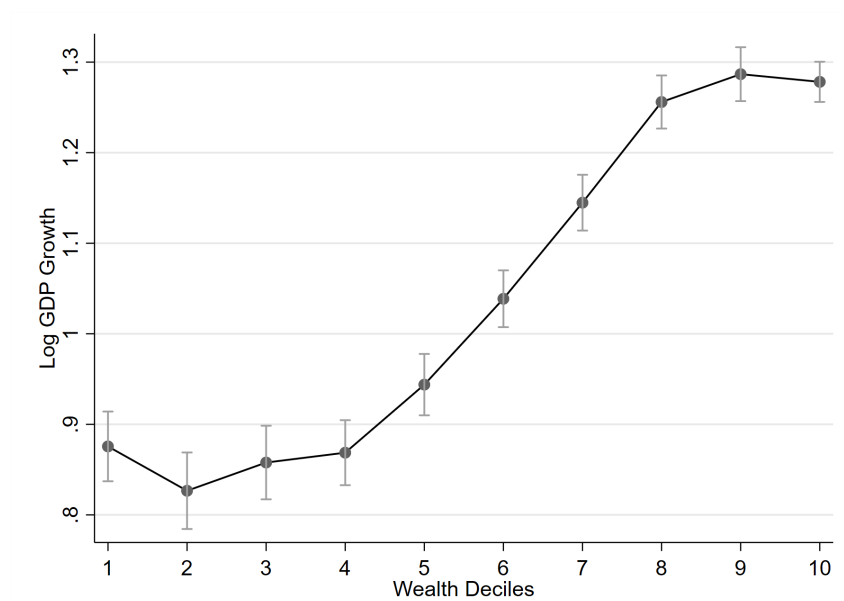
Data. European Mortgage Federation.

Figure A.13. Least distance to coalfields in Germany



Notes. The map shows the distance of a county's centroid to the nearest coalfield in kilometers.  
Data. [Fernihough and O'Rourke \(2021\)](#).

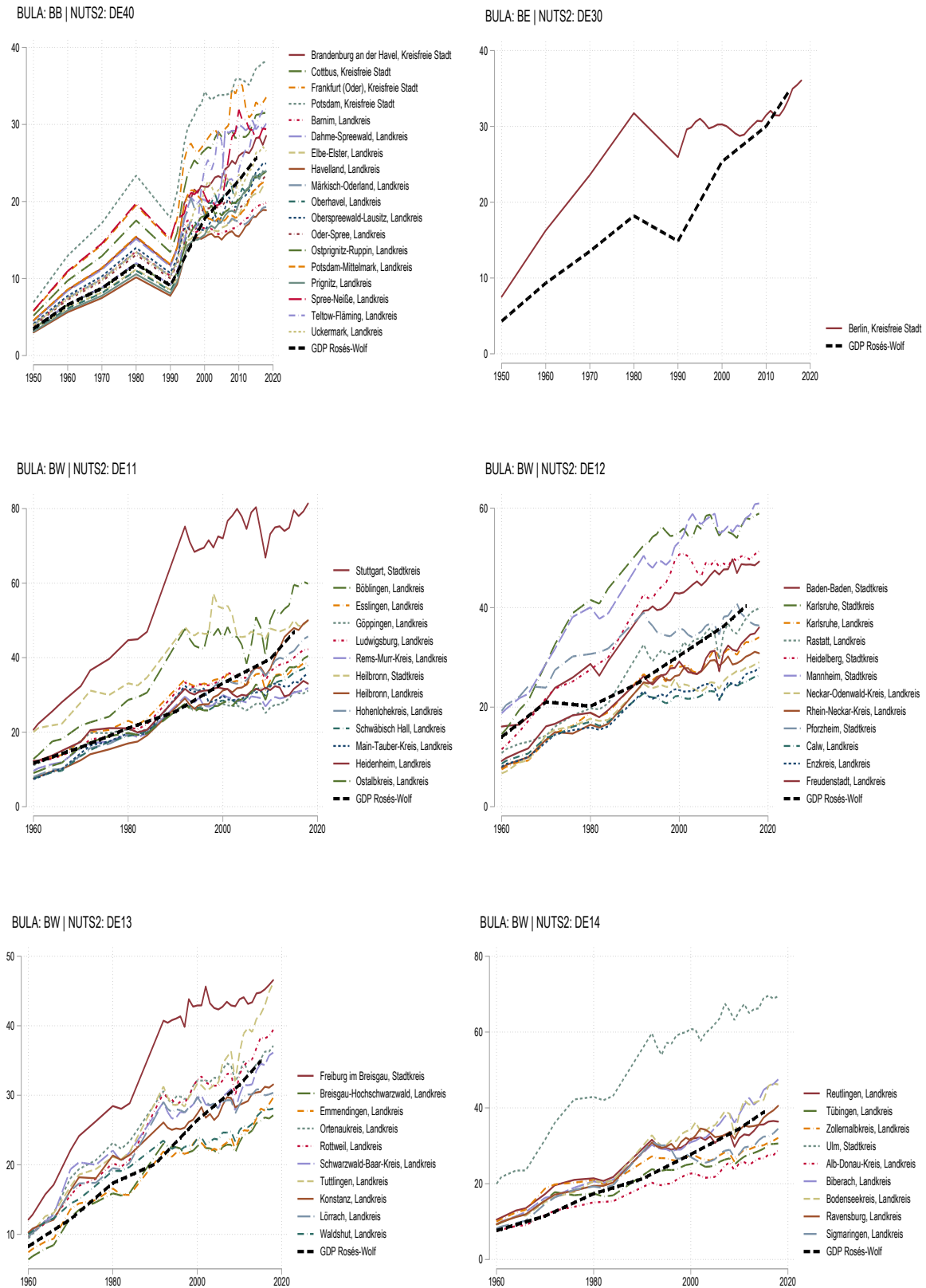
Figure A.14. GDP Growth by Wealth Decile



Notes. The figure shows GDP per capita growth rate since birth by wealth decile in 2019 estimated on the county-level.  
Data. SOEP 2019 (v36).



