Intra- and Intergenerational Labor Market Inequality and Mobility

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Contents

Introduction: Intra- and Intergenerational Labor Market Inequality and Mobility

Some degree of income concentration is necessary in well-functioning market economies as it financially incentivizes individuals to work harder or take the risks of entrepreneurship. But if inequality becomes too high, it is not only morally concerning and poses a risk to social cohesion and democratic cooperation, but carries real economic consequences. It can lead to economic instability, hinder economic growth, and jeopardize labor market functionality if the belief in upward mobility through work is lost. In recent decades, empirical evidence has shown a steep rise in income inequality for many industrialized countries including Germany (e.g., Chancel and Piketty, 2021), elevating this topic to be among the major issues of our time.

To mitigate rising income inequality, understanding both the secular evolution of income inequality and its drivers is crucial. But this is a rather complex task; income inequality is extremely multidimensional and can be measured in many different ways. Most studies measure cross-sectional wage or income inequality (e.g., Antonczyk et al., 2010; Card et al., 2013), while the life-cycle perspective is still rather scarce due to high data requirements (e.g., Bönke et al., 2015; Guvenen et al., 2022). Studies can analyze different socio-demographic subgroups (e.g., by age, gender, race and ethnicity, education, region) and document differences across their respective income inequality evolutions. Lastly, labor market inequality and mobility can be measured not only within generations, but also across generations (e.g., Black and Devereux, 2011; Chetty et al., 2017). As there are merits to each of these different types of measurement and segmentation, to see a complete picture of income inequality, all the pieces must be put together. The goal of this dissertation is to contribute to a more comprehensive understanding of labor market inequality and mobility in Germany. In particular, it is guided by the following research questions: Using different measurement approaches, how has labor market inequality and mobility evolved within generations? How has it evolved across generations? And how do current trends in inequality compare to historical trends?

Chapter 1 analyzes short- and medium-run earnings of labor market entrants and prime-age workers through four major business cycles in Germany using pension register data on birth cohorts 1935 through 1982. To examine the earnings growth of prime-age workers through business cycles, I use non-anonymous growth incidence curves (Bourguignon, 2011). I document that prime-age workers at the lower end of the prerecession earnings distribution experienced the highest average earnings losses. These losses gradually decreased in magnitude with higher prerecession earnings. Further, I find that the majority of the German population were unable to recover from their average earnings losses in subsequent economic expansions. I show that only the top 30 percent of the prerecession earnings distribution experienced real earnings gains since 1980.

I also utilize year-to-year variation in unemployment rates in the Mincerian graduation year to estimate the impact of entering the labor market during recessions on labor market entrants' earnings (e.g., Schwandt and Von Wachter, 2019). I find that lower educated men entering the labor market during poor economic conditions face a significant earnings reduction. A one-point increase in the initial unemployment rate leads to, on average, a six percent decrease in annual earnings in the first year after graduation. This negative effect attenuates only after five years.

Analyzing short- and medium-run earnings, as Chapter 1 does, provides insights into differential impacts of economic conditions by work life phases. That said, this approach can only provide snapshots of individuals' labor market activity. Earnings changes and inequalities can compound or balance out over the entire work life, making it necessary to additionally account for the biographical dimension of earnings inequality. Due to more regular discontinuities in female employment biographies (e.g., Bertrand et al., 2010; Blau and Kahn, 2017), this approach is especially important for women. To address this, Chapter 2 analyzes earnings inequality from a life-cycle perspective with a particular emphasis of differences in lifetime earnings between men and women.

Chapter 2 is joint work with Rick Glaubitz and Miriam Wetter. This study analyzes the differences in cross-sectional and lifetime earnings with a focus on gender inequalities. Using an Oaxaca Blinder decomposition, we show that the gender gap in annual earnings is largely driven by women's lower work experience and the intensive margin of labor supply. Based on a dynamic microsimulation model, we then estimate how gender differences accumulate over work lives to account for the biographical dimension of cross-sectional earnings. We observe an average gender lifetime earnings gap of 52 percent for birth cohorts 1964 through 1972. We show that this unadjusted gender lifetime earnings gap increases strongly with the number of children, ranging from 17 percent for childless women to 68 percent for women with three or more children. However, using a counterfactual analysis we find that the adjusted gender lifetime earnings gap of 10 percent differs only slightly by women's family background.

Chapters 1 and 2 measure earnings growth and inequality predominantly within the same generation, a common and important way to measure labor market inequality. However, another important puzzle piece in understanding the secular evolution of inequality and its drivers is to compare work and living standards across generations. Individuals often assess their own economic progress by comparing their earnings to their parents (e.g., Goldthorpe, 1987; Hochschild, 2016). While the vast majority of these studies focus on relative intergenerational mobility (e.g., Chetty et al., 2014; Bratberg et al., 2017), measuring how children's outcomes depend on parental income ranks, research has shown that people tend to think in absolute rather than in relative terms (Amiel and Cowell, 1999; Ravallion et al., 2018). Therefore, Chapter 3 uses a relatively novel measure to assess intergenerational mobility: absolute income mobility. It measures the fraction of children who earn weakly more than their parents did.

Chapter 3 is joint work with Timm Bönke and Holger Lüthen. It provides the first absolute income mobility estimates for postwar Germany. Using various micro data sources, we uncover a steep decline in absolute mobility rates from 81 percent to 59 percent for children's birth cohorts 1962 through 1988. This trend is robust across different ages, family sizes, measurement methods, copulas, and data sources. Across the parental income distribution, we find that children from middle class families experienced the largest percentage point drop in absolute income mobility (-31pp). Our counterfactual analysis shows that lower economic growth rates and higher income inequality contributed similarly to the downward trend in absolute income mobility.

Using distinct inequality measurements, Chapters 1 through 3 confirm a steep rise in both intra- and intergenerational labor market inequality in recent decades. But so far it has remained unclear how today's inequality and mobility levels compare to historical trends. To that end, Chapter 4 provides a comprehensive picture of the evolution of earnings growth, inequality, and absolute mobility since 1882. This broad scope enables the historical contextualization of the other chapters' findings.

Chapter 4 is joint work with Timm Bönke and Hannah Penz. Utilizing six different data sources, this study provides long-term trends in earnings growth, inequality, and absolute mobility for Germany between 1882 and 2019. We document that today's earnings inequality is higher than it was in 1882. This comes after significant variation in inequality over time including Gini coefficients of over 0.5 at the end of the Weimar Republic and estimates below 0.2 during the mid-1970s. We also find that mean rates of absolute earnings mobility declined from 70 percent to 48 percent for children's birth cohorts 1882 through 1989. While children born between 1932 and 1962 experienced unusually high absolute mobility rates of over 90 percent due to the postwar economic miracle years, estimates for all other birth cohorts ranged between 41 and 72 percent.

1 Many Lose, Few Win: Patterns of Earnings Growth Across Business Cycles

1.1 Introduction

Economies tend to move in business cycles of growth and contraction. While recessions often come with job losses, reduced hours, wage cuts, and decreased hiring, expansions are conversely associated with positive labor market characteristics. Ideally, earnings losses during recessions should be at least offset by earnings gains during subsequent expansions. However, empirical evidence for the US suggests that the earnings of most prime-age workers did not recover from the losses incurred during previous recessions and that only the top 10 percent saw steep earnings growth over time (Guvenen et al., 2014). But is this imbalanced growth trend also observable in social market economies like Germany? Or did stronger employment protection, job security, and higher levels of unionization lead to more evenly distributed earnings growth patterns across business cycles?