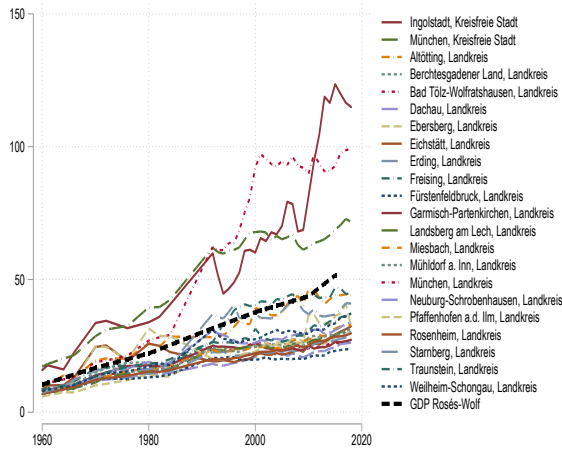
Figure A.15. Real GDP per capita in German counties (NUTS-3), 1950-2019



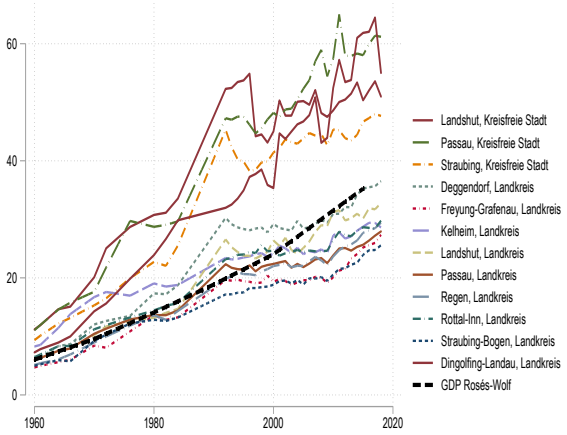
*Note:* NUTS-3-level GDP per capita in 2010 Euros from various publications of the German federal statistical office, compared to NUTS-2-level from Rosés-Wolf Database, version 6 (2020), harmonized geographically to county borders 2019 in 1,000 Euros. Series for the federal states of Brandenburg (BB), Berlin (BE) and Baden-Wuerttemberg (BW).

Figure A.16. Real GDP per capita in German counties (NUTS-3), 1950-2019

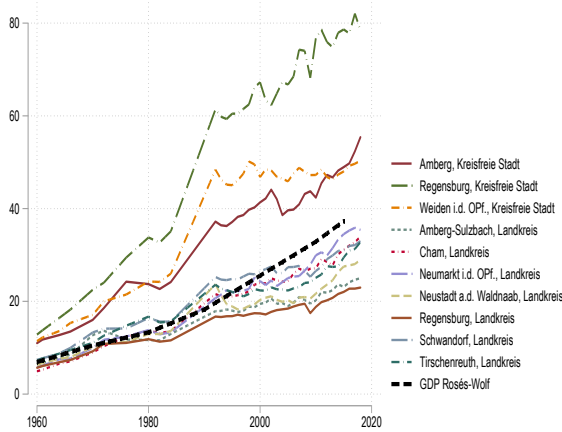
BULA: BY | NUTS2: DE21



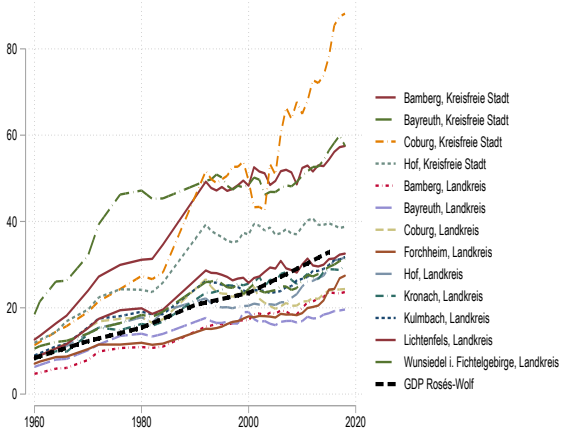
BULA: BY | NUTS2: DE22



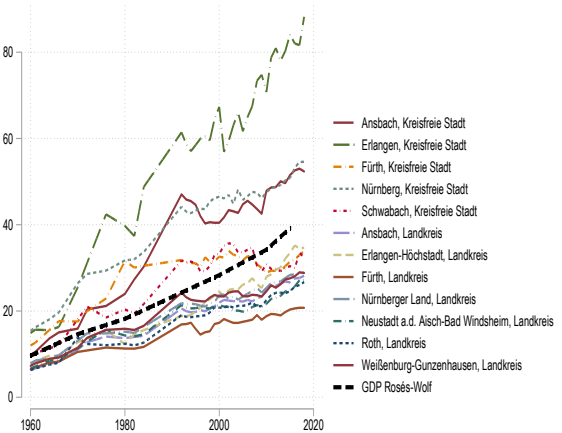
BULA: BY | NUTS2: DE23



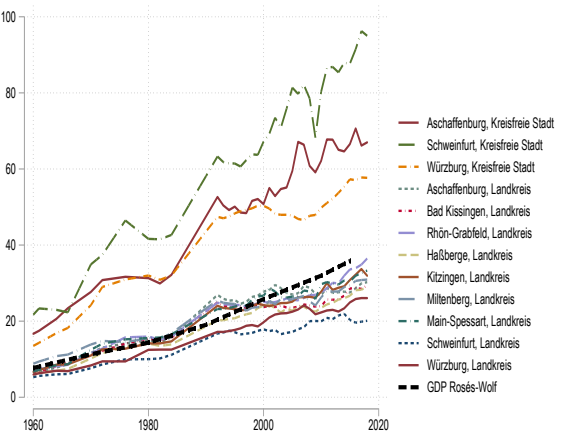
BULA: BY | NUTS2: DE24



BULA: BY | NUTS2: DE25

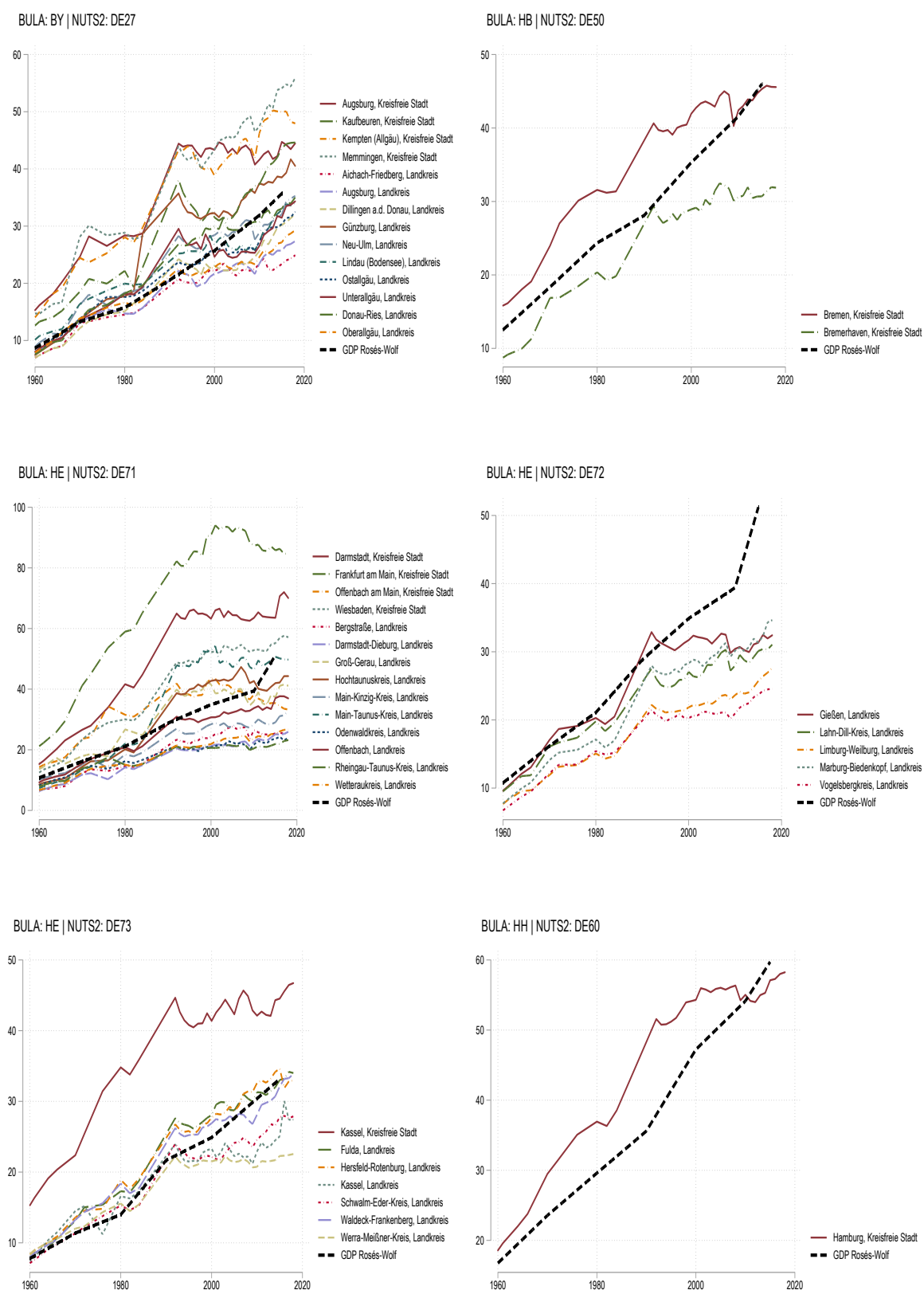


BULA: BY | NUTS2: DE26



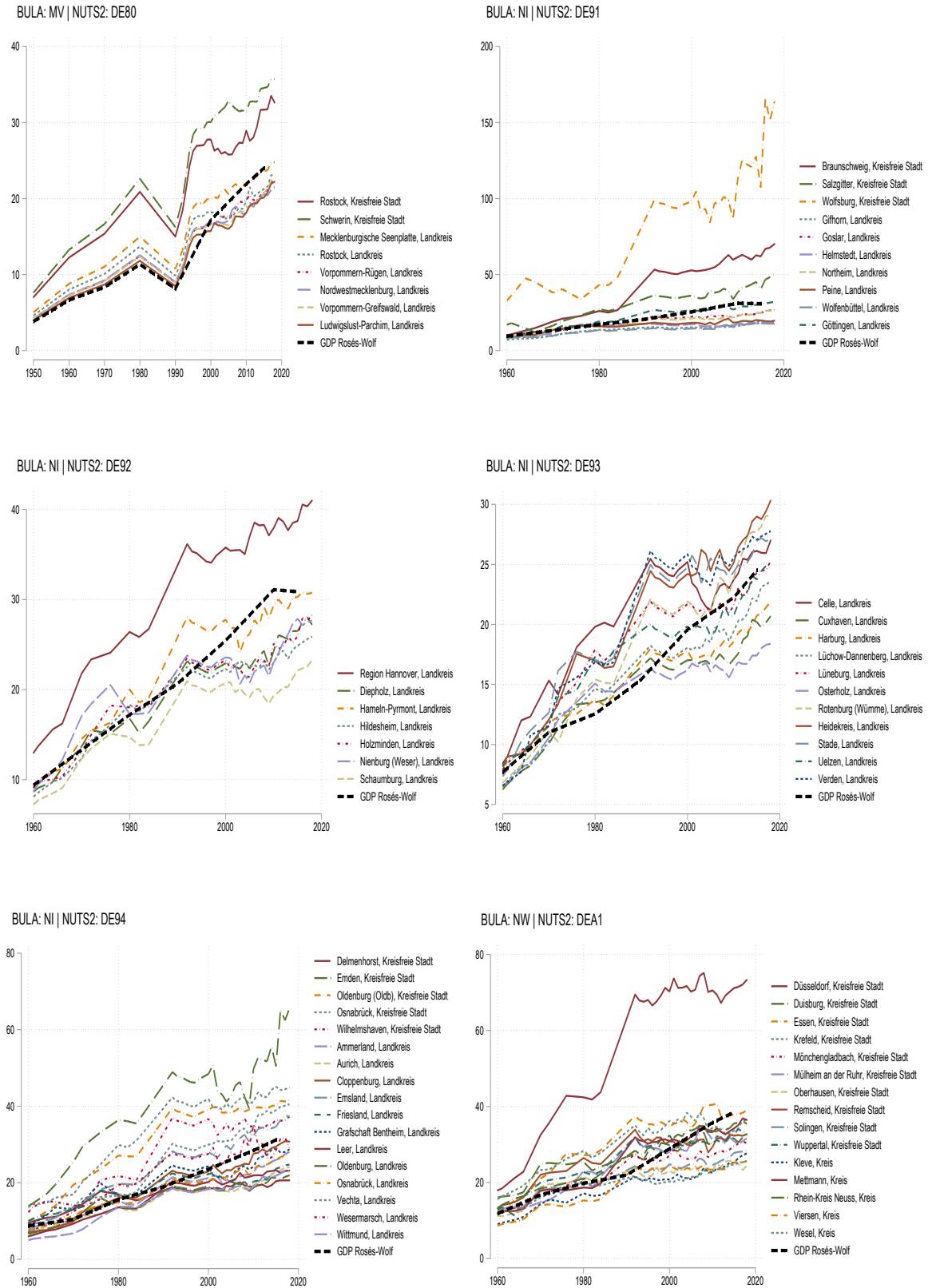
*Note:* NUTS-3-level GDP per capita in 2010 Euros from various publications of the German federal statistical office, compared to NUTS-2-level