To answer these questions, I use German pension register data on birth cohorts 1935 through 1982 to look at the impact of four business cycles between 1980 and 2017 on the earnings of both labor market entrants and prime-age workers in Germany. Business cycles are defined as recessions and their subsequent expansions. To examine the earnings growth of prime-age workers through business cycles, I use non-anonymous growth incidence curves (Bourguignon, 2011). I find that all workers except the top 10 percent of the prerecession earnings distribution experienced earnings losses during recessions. Average earnings losses were largest for workers at the bottom of the distribution and decreased with higher prerecession earnings. The most significant decline in earnings occurred during the high-tech crisis (2001-2005) with average earnings changes ranging from -23.7 log points (-26.7%) for the bottom 10 percent of the prerecession earnings distribution to 2.4 log points (2.4%) for the top 10 percent.

In subsequent economic expansions, earnings growth followed a u-shaped pattern across the prerecession earnings distribution, with highest earnings gains at the margins and no earnings gains or even earnings losses for the middle class. When weighing all earnings changes during recessions and expansions against each other, I show that only the top 30 percent of the prerecession earnings distribution experienced real earnings gains since 1980. The remainder of the distribution were unable to achieve any net gain over this time period. This result is similar to the findings for the US (see Guvenen et al., 2014), suggesting that earnings growth were not more evenly distributed in social market economies such as Germany.

Labor market entrants form a more vulnerable group as existing research suggests long-lasting negative effects of entering the labor market during a recession (e.g., Kahn, 2010; Oreopoulos et al., 2012). To estimate the effect of initial labor market conditions on labor market entrants' earnings, I utilize year-to-year variation in unemployment rates in the Mincerian graduation year. I find that lower educated men face the largest decline in earnings when entering the labor market during poor economic conditions. A one-point increase in the initial unemployment rate leads, on average, to a six percent reduction in annual earnings in the first year after graduation. This effect increases to seven percent in the second year after graduation before slowly fading out after five years. This negative impact is substantial since unemployment rates often increase not only by one, but several percentage points during recessions. In addition, lower educated labor market entrants are more likely to find themselves in the bottom 30 percent of the general earnings distribution later in life, placing them at higher risk of suffering more earnings losses across subsequent business cycles.

This paper is connected to several strands of literature. First, it relates to the large literature investigating how recessions and business cycles impact outcomes of workers and families (e.g., Hines et al., 2001; Hoynes et al., 2012; Berman, 2022a). Many of the more recent studies in this field have focused on the negative effects and aftermath of the Great Recession in the U.S. (e.g., Moffitt, 2013; Redbird and Grusky, 2016). Closest to my study is the work of Guvenen et al. (2014). Using U.S. Social Security Administration data, the study shows that the lower a worker's prerecession earnings were, the higher their earnings losses were during subsequent recessions.[1] Using high-quality administrative data, this paper contributes to the literature by applying the methodological approach of Guvenen et al. (2014) to Germany for the first time. This paper thereby provides a view of German earnings growth patterns across recessions and expansions over 37 years, while specifically highlighting differences across the earnings distribution.

Second, this paper contributes to the growing literature studying the long-term impacts of entering the labor market during poor economic conditions. Some studies find that U.S. or Canadian college graduates who enter the labor market during a recession face persistent earnings losses (Kahn, 2010; Oreopoulos et al., 2012; Rothstein, 2021). Other studies find only short-lived earnings losses for the US (Genda et al., 2010; Speer, 2016). My work and methodological approach is closest to the study by Schwandt and Von Wachter (2019). The authors analyze the impact of recessions on labor market entrants' earnings by education, gender, and race and ethnicity and also find that lower educated and non-White labor market entrants experience the largest earnings losses.

For Germany, only limited empirical evidence exists on the long-term career effects of entering the labor market during a recession. Using data from the Institute of Employment Research (IAB) data for birth cohorts 1965 through 1977, Stevens (2008) investigates the effect of entering the labor market during adverse economic conditions for non-college high school graduates. She finds that this group faces three to six percent lower earnings when entering the labor market during a recession and that this earnings shock only fades out after several years. Umkehrer (2019) also uses IAB data, but focuses on apprentices who graduated between 1992 and 1996. For his sample, he finds that a two percentage point higher initial unemployment rate leads to almost ten percent lower average earnings in the first year after graduation. This impact reduces to one percent by the fifth year. However, since his sample covers only one recession, the external validity of his results is limited.

[1] This statement excludes the top one percent. In stark contrast to prior recessions, earnings losses for the top 1 percent were much steeper than for most of the earnings distribution in recessions following the high tech crisis (2001-2005) and financial crisis (2008-2009).

Advancing the literature, this paper extends the impact estimation of labor market entry during recessions in Germany to all labor market entrants including college graduates for the first time. College graduates reflect a distinctly different subpopulation than those with lower education levels and are very likely to have different resources and abilities to weather recession periods. Including them in these analyses provides a more comprehensive view of the impact of poor labor market conditions at the time of labor market entry. Further, I significantly expand the scope of previous investigations by covering 43 cohorts of labor market entrants (born between 1940 and 1982) and four major economic recessions and subsequent expansions. This expansion sheds light on the generalizability of previous results.

This paper is organized as follows. Section 1.2 gives an overview of recessions and expansions in postwar Germany. In Section 1.3, I describe the data. Section 1.4 quantifies the earnings losses of prime-age workers during recessions and their recovery patterns in subsequent expansions. In Section 1.5, I estimate the impact of entering the labor market during poor economic conditions on earnings . Section 1.6 concludes.

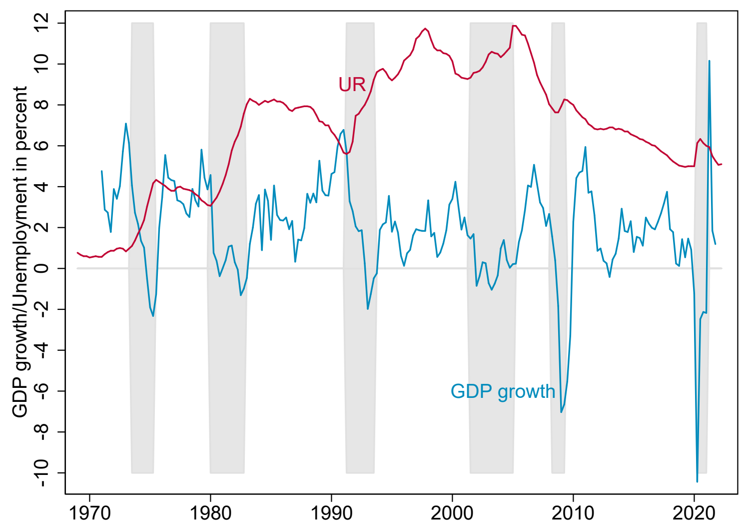
1.2 Recessions and expansions in postwar Germany

Figure 1.1 shows the quarterly GDP growth and unemployment rate in Germany from 1971 through 2021. Recessions are marked in grey and defined as economic phases when GDP growth rates were negative for at least two quarters accompanied by a rise in unemployment. Expansions are defined as the economic recovery phases after recessions, prior to the start of the next recession. Together, a recession and its subsequent expansion complete a business cycle. Table 1 outlines the economic recessions covered by this paper and their time periods.

The Second World War left large parts of Germany destroyed and rebuilding housing, infrastructure, and firms increased the demand for labor and goods extensively (Buenstorf and Guenther, 2011; Bartels, 2014). Hence, the 1960s and early 1970s were marked by historically low unemployment and high GDP growth rates. This picture changed when economies worldwide were hit by the first and second oil crises (1973-1975 and 1980-1982, respectively). The Organization of Arab

Petroleum Exporting Countries (OAPEC) enforced an oil embargo to condemn Canada, Japan, the Netherlands, Portugal, Rhodesia, South Africa, the UK, and the US for supporting Israel during the 1973 Yom Kippur War. As a result, the worldwide oil price tripled, GDP growth rates plummeted, and unemployment rose steeply in many countries including Germany. At the end of the recession following the second oil crisis, unemployment had reached eight percent.