from Rosés-Wolf Database, version 6 (2020), harmonized geographically to county borders 2019 in 1,000 Euros. Series for the federal state of Bavaria (BY).

Figure A.17. Real GDP per capita in German counties (NUTS-3), 1950-2019



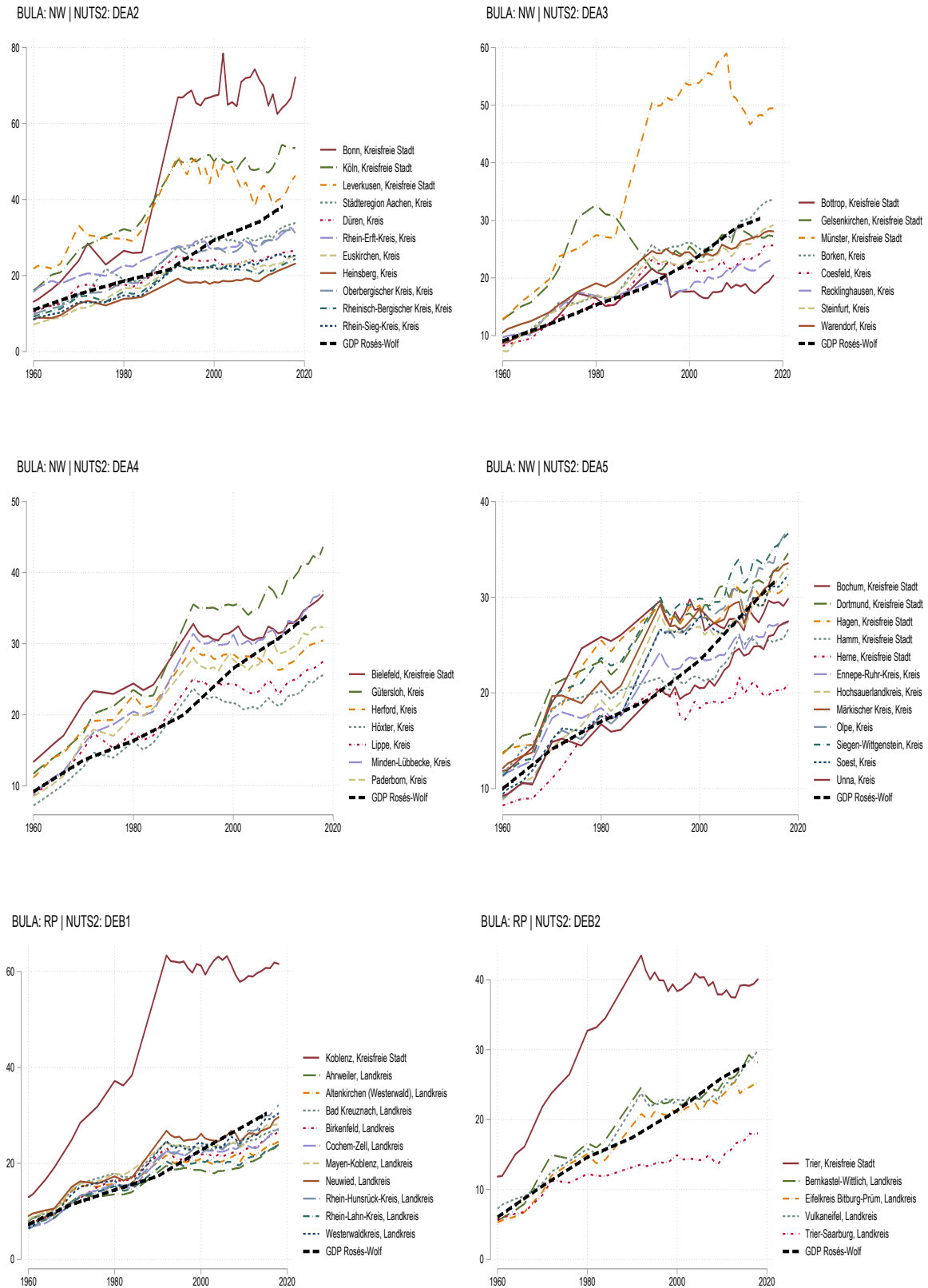
*Note:* NUTS-3-level GDP per capita in 2010 Euros from various publications of the German federal statistical office compared to NUTS-2-level from Rosés-Wolf Database, version 6 (2020), harmonized geographically to county borders 2019 in 1,000 Euros. Series for the federal states of Bavaria (BY), Bremen (HB), Hesse (HE) and Hamburg (HH).

Figure A.18. Real GDP per capita in German counties (NUTS-3), 1950-2019



*Note:* NUTS-3-level GDP per capita in 2010 Euros from various publications of the German federal statistical office, compared to NUTS-2-level from Rosés-Wolf Database, version 6 (2020), harmonized geographically to county borders 2019 in 1,000 Euros. Series for the federal states of Mecklenburg-Western Pomerania (MV), Lower Saxony (NI) and North Rhine-Westphalia (NW).

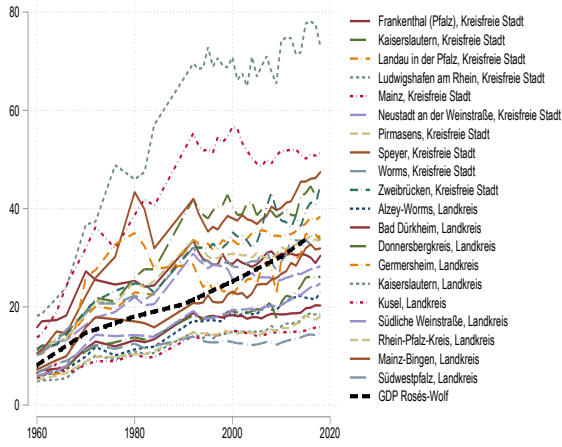
Figure A.19. Real GDP per capita in German counties (NUTS-3), 1950-2019



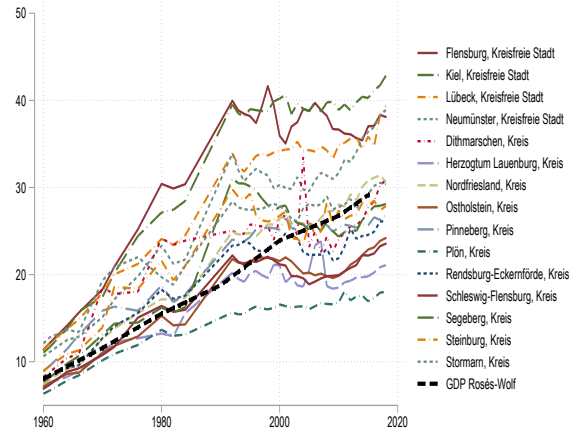
*Note:* NUTS-3-level GDP per capita in 2010 Euros from various publications of the German federal statistical office, compared to NUTS-2-level from Rosés-Wolf Database, version 6 (2020), harmonized geographically to county borders 2019 in 1,000 Euros. Series for the federal states of North Rhine-Westphalia (NW) and Rhineland-Palatinate (RP).