Figure 1.1. Quarterly unemployment and GDP growth in Germany 1971-2021



Source: OECD, 2016 and FRED, 2023.

Note: This figure shows the quarterly unemployment rate (seasonally adjusted) for Germany between 1970 through 2021. Recessions are marked grey and are defined as periods with at least two quarters of negative GDP growth combined with a high unemployment rate. For periods defined as recessions, I use the recession indicator *DEUREC* retrieved from the Federal Reserve Bank of St. Louis to identify the exact start and end quarter of the economic downturn episode. Please note that I identify a smaller number of recessions than noted under *DEUREC* since this study uses the more traditional, two-folded definition of recessions requiring both a rise in unemployment and negative GDP growth.

The economic recovery after the second oil crisis (1980-1982) was slow. Unemployment remained high and was still at 7.2 percent in early 1989 just before the Berlin Wall came down and the German reunification process began. The subsequent opening of the borders and the loss of many employment opportunities in the Eastern parts intensified employment pressure in all parts of Germany, particularly for low educated workers. Throughout the rest of the decade, the German economy was characterized by low GDP growth rates, high unemployment rates, and increasingly high national debt. As a result, the Economist (2004) described Germany as the "sick man of Europe."

Table 1.1. Recessions in postwar Germany

Recession following the	Time Period
First oil crisis	1973Q3 – 1975Q2
Second oil crisis	1980Q1 – 1982Q4
Reunification crisis	1991Q2 – 1993Q3
High-tech crisis	2001Q3 – 2005Q1
Financial crisis	2008Q2 – 2009Q1
COVID-19	2020Q2 – 2021Q1

In 2003, the economically challenging situation led to the introduction of a large policy reform package known as Agenda 2010 under former chancellor Gehard Schröder. Agenda 2010 included numerous labor market policies further deregulating the German labor market with the goal of ensuring the economy's flexibility and competitiveness in an increasingly globalized market.[2] Shortly after, the German economy started improving with higher GDP growth rates and a significant decrease in unemployment (-3.8 percentage points between 2005Q1 and 2008Q1). In the second quarter of 2008, the financial crisis (2008-2009) hit the German economy, but contrary to many other countries the following recession was only short-lived and did not stop the country's journey to becoming one of the most powerful economies in the world only a decade later. Despite the temporal connection of the economy's uptick and the introduction of Agenda 2010, research suggests that it was not Agenda 2010 that laid the foundation for Germany's success. Rather, it was precursor policy changes in the mid-1990s which already allowed for more labor market deregulation and decentralization in wage bargaining (Dustmann et al., 2014). The impact of these reforms was delayed due to the pressure on the labor market by the German reunification. The positive labor market trend continued until the COVID-19 pandemic hit (2020-2021), leaving economies worldwide struggling due to lockdowns and supply shortages.

[2]See Bönke et al. (2019) for a more detailed overview of labor market policy changes in Germany from 1950 to 2019.

1.3 Data

This paper utilizes administrative pension register data. In Germany, enrollment in the national pension insurance is mandatory for most employees and data on pensions include over 90 percent of the entire population (Rehfeld and Mika, 2006).[3] Employers are required to report monthly earnings to the German Federal Pension Insurance (*Deutsche Rentenversicherung*) which collects a relative share of the earnings.

The Research Data Center of the German Federal Pension Insurance (FDZ-RV) provides scientific use files (SUF) of the Insurance Account Sample (Versicherungskontenstichprobe, VSKT) of the German Federal Pension Register.[4] Individuals are followed over time to construct panel data. I use the SUF waves 2002 to 2017 to obtain a history of monthly earnings and unemployment data starting with age 14 for birth cohorts 1935 through 1987.[5] Each SUF includes a 25 percent stratified random sample of all individuals in the VSKT, except the 2015 SUF which includes the full VSKT sample.

Even though these administrative data are basically free from measurement error, following Bönke et al. (2015) I make three adjustment to prepare the data to my analysis. First, one-time payments were not recorded in the social security records prior to 1984 and were therefore imputed for those earlier years. Second, I add the employer's social security contributions to the employee's gross earnings (e.g., for pensions, unemployment, and health insurance). This is important to take into account the differences in workers' insurance protections that have also changed over time. That way earnings really reflect the market value of labor. And third, roughly seven per-

[3]Some subgroups are excluded from the German pension insurance system including civil servants working with the government or most self-employed individuals. The omission of these groups inherently introduces limits to the external validity of my results. That said, only 8.8 percent of the German working population are self-employed (OECD, 2023) and 3.7 percent are civil servants (Statistisches Bundesamt, 2020), so these concerns are limited and my findings still apply to a broad and largely representative work population.

[4]See Himmelreicher and Stegmann (2008) for a detailed overview of the VSKT data.

[5]Each SUF wave covers the earnings and work biographies of individuals who are aged 30 to 67 in the reference year. Data on cohorts 1935 and 1936 stem from the 2002 wave, on cohort 1937 from the 2004 wave, on cohort 1938 from 2005 wave, on cohort 1939 from the 2006 wave, on cohort 1940 from the 2007 wave, on cohort 1941 from the 2008 wave, on cohort 1942 from 2009 wave, on cohort 1943 from the 2010 wave, on cohort 1944 from the 2011 wave, on cohort 1945 from the 2012 wave, on cohort 1946 from the 2013 wave, on cohort 1947 from the 2014 wave, on cohort 1948 from the 2015 wave, and on cohorts 1949 through 1982 from the 2017 wave.

cent of social security contributions are top-coded. To still take advantage of the entire sample, earnings for the top 10 percent are imputed using a Pareto imputation. Bönke et al. (2015) show that the resulting earnings distribution can be validated with the German Socio-economic Panel.

Next, I restrict the sample in the following three ways: (1) Since women's extensive and intensive labor market margins have been changing significantly over the past few decades (e.g., Bertrand et al., 2010; Blau and Kahn, 2017; Glaubitz et al., 2022), I restrict my sample to men. (2) I exclude individuals with incomplete earnings biographies in Germany to abstract from immigration effects. (3) Since wage levels between the Federal Republic of Germany and the German Democratic Republic lack comparability, any earnings data before the reunification in 1990 cannot be used. Hence, my analysis concentrates on individuals living and working in West Germany. After applying these restrictions, my base sample consists of 73,042 men born from 1935 through 1982.

1.4 Prime-age workers

This chapter analyzes if, akin to the findings of Guvenen et al. (2014) for the US, the majority of the German earnings distribution experience long-term earnings losses across business cycles. Or if, instead, the German social market economy with its stronger employment protection, job security, and higher level of unionization has led to more evenly distributed earnings growth.

1.4.1 Methodology

For each business cycle defined as a crisis-induced recession and its subsequent expansion, I follow Guvenen et al. (2014) and add the following sample restrictions for this part of my analysis:

1. **Measurable earnings change**. Individuals must be observed both at the start and end of the recession and at the start and end of the expansion in order to estimate the earnings growth during business cycles.

2. **Age.** The analysis focuses on prime-age workers to extrapolate away from labor market

entry or exit decisions. Hence, I restrict the base sample to individuals who are aged 35 to 55 at the start of the recession. Since the rank correlation between annual earnings and lifetime earnings is very high for individuals in this age range (see Björklund, 1993; Bönke et al., 2015), this restriction also maximizes the likelihood that the short-term earnings rank approximates an individual's long term earnings position accurately.