Figure A.20. Real GDP per capita in German counties (NUTS-3), 1950-2019

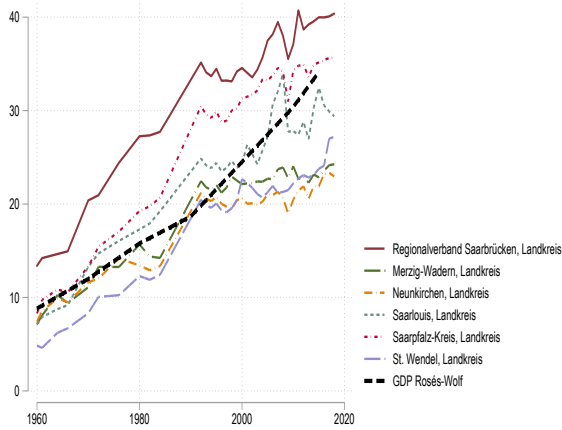
BULA: RP | NUTS2: DEB3



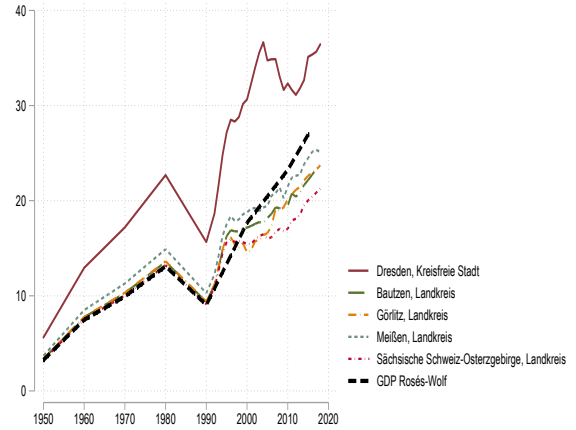
BULA: SH | NUTS2: DEF0



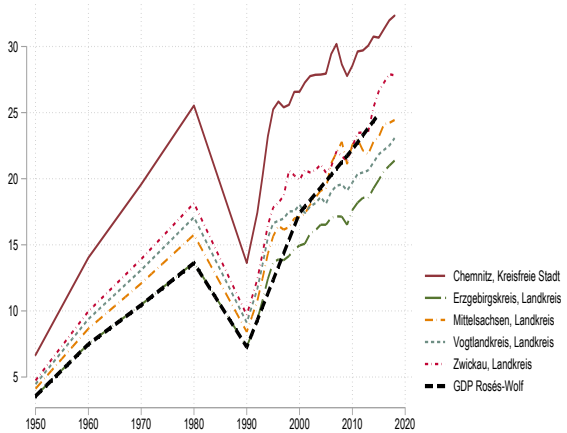
BULA: SL | NUTS2: DEC0



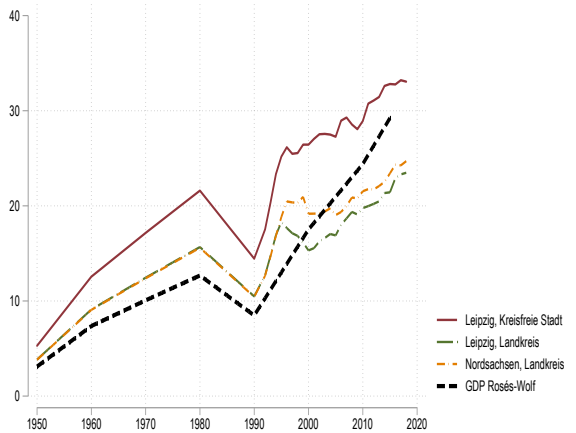
BULA: SN | NUTS2: DED2



BULA: SN | NUTS2: DED4

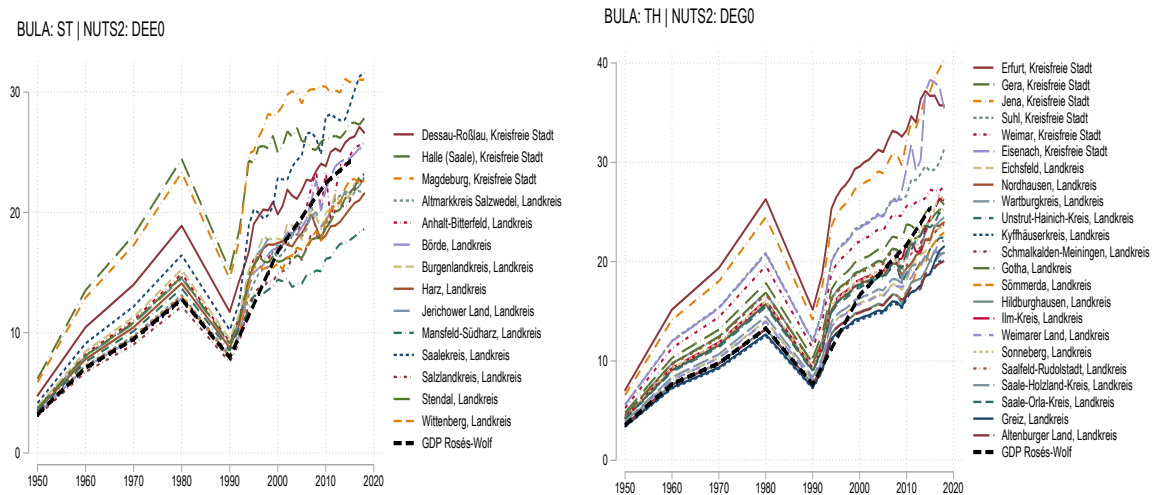


BULA: SN | NUTS2: DED5



*Note:* NUTS-3-level GDP per capita in 2010 Euros from various publications of the German federal statistical office, compared to NUTS-2-level from Rosés-Wolf Database, version 6 (2020), harmonized geographically to county borders 2019 in 1,000 Euros. Series for the federal states of Rhineland-Palatinate (RP), Schleswig-Holstein (SH), Saarland (SL) and Saxony (SN).



Figure A.21. Real GDP per capita in German counties (NUTS-3), 1950-2019




*Note:* NUTS-3-level GDP per capita in 2010 Euros from various publications of the German federal statistical office, compared to NUTS-2-level from Rosés-Wolf Database, version 6 (2020), harmonized geographically to county borders 2019 in 1,000 Euros. Series for the federal states of Saxony-Anhalt (ST) and Thuringia (TH).

Figure A.22. Personal questionnaire 2001: Inheritance question

**108. Have you yourself ever inherited something or received a gift of great value?**  
**We are referring to gifts or inheritance of house or land, securities, investments, other forms of wealth or large amounts of money.**

Yes ..... ☐  No ..... ☐  Skip to question 109!

 Please answer the additional questions a) to e) for each inheritance or gift.  
 If you have received an inheritance or other type of large gift more than once,  
 then please list the first gift or inheritance under the heading "1<sup>st</sup> Time", the second one under  
 "2<sup>nd</sup> Time" and the third under "3<sup>rd</sup> Time".


	1 <sup>st</sup> Time	2 <sup>nd</sup> Time	3 <sup>rd</sup> Time
a) What year was that? Year:	<div style="border: 1px solid black; width: 40px; height: 20px;"></div>	<div style="border: 1px solid black; width: 40px; height: 20px;"></div>	<div style="border: 1px solid black; width: 40px; height: 20px;"></div>
b) Was it –			
– an inheritance? .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
– a gift or other form of transfer? .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
c) What type of wealth was that?			
House, land, condominium .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Securities (treasury obligations, stocks, investment funds, etc.) .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Cash, bank deposits, etc. ....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Shares or ownership of a company .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Another type of wealth or material gift .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
d) What was the value of this inheritance or gift at the time you received it			
 Please state the market value of house or land.	DM <div style="border: 1px solid black; width: 80px; height: 20px;"></div>	<div style="border: 1px solid black; width: 80px; height: 20px;"></div>	<div style="border: 1px solid black; width: 80px; height: 20px;"></div>
Don't know .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
e) From whom did you receive this inheritance or gift?			
One or both parents .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Parents-in-law .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Grandparents .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Husband or wife .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Other(s) .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>



Figure A.23. Personal questionnaire 2017: Inheritance question

**155. Have you personally received an inheritance or larger endowment in the last 15 years?**  
 We are referring mainly to transfers of home or property ownership, securities, participating interests, and other assets or larger sums of money.

Yes..... ☐   
 No ..... ☐ ➔ *Question 157!*

**156. Please answer questions a) to d) with regard to the inheritance or endowment.**  
 ☞ *If you have received more than one inheritance or endowment, please give your answers about these in the columns for the second and third inheritance or endowment..*

	First Inheritance Endowment	Second Inheritance Endowment	Third Inheritance Endowment
a) What year was that? .....	<input type="text"/>	<input type="text"/>	<input type="text"/>
b) Was it an ...			
– inheritance? .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
– endowment or transfer of property?.....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
c) What type of assets did it consist of? ☞ <i>Please state all that apply.</i>			
Building and property ownership, owner-occupied housing .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Securities (treasury bills, stocks, investment funds, etc.)...	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Cash, bank balances, etc. ....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Company ownership or partial ownership .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Other assets or non-cash gifts .....	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
d) What was the value of the inheritance or endowment at that time? ☞ <i>In the case of building and land ownership, please state the <u>market value</u> at that time!</i>			
euros ...	<input type="text"/>	<input type="text"/>	<input type="text"/>
Don't know ...	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure A.24. Personal questionnaire 2019: Inheritance question

**141. Haben Sie persönlich jemals eine Erbschaft gemacht oder eine größere Schenkung erhalten?**  
Wir meinen dabei Übertragungen von Haus- und Grundbesitz, von Wertpapieren, Beteiligungen, sonstigem Vermögen oder größeren Geldbeträgen.

Ja..... ☐ 1 **PERB**      Nein..... -1 ☐ 2 ➔ Frage 143

**142. Bitte beantworten Sie für die Erbschaft oder Schenkung die Fragen a) bis d).**  
☞ Sollten Sie mehr als eine Erbschaft oder Schenkung erhalten haben, geben Sie diese bitte in den Spalten für die zweite und dritte Erbschaft / Schenkung an.

	Erste Erbschaft Schenkung	Zweite Erbschaft Schenkung	Dritte Erbschaft Schenkung
a) In welchem Jahr war das?.....	<input type="text"/> <input type="text"/> <input type="text"/> -1	<input type="text"/> <input type="text"/> <input type="text"/> -1	<input type="text"/> <input type="text"/> <input type="text"/> -1
	<b>PERBA1</b>	<b>PERBA2</b>	<b>PERBA3</b>
b) Handelte es sich um ...			
– eine Erbschaft?.....	<b>PERBB1</b> <input type="checkbox"/> 1	<b>PERBB2</b> <input type="checkbox"/> 1	<b>PERBB3</b> <input type="checkbox"/> 1
– eine Schenkung oder Überschreibung?.....	<input type="checkbox"/> 2 -1	<input type="checkbox"/> 2 -1	<input type="checkbox"/> 2 -1
c) Um welche Art von Vermögen ging es dabei? ☞ Bitte geben Sie jeweils alles Zutreffende an.			
Haus- und Grundbesitz, Eigentumswohnung.....	<b>PERBC11</b> <input type="checkbox"/> 1	<b>PERBC21</b> <input type="checkbox"/> 1	<b>PERBC31</b> <input type="checkbox"/> 1
Wertpapiere (Schatzbriefe, Aktien, Fonds usw.).....	<b>PERBC12</b> <input type="checkbox"/> 1	<b>PERBC22</b> <input type="checkbox"/> 1	<b>PERBC32</b> <input type="checkbox"/> 1
Bargeld, Bankguthaben usw.....	<b>PERBC13</b> <input type="checkbox"/> 1	<b>PERBC23</b> <input type="checkbox"/> 1	<b>PERBC33</b> <input type="checkbox"/> 1
Unternehmensbesitz oder -beteiligung.....	<b>PERBC14</b> <input type="checkbox"/> 1	<b>PERBC24</b> <input type="checkbox"/> 1	<b>PERBC34</b> <input type="checkbox"/> 1
Sonstige Vermögenswerte / Sachgeschenke.....	<b>PERBC15</b> <input type="checkbox"/> 1 -1	<b>PERBC25</b> <input type="checkbox"/> 1 -1	<b>PERBC35</b> <input type="checkbox"/> 1 -1
d) Wie hoch war der damalige Wert dieser Erbschaft oder Schenkung? ☞ Bei Haus- und Grundbesitz bitte damaligen Verkehrswert angeben!			
Euro.....	<input type="text"/>	<input type="text"/>	<input type="text"/>
Weiß nicht.....	<input type="checkbox"/> 1 -1	<input type="checkbox"/> 1 -1	<input type="checkbox"/> 1 -1
	<b>PERBD11</b>	<b>PERBD21</b>	<b>PERBD31</b>