3. **Average pre-episode earnings.** Individuals must have positive and greater than social minimum earnings (i) in the year before the recession (t-1) and (ii) in at least one additional year between t-2 and t-5. This restriction excludes individuals who were already permanently unemployed or had below social minimum earnings before the start of the recession since I want to investigate the recession's effect on employment. Next, I use the average of these pre-episode earnings to rank individuals against their peers to smooth out short-term income shocks that would not reflect an individual's long-term income rank.

After applying these additional restrictions, the number of prime-age men for each of the four recessions and subsequent expansions analyzed in this paper ranges from 2,927 to 23,420 (see Appendix, Tables 1.3-1.6).

This chapter then investigates how individuals weather economic downturns and recover through expansions. Therefore, the log change of an individual's earnings between the start t and the end $t+k$ of an recession or expansion would be an instinctive method of measurement. However, using this difference of log earnings would only allow the inclusion of positive earnings and therefore exclude all individuals who lose a job or get a job during the recessions or expansions. Such a restriction would be problematic as transitions in employment status are precisely a channel through which individuals can experience earnings gains and losses over time. In order to capture these instances as well, I continue to follow Guvenen et al. (2014) and use the following measure:

$$f(V_{t-1}^i) \equiv logE(Y_{t+k}^i|V_{t-1}^i) - E(Y_t^i|V_{t-1}^i)$$

with $Y_t^i \equiv exp(y_t^i)$

The form of f reveals the changes in the earnings y for individuals with different pre-episode earnings V^i_{t-1} during a recession or expansion while allowing for both changes in the extensive and the intensive labor margins. Using longitudinal data, this methodological approach therefore relies on non-anonymous growth incidence curves (Bourguignon, 2011).[6]

Before measuring earning changes with the equation above, I also need to adjust for the positive correlation between age and earnings. It would be misleading to compare younger and older workers without any adjustment. To obtain age-adjusted earnings, I use all earnings observations of the full base sample of individuals aged 25 to 55 and run a pooled regressions of log earnings on age and cohort fixed effects without a constant to characterize the relationship between age and log earnings. For each cohort, I then use the point estimate for a 25-year-old individual to scale the point estimates for all other ages. This results in a dummy d_{ch} for each cohort c and age h that matches the average log earnings of 25-year-old individuals from the same cohort and with the same age used in the regression. The age-adjusted earnings are then derived using the following equation:

$$\bar{Y} = \sum_{t=-5}^{t=-1} y_{itc} * d_{ch}$$

I multiply individuals' real earnings at a given age with their appropriate age and cohort dummy to get age adjusted earnings for all individuals enabling direct comparison across cohorts. Lastly, I average each individual's age adjusted earnings across all observed prerecession years (t-5 to t-1) and sort these prerecession average age-adjusted earnings into deciles. This grouping procedure is conducted on the pooled sample which includes all cohorts after correcting for age and cohort effects. This pooled decile ranking serves as my baseline earnings distribution with which I can

[6]Earnings growth through recessions or expansions is often measured using growth incidence curves, simply comparing the mean growth in the quantiles of the pre- and post-growth earnings distribution due to the lack of longitudinal data. However, this method is based on implicit re-ranking of individual earnings and overlooks income mobility by prioritizing only post-growth earnings. The term *non-anonymous* growth incidence curves then refers to an approach where earnings growth rates are ploted against the quantiles of the initial earnings distribution. This approach requires longitudinal data since we need to observe the quantile to which each individual belongs pre- and post-recession. Please see Bourguignon (2011) for a detailed overview of the advantages of and assumptions behind non-anonymous growth incidence curves.

evaluate log changes in earnings by prerecession decile between the start and end of recessions and expansions.

1.4.2 Recessions

Figure 1.2 graphs the change in log average earnings during recessions across my constructed prerecession earnings distribution separately for each recession. The slope of f then shows the relationship between the change in average log earnings during recessions and average prerecession earnings V_{t-1}^{i} for four crises from from 1980 through 2017.[7]

The first recession with available data is the second oil crisis from 1980-82 (in grey). During this recession, the bottom 10 percent of the average prerecession earnings distribution were hit hardest and saw their earnings decline by 8.9 log points (-8.5%). In contrast, workers with prerecession earnings in the top 10 percent experienced small earning gains. Average losses for the rest of the population ranged between 1.5 to 6.7 log points (-1.5 to -6.5%).

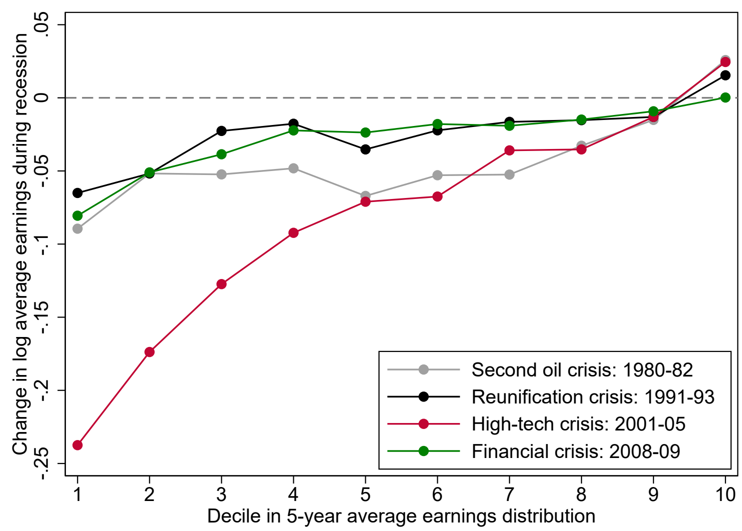
The slope of f followed very similar patterns during the reunification crisis (1991-1993, in black) and the financial crisis (2008-2009, in green). Compared to the second oil crisis and reunification crisis, earnings losses were slightly steeper for the bottom decile and similar for the second decile, but less pronounced between the third and ninth decile. On average, earnings for the bottom 90 percent of the prerecession earnings distribution decreased between 1.3 to 6.5 log points (-1.3 to -6.3%) during the reunification crisis and 0.1 to 8.1 log points (0.0 to -7.7%) during the financial crisis. In contrast, the top 10 percent saw slight earnings gains (second oil crisis, 1980-1982) or earnings remained stable (financial crisis, 2008-2009).

Compared to the US (see Guvenen et al., 2014), the impact of the financial crisis on the German labor market was surprisingly mild. Across all prerecession earnings deciles, earnings losses in the US were more than twice as large as those in Germany. This is especially surprising when

[7] Note that here I refer to the recession spurred by a crisis with the name of the crisis and will do so throughout this chapter. In reality, a crisis prompts a recession and it is that recession, not the crisis itself, that characterizes the unemployment and GDP growth rates. That said, for brevity and ease of understanding, I refer to the corresponding recession for each crisis as the crisis period itself (e.g., "during the second oil crisis" rather than "during the recession prompted by the second oil crisis").

taking into account Germany's larger drop in GDP growth during the financial crisis relative to the US. But since the crisis mainly affected Germany's export industry through its manufacturing companies, the GDP hit did not translate into comparable labor market consequences. When the financial crisis occurred, the German manufacturing sector was already experiencing a shortage of skilled workers coupled with an aging workforce. Hence, they chose to hold on to their qualified workforce through the economic contraction. This together with the extension of government subsidized short-time work, time buffers due to working time accounts, and the increased flexibility of the labor market due to earlier policy changes prevented more severe effects on the labor market (e.g., Rinne and Zimmermann, 2012).

Figure 1.2. Change in log average earnings during recessions 1980-2017



Source: FDZ-RV — VSKT Scientific Use Files 2002-2017, own calculations.