aus 2017 F155  
Text geändert  
  
aus 2017 F156

## B Mediation Analysis

We conduct a mediation analysis following [Heckman and Pinto \(2015\)](#) and [Fagereng et al. \(2021\)](#) to weigh the importance of wealth accumulation channels like intergenerational transfers and human capital. Our measured mediators – market income, years of schooling, and transfers – are chosen to replicate [Fagereng et al. \(2021\)](#) and to reflect the dichotomy between transfers and human capital.

$G$  denotes hometown growth, which is our multi-valued treatment. Then, let  $w_g$  be the potential log net wealth of the person growing up with log economic growth  $g$ . We use a linear equation to specify the relationship:

$$w_g = \tilde{\tau}_g + \sum_{k \in \mathcal{K}_p} \alpha^k \theta_g^k + \sum_{k \in \mathcal{K}/\mathcal{K}_p} \alpha^k \theta_g^k + \mathbf{X}\gamma + \tilde{\epsilon}_g \quad (\text{B.1})$$

$$w_g = \tau_g + \sum_{k \in \mathcal{K}_p} \alpha^k \theta_g^k + \mathbf{X}\gamma + \epsilon_g, \quad (\text{B.2})$$

where  $\mathcal{K}$  is the index of mediator variables,  $\mathcal{K}_p$  is the set of measured mediators (market income, years of schooling, and transfers),  $\tau_g$  is the treatment specific intercept,  $\mathbf{X}$  is a set of pre-assignment variables (age, gender, migration background, parental characteristics),  $\theta^k$  are the mediator variables, and  $\tilde{\epsilon}_g$  is an error assumed to be uncorrelated with the pre-assignment and mediator variables. Note that our model does not allow for treatment specific coefficients for the pre-assignment or mediator variables. The exercise in [Fagereng et al. \(2021\)](#) has shown that allowing for treatment specific coefficients does not appear to be of major importance. Therefore, we use the more parsimonious formulation shown in Eq. (B.3).

Our measure of market income is the sum of labor income and social security and company pensions so that we can keep pensioners in the sample of analysis. Note that social-security and company pensions are earnings-related in Germany so that they serve as a proxy for previous earnings.

We reformulate Eq. 8 to include the mediator variables :

$$\log(w_i) = \alpha + \beta_1 \log(G_i) + \beta_2 \log(y_{b,r}) + \mathbf{M}_i \zeta + \mathbf{X}_i \gamma + \mathbf{P}_i \delta + \epsilon_i, \quad (\text{B.3})$$

where  $\mathbf{M}_i$  is the set of measured mediators  $m$ . We flexibly include the mediators in Eq. (B.3) by including years of schooling as a dummy set, inheritances as a dummy set based on 20 quantiles of the positive values, and market income as a dummy set based on 30 quantiles. The equations for any given mediator  $m$  are also linear, and take the form:

$$m_i = \beta_1^m \log(G_i) + \beta_2^m \log(y_{b,r}) + \mathbf{X}_i \gamma^m + \mathbf{P}_i \delta^m + \epsilon_i^m, \quad (\text{B.4})$$

We run the OLS regressions for log net wealth and the mediators and recover the coefficients for log GDP growth from each of these regressions. The decomposition into direct and indirect effects is illustrated in equations (B.5):

$$TE = DE + IE \quad (\text{B.5})$$

$$DE = \beta_1 \Delta \log G$$

$$IE = \sum_{m=1}^M \zeta_m \beta_1^m \Delta G$$

For a given change in log GDP growth  $\Delta \log G$ , the direct effect ( $DE$ ) can be recovered as the change in growth times the coefficient of growth ( $\beta_1$ ) in equation B.3. The indirect effect ( $IE$ ) is the change in growth times the coefficient of growth in the mediator OLS equation ( $\beta_1^m$ ) times the coefficient of the relevant mediator ( $\zeta$ ) summed over all the mediators up to  $M$ . Adding up direct and indirect effects, we obtain the total effect ( $TE$ ).

## C Calibration of the Overlapping Generations Model

We summarize the calibration of the model in Table C.8.

Table C.8. Calibration of the OLG Model

parameter	description	calibration	source
Production			
$\alpha$	output elasticity of labor	0.7	<a href="#">Douglas (1976)</a> ; <a href="#">Kaymak and Poschke (2016)</a>
$c_A$	constant term of TFP	8.5	own choice to match wealth levels in SOEP data
$g_r$	linear term of TFP growth	range of values: 0.01 to 0.5	own choice, main object for calibration
$d$	quadratic term of TFP growth	0.02	own choice based on decline of average GDP growth rate of Germany in Figure ??.
Preferences and Demography			
$\eta$	inverse intertemporal elasticity of substitution	2.5	<a href="#">Havránek (2015)</a>
$\chi$	bequest motive	6	own choice based on relationship to second period consumption
$\beta$	patience parameter	0.98	<a href="#">De Nardi (2004)</a> ; <a href="#">Heathcote et al. (2017)</a> ; <a href="#">Hubmer et al. (2021)</a>
$h$	share of heirs in a generation	0.3	own choice based on SOEP data

Notes. Shows calibrations of the model parameters in the OLG model described in Section C.