Across all four recessions, earnings losses were steepest during the high-tech crisis (2001-2005, in red), ranging from -23.7 log points (-26.7%) for the bottom 10 percent of the prerecession earnings distribution to 2.4 log points (2.4%) for the top 10 percent. Earnings losses among the bottom 60 percent of the prerecession earnings distribution were greater than for all other subgroups during the other three recessions investigated in this study.

There are several reasons why Germany's economy and labor market was particularly hard-hit during this time period. First, when the high-tech crisis hit (2001-2005), the German economy was already struggling due to the aftermath of the reunification. Second, Germany's economy depends largely on exports.[8] The high-tech crisis had a major impact on international trade, leading to a decline of German exports, which in turn impacted the broader German economy and trickled down to the labor market yet to experience the effect of modernizing labor market reforms during the 1990s and early 2000s. Third, the high-tech crisis also impacted the banking sector, which contributed to the severity of the economic contraction in the country. The banks in Germany had made significant investments in the technology sector, hoping to capitalize on the boom in the industry. When the demand for technology products and stock prices for this sector declined, they faced significant losses. This had a carry-through effect on the rest of the economy, as the banks became more cautious in their lending practices, which in turn reduced the availability of credit and slowed down economic activity.

To summarize, individuals' earnings growth follows a systematic pattern during recessions. In Germany, average earnings losses decreased with higher prerecession earnings. During all four recessions within my observation period, individuals from the bottom 10 percent were hit hardest. Workers with prerecession earnings in the 20th to the 90th percentile also experienced significant earnings losses, while only the top 10 percent remained unscathed during economic downturns. The slope of f depends on the severity of each crisis, with the high-tech crisis (2001-2005) exhibiting the strongest and the reunification and financial crisis (1991-1993 and 2008-2009, respectively) showing the weakest relationship between the change in average log earnings during the recession period and the prerecession earnings decile.

1.4.3 Expansions

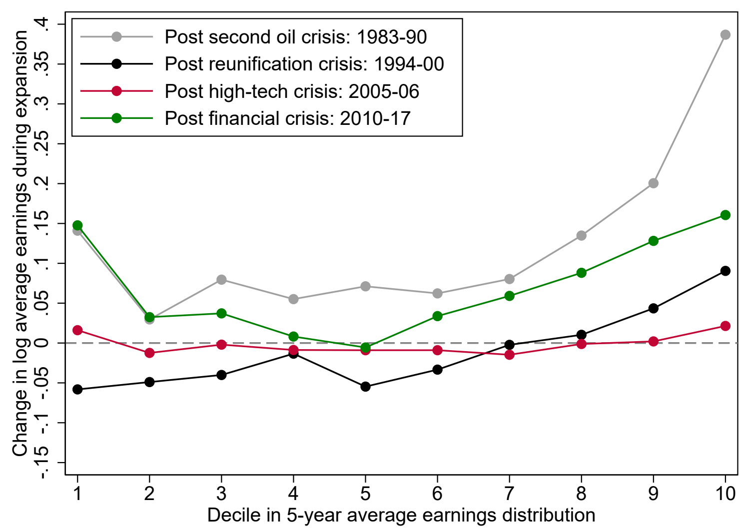
Economic expansions represent times of economic recovery following a recession, ideally characterized by increased consumer spending, investment, and business activity that lead to economic growth. But did workers economically recover from their earnings losses during previous reces-

[8]For example, the foreign trade balance exceeded 100 billion Euro in 2022 (Federal Statistical Office, 2023).

sions? And did recovery patterns change over time?

To answer these questions, Figure 1.3 shows the change in average log earnings by prerecession earnings decile for the four expansions following the crises I just investigated. The first expansion I can observe takes place from 1983 through 1990, right after the second oil crisis (1980-1982). Almost the entire population experienced earnings gains between the start and the end of this boom period. Clearly, f follows an inverse u-shape; workers with prerecession earnings in the first decile experienced average earnings gains of 14.1 log points (15.1%), while earnings changes for those in the second through seventh decile only ranged between 2.9 log and 8.0 log points (2.9 to 8.3%). For the top 30 percent of the prerecession earnings distribution, earnings gains increased significantly more, peaking at 38.7 log points (47.3%) for the top decile.

Figure 1.3. Change in log average earnings during expansions



Source: FDZ-RV — VSKT Scientific Use Files 2002-2017, own calculations.

The second expansion after the reunification crisis ranges from 1994 to 2000. Earnings changes during this expansion were negative for workers in the bottom 60 percent of the prerecession earnings distribution, ranging from -5.8 log points (-5.6%) for the first decile to -3.3 log points (-3.2%) for the sixth decile. Only the top 40 percent saw moderate positive earnings changes between 0.2 and 9.1 log points (0.2 to 9.5%) during these years. In contrast to the all other expansions, here f is increasing with higher deciles across the whole prerecession earnings distribution and therefore looks very similar to the earnings patterns observed in Figure 1.2 during recessions. This underlines the pressure on the German economy and labor market in the 1990s and helps explain why the high-tech crisis hit German workers especially hard.

The high-tech crisis and financial crises happened only a few years apart (2001-2005 and 2008-2009, respectively). Hence, the expansion period between these two crises was unusually short (2006-2007). Earnings barely changed over this short time window and changes ranged from only -1.6 to +2.1 log points (-1.6 to 2.1%) across the whole population. Additionally, the following financial crisis was also short-lived and did not translate into significantly negative labor market effects. Hence, 2010 was the first time since the start of the reunification crisis in 1991 that the German economy and labor market entered a traditional economic boom period. Again, f is inversely u-shaped, but lies at every point on or below the growth curve of the first expansion following the second oil crisis (1983-1990). Another difference is that the earnings gains of the bottom and top decile are quite similar (14.8 log point or 15.9% and 16.1 log points or 17.5%, respectively), in contrast to the first expansion where the top decile earnings gains increased by more than double as much as the earnings of those workers with the lowest pre-recession earnings.

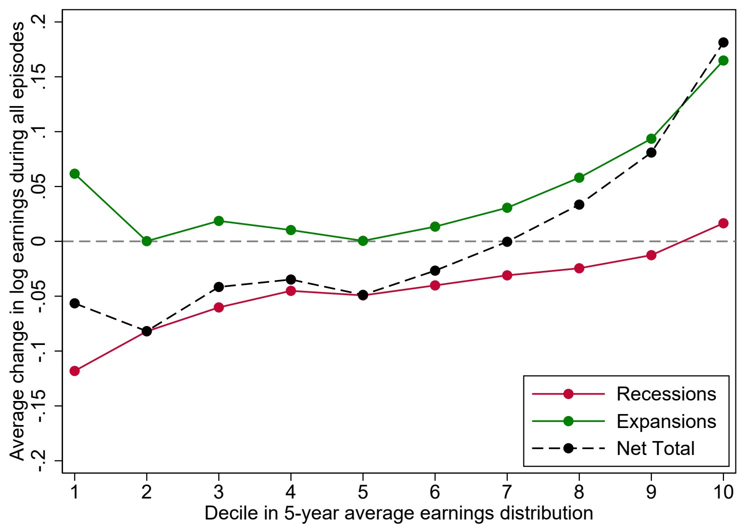
1.4.4 Recessions and expansions: The net total

After analyzing 37 years of data including four major economic crises and their subsequent expansions, I next analyze the overall net effects on earnings. Which groups were able to increase their average earnings, which were able to recover, and which lost?

Figure 1.4 combines the log earning changes of all four crises (in red), the four subsequent expansions (in green), and the four composite business cycles (in black). Notably, all workers except those from the top decile of the prerecession earnings distribution experienced earnings losses during recessions. The average earnings losses were highest for workers from lower earnings deciles and decreased with higher prerecession earnings. The top 10 percent realized small earnings gains (1.6 log points, or 1.6%).

In the expansions following the four recessions, all workers experienced positive earnings gains on average. However, for those workers from the second through sixth decile, those earnings changes were very small, ranging only from 0.0 log points (0.0%) to 1.8 log points (1.8%). Average earnings gains were significantly higher for the top 40 percent, increasing steadily with every decile and peaking for the top 10 percent at 16.5 log points (17.9%).

Figure 1.4. Change in log average earnings: recessions versus expansions



Source: FDZ-RV — VSKT Scientific Use Files 2002-2017, own calculations.

Combining the average earnings losses and gains for all four business cycles, I find that only the top 30 percent were able to increase their real earnings since 1980. Among that group, real earnings gains were smallest for workers from the 8th decile (3.3 log points or 3.4%) and highest for those from the top decile (18.1 log points or 19.9%). The rest of earnings distribution lost money, with the first and second deciles seeing the largest losses (-5.6 and -8.2 log points, or -5.8% and -8.5%, respectively). This dynamic contributes largely to the rising earnings inequality that has been documented over the past decades (e.g., Bönke et al., 2015), and further research is needed to determine the causal effect of crises on recovery patterns of male prime-age workers from different socioeconomic backgrounds.

So after all, how do the trends observed in Germany compare to those from Guvenen et al.

(2014) for the US, an economy with much less (labor) market regulations? Both Germany and the US show very similar functional forms of f during recessions and expansions. In recessions, earnings losses were higher for lower deciles in the prerecession earnings distribution and decrease with higher deciles. The only notable difference is that even US workers from the top 10 percent experienced earnings losses during recessions, while those in Germany were able to realize small earnings gains. During expansions, f were u-shaped in both countries, with those at the margins of the distributions experiencing higher earnings growth than the middle of the prerecession earnings distribution. When combining all recessions and expansions, Guvenen et al. (2014) show that in the US only the bottom and the top deciles of the pre-recessions earnings distribution were able to achieve real earnings gains over the past decades. This differs from what we see for Germany, where (1) a higher share of workers were able to realize earnings gains across business cycles (30 percent of the workforce instead of 20 percent in the US), and (2) the winners were solely concentrated at the top of the earnings distribution.

1.5 Labor market entrants

Labor market entrants form a group that might be far more vulnerable to recessions than prime-age workers. First, job market entrants often lack the experience and skills that prime-age workers have accumulated over the years. They may have just graduated from high school, vocational school or college and likely do not have significant work experience. This can make it difficult for them to compete with more experienced workers for jobs, particularly during recessions. Second, entering the job market during a recession might make it more difficult to find a job opening, as many companies may be laying off workers rather than hiring new ones. And even if they find a job, they may be more likely to be employed in temporary or contract positions, which offer less job security. Lastly, some studies find that entering the labor market during adverse conditions might not only have a short-lived effect, but can decrease long-term earnings (e.g., Kahn, 2010; Berniell et al., 2023).

1.5.1 Methodology

The sample used to estimate the impact of entering the labor market in poor economic conditions on earnings now includes all individuals who had positive earnings reported to the German pension register by age 30. Since this section concentrates on labor market entrants, younger birth cohorts up to individuals born in 1982 can be included. An overview of all cohorts can be found in the Appendix (Table 1.8).

Following the literature (e.g., Kahn, 2010; Oreopoulos et al., 2012), I use national unemployment rates between 1960 and 2015 as an indicator for the economic conditions in the year an individual graduated. However, VSKT data does not include any information on the graduation year of individuals. Therefore, I apply the methodology of Schwandt and Von Wachter (2019) and use the employment rate in the Mincerian graduation year g, defined as the year of birth plus six years and the total years of education. While I can also not observe the number of school years nor the education level directly in VSKT data, a twofold logical imputation approach still allows me to reliably obtain the Mincerian graduation year for all individuals:

1. In the rigid German education system, it is straightforward to identify the number of school years for each of the three education levels (see Appendix 1.7.2 for a detailed overview).

2. VSKT data include monthly earnings biographies starting at age 14 for all individuals. Hence, even though I cannot observe the timing of the graduation, I can observe the actual timing of the first labor market entrance.[9] This, in combination with the rigid educational time schedules for each of the three main education pathways, allows for a reliable logical imputation of the Mincerian graduation year.

The resulting educational distribution of my sample after applying this logical imputation strategy is shown in Table 1.7 in the Appendix. The shares of each education group align well with what other studies observe using alternative national data sources (e.g., Bönke et al., 2019 or Federal

[9] Since some summer jobs also report earnings to the German pension register, I define the first labor market entrance as the first time an individual earned more than $2,400 in 2015 prices (roughly half the social minimum) to abstract from these outliers.

Agency for Civic Education, 2022[10]), underlining the reliability and robustness of my approach. Please see Appendix 1.7.2 for a more detailed comparison.

My methodological approach assumes the timing of the labor market entry to be exogenous. However, individuals can extend their education to avoid having to enter the labor market during economically challenging times. If the timing of labor market entry is uniformly distributed among new entrants, the endogeneity will attenuate my estimates towards zero. If there were selection into timing, the direction of the bias is unclear (Schwandt and Von Wachter, 2019). As Appendix 1.7.2 discusses in more detail, due to the rigidity of the German education system, prolonging educational attainment is difficult for students on the lower and advanced education (middle track) pathways. However, college students have more flexibility regarding their graduation timing. Therefore, the proposed identification strategy works better for lower and advanced education pathways, while the results for college students should be treated with caution.

To avoid bias due to differences across groups, I run the following regression separately for each of the three education levels e (lower, advanced, and college education):

$$\bar{y}_{c,t,e} = \alpha + \beta_1 u_g + \gamma_w + \theta_t + \epsilon_{g,t,e}$$

where $\bar{y}_{c,t,e}$ are the average earnings for cohort c in year t by education level e.[11] u_g is the unemployment rate in the Mincerian graduation year g, and γ_w and θ_t are potential work experience and calendar year fixed effects, respectively. Since this regression does not include the current unemployment rate, β_1 captures the causal effect of graduation during adverse economic conditions, assuming the regular subsequent evolution of unemployment rates (see Arellano-Bover, 2022).

[10]In German: *Bundespolitische Zentrale für Bildung*

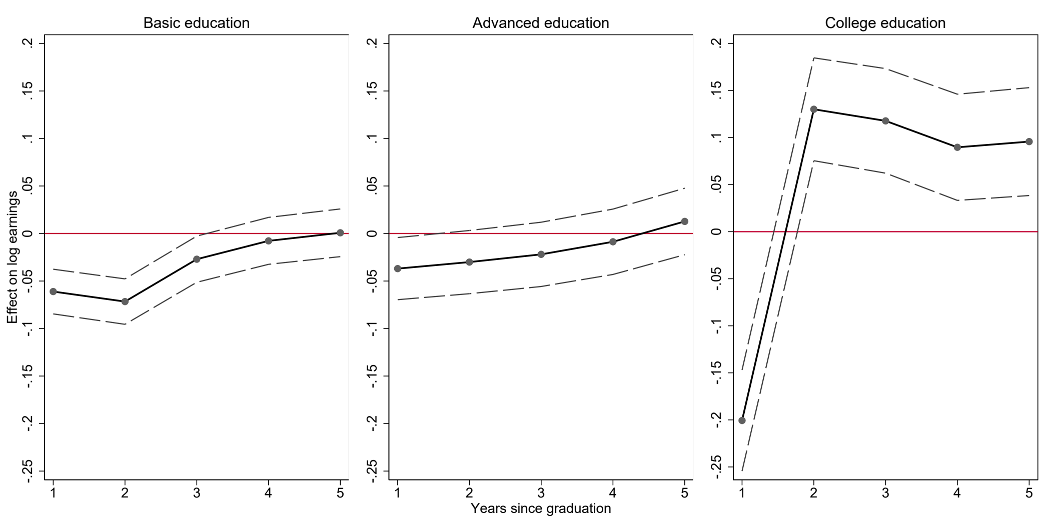
[11]Note that using the Mincerian graduation year instead of the observed graduation year means that this regression also controls for cohort effects since all individuals born in the same year with the same education level have the same Mincerian graduation year.

1.5.2 Results

Figure 1.5 shows the effect of unemployment rate at graduation on log annual earnings in the first five years after graduation. The figure shows the coefficients of the interaction of u_g and years since graduation dummies for labor market entrants with basic, advanced, and college education.

West German men with basic education experience the most long-lasting earnings losses when entering the labor market during times of higher unemployment. A one-point increase in the initial unemployment rate leads on average to a six percent decrease in annual earnings in the first year after graduation. This effect is quite large. Recessions often lead to an average increase in the unemployment rate by three percentage points, which would mean that individuals from this group entering the labor market during a recession experience an average earnings loss of 18 percent. This effect is even slightly stronger in the second year (7.0 percent) before it attenuates after five years.

Figure 1.5. Effect on unemployment rate at labor market entry on log annual earnings



Source: FDZ-RV — VSKT Scientific Use Files 2002-2017, own calculations.

As expected, the negative impact of the initial unemployment rate on earnings is smaller for labor market entrants with advanced education. This group only shows a statistically significant decrease in earnings in the first year after graduation, and even there, the effect is more limited (-

3.6%). Looking at college graduates, they experience a very drastic decrease in earnings in the first year after graduation (-20.1%), immediately followed by a large increase in the second and third year after graduation (+13.0% and +11.8%, respectively). Hence, the negative effect of entering the labor market during times of higher unemployment is already completely offset in the third year after graduation for college educated workers. This result is driven by the fact that the timing of college graduation is not as rigid in Germany and college students can postpone their graduation at relatively low costs.[12] My identification strategy using the Mincerian graduation year would not be able to capture such behavioral changes. Therefore, it is likely that the large first-year effect is driven by the voluntary choice of college graduates to delay their labor market entrants under especially challenging labor market conditions. To support this hypothesis, I also find that a higher share of college graduates had still not entered the labor market when entering during times with an unemployment rate of six percent or higher (12.0% compared to only 9.2% when the unemployment rate was lower than six percent).

1.6 Conclusion

In conclusion, this study utilizes German pension register data on birth cohorts from 1935 through 1982 to analyze the impact of four major business cycles between 1980 and 2017 on the earnings of labor market entrants and prime-age workers in Germany. My findings suggest that the impact of recessions and subsequent expansions on earnings is not evenly distributed across the population.

Prime-age workers at the bottom of the pre-recession earnings distribution experienced the steepest decline in earnings and this decline decreased as pre-recession earnings increase. The most significant decline in earnings occurred during the high-tech crisis, with earnings growth ranging from -23.7 log points (-26.7%) for the bottom 10 percent of the pre-recession earnings distribution to 2.4 log points (2.4%) for the top 10 percent.

Moreover, the majority of the population were unable to recover from their average recession

[12] In Germany, college tuition is only around $1,000 per year and students mostly just face their own rental costs and the opportunity costs from foregone earnings if they choose to graduate later. However, of course, only students from better off family backgrounds are able to afford this strategy.

losses in subsequent expansions. My analysis shows that only the top 30 percent of individuals in the pre-recession earnings distribution achieved real earnings gains since 1980, while all other male prime-age workers experienced losses on average. The German earnings pattern look similar to the US (see Guvenen et al., 2014), with a few notable differences: (1) Germany has a higher proportion of workers (30 percent of the workforce) who were able to achieve earnings gains across various business cycles, as opposed to only 20 percent in the US; (2) Germany's earnings gains were only concentrated at the top, while in the US, the bottom and top decile of the pre-recessions earnings distribution realized earnings gains.

To better understand the impact of recessions on more vulnerable labor market participants, I also estimate the impact of initial labor market conditions on the earnings of labor market entrants. My analysis shows that lower-educated men are the most affected by poor economic conditions when entering the labor market, experiencing the longest-lasting decline in earnings. A one-point increase in the initial unemployment rate leads to an average decline of six percent in annual earnings in the first year after graduation; this is a substantial impact given that unemployment rates often increase by several percentage points during recessions. This effect slowly attenuates after five years. Still, this might make it difficult for those individuals to plan for their future or make long-term financial decisions such as purchasing a home or starting a family since the broader impacts of such large earnings losses during formative years may persist in the long-run.

Together these findings suggest that lower educated workers have suffered the most during past recessions. Not only did they experience the largest negative impact on earnings when entering the labor market during recessions, but are also the most likely to be in the bottom of the earnings distribution as earnings and education are positively correlated. Hence, when recessions hit the economy during their prime-age working years, they also saw the steepest earnings losses and were least likely to recover during subsequent expansions. Germany's social market economy was not able to protect lower educated workers' earnings and further research on effective policies should be prioritized to address this issue.

1.7 Appendix

1.7.1 Samples: Prime-age workers

Table 1.2. Age at the start of the recession

Recession	Average Age	Median Age
Second oil crisis	34.98	35
Reunification crisis	34.28	34
High-tech crisis	36.09	36
Financial crisis	36.83	37

Table 1.3. Second oil crisis: Sample

Cohort	Frequency	Percent
1935	256	8.3
1936	271	8.8
1937	303	9.8
1938	286	9.2
1939	305	9.9
1940	277	9.0
1941	288	9.3
1942	267	8.6
1943	284	9.2
1944	243	7.9
1945	313	10.1
Total	3093	100.0

Table 1.4. Reunification crisis: Sample

Cohort	Frequency	Percent
1945	313	1.9
1946	307	1.9
1947	294	1.8
1948	1572	9.7
1949	1546	9.5
1950	1618	10.0
1951	1707	10.5
1952	1639	10.1
1953	1737	10.7
1954	1775	10.9
1955	1857	11.4
1956	1878	11.6
Total	16243	100.0

Table 1.5. High-tech crisis: Sample

Cohort	Frequency	Percent
1953	1737	6.0
1954	1775	6.1
1955	1857	6.4
1956	1878	6.5
1957	1915	6.6
1958	1971	6.8
1959	2021	7.0
1960	2069	7.1
1961	2184	7.5
1962	2278	7.8
1963	2339	8.1
1964	2280	7.9
1965	2318	8.0
1966	2417	8.3
Total	29039	100.0

Table 1.6. Financial crisis: Sample

	Frequency	Percent
1959	2021	5.8
1960	2069	6.0
1961	2184	6.3
1962	2278	6.6
1963	2339	6.8
1964	2280	6.6
1965	2318	6.7
1966	2417	7.0
1967	2406	7.0
1968	2335	6.8
1969	2464	7.1
1970	2454	7.1
1971	2297	6.6
1972	2311	6.7
1973	2383	6.9
Total	34556	100.0

1.7.2 The German education system

Figure 1.6 shows the three pillars of the German education system: elementary, secondary and post-secondary education. School years start in late summer (August/September) and end in June/July depending on the states students live in.

Children attend elementary school from grades 1 through 4.[13] In fourth grade, teachers assign students to the lower, intermediate, or higher education pathway based on their academic performance in elementary school. Students who are assigned to the lower or intermediate high school track finish their secondary schooling after 10 years of schooling at age 16. Afterwards, the highest performing students of these education pathways are eligible for further secondary schooling if they are interested in continuing their education. However, the vast majority of graduates from the lower and intermediate high schools join a registered apprenticeship program. Apprenticeship programs combine on-the-job training with classroom instructions and usually last three years [14]. Hence, these youth will enter the labor market for the first time at age 19. This is the *lower educated* group and their Mincerian graduation year is their birth year plus 19 years.

Students who are assigned to the higher education pathway go on to attend the *Gymnasium* for grades 5 to 13.[15] Afterwards, they are eligible to apply and attend college to obtain a university diploma or, after the higher education reform in 2022, Bachelor's and Master's degrees. However, they can also choose to join an apprenticeship program instead.

Some more advanced apprenticeships are only open to those who obtain the highest German secondary school diploma (e.g., air traffic controller), and these occupations often have a higher earnings potential than the apprenticeship programs open to all other education pathways. These apprenticeship programs also last on average three years. Hence, this /textitadvanced education group's Mincerian graduation year is their birth year plus 22.

While the time schedule for the lower and advanced education groups are quite rigid and make

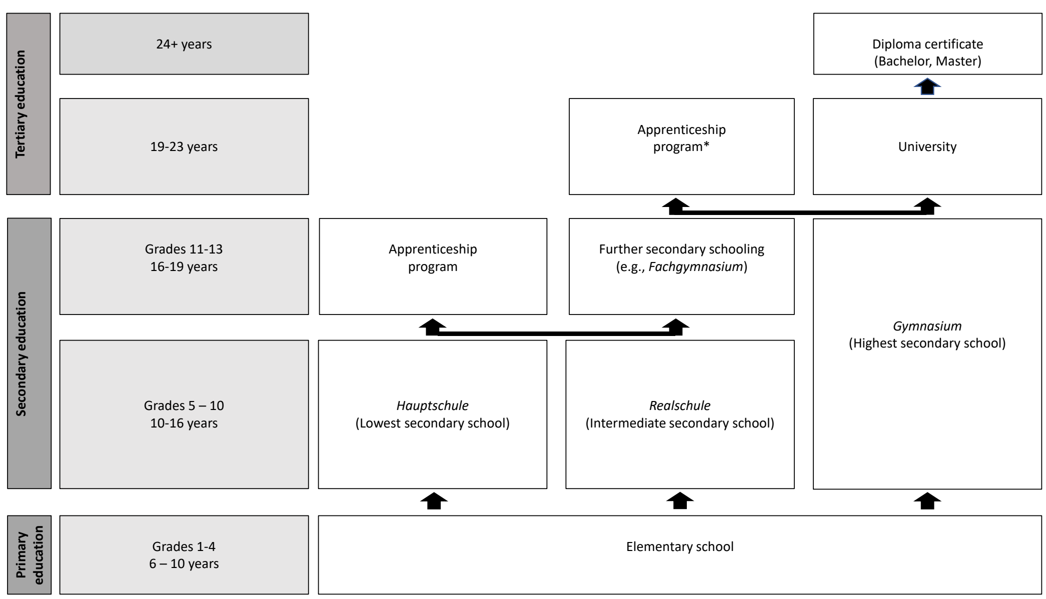
[13] In a few select states, elementary schools run through grade 6. This does not affect this methodological approach in any way though.

[14] Few apprenticeship programs only require 2-2.5 years of training (e.g., chefs)

[15] In the late 2000s, secondary schooling for the higher education pathway was reduced from 13 to 12 school years. Since the youngest birth cohort of my sample turned 19 in 2001, this policy change does not affect my sample.

it easy to estimate the Mincerian graduation year, this approach is more challenging for college students. While it takes usually around 5 years to receive a university diploma (equivalent to a Master's degree in Germany), it is relatively easy to delay graduation for up to one or two years since college tuition is very low and no special administrative approval is required. However, prolonging education comes with high opportunity costs in terms of foregone earnings, so it is still an expensive decision. Therefore, I assume that most students will enter the labor market upon completion regardless of the economic conditions. This leads to a Mincerian graduation year of the birth year plus 24 for the *college education* group. While this will be correct on average, there will be more variation across individuals than for the other education groups.

Figure 1.6. The German education system



Source: Based on a report from the Bunderzentrale für Bildung (2021).
*Some advanced apprenticeship programs are only open to those who obtain the highest German HS diploma after 13 school years (e.g., air traffic controller).
Note: This overview describes the education pathways for the vast majority of the German population born between 1940 and 1985. However, there are some other options in the later postsecondary and tertiary education phase that are not included in this figure. Please see Bundeszentrale für Bildung (2021) for a more detailed overview.

Table 1.7 summarizes the resulting educational distribution of my sample using this logical imputation strategy. In birth cohorts 1940 through 1949, only 9.1 percent of the sample are identified as college graduates. This share grows over time so that college graduates account for 18.6 percent of those born 1965 or later. Both the magnitude of these shares as well as their change over time are in line with other studies for Germany. For example, using German census data, Bönke et al. (2019) show that college graduates accounted for 8.2 percent of West German men in 1970, covering birth cohorts born 1950 or older. In 2012 (covering birth cohorts 1992 and younger), they then find that the share of college graduates had increased to 20.1 percent. Another supporting source is provided by the federal agency for Federal Agency for Civic Education (2022): They published that college graduates made up for 22.2 percent of the German population in 2005, covering birth cohorts up to 1995.

Table 1.7. Labor market entrants: Education

Education level	Cohorts 1940-1949	Cohorts 1950-1964	Cohorts 1965-1982
Basic/advanced education	3,095 (90.9%)	15,189 (89.3%)	22,888 (81.4%)
College education	309 (9.1%)	1,813 (10.7%)	5,241 (18.6%)
Total	3,404 (100%)	17,002 (100%)	28,129 (100%)

1.7.3 Sample: Labor market entrants

Table 1.8. Labor market entrants

Cohort	Frequency	Percent
1940	150	0.3
1941	181	0.4
1942	145	0.3
1943	165	0.3
1944	164	0.3
1945	212	0.4
1946	198	0.4
1947	188	0.4
1948	1010	2.1
1949	991	2.0
1950	1022	2.1
1951	1052	2.2
1952	965	2.0
1953	1015	2.1
1954	1031	2.1
1955	1081	2.2
1956	1062	2.2
1957	1085	2.2
1958	1120	2.3
1959	1163	2.4
1960	1195	2.5
1961	1276	2.6
1962	1239	2.6
1963	1342	2.8
1964	1354	2.8
1965	1346	2.8
1966	1422	2.9
1967	1402	2.9
1968	1379	2.8
1969	1473	3.0
1970	1457	3.0
1971	1425	2.9
1972	1402	2.9
1973	1543	3.2
1974	1378	2.8
1975	1440	3.0
1976	1386	2.9
1977	1723	3.6
1978	1718	3.5
1979	1772	3.7
1980	1942	4.0
1981	1965	4.0
1982	1956	4.0
Total	48535	100.0

2 The Gender Gap in Lifetime Earnings: The Role of Parenthood

2.1 Introduction

While most research on the gender pay gap has focused on differences in cross-sectional data, gender inequalities can add up over the life course as previous work experience, career pathways and earnings determine future labor market outcomes. Hence, a purely cross-sectional analysis cannot account for the biographical dimension of gender inequalities. However, due to high data requirements, there is only scarce empirical evidence on gender lifetime earnings gaps (e.g., Boll et al., 2017; Guvenen et al., 2021, 2022). In addition, these studies are often limited by their use of administrative data and subsequent lack of family-related information such as marital status or number of children. Since, on average, the labor market participation of women is lower than that of men at both the intensive and extensive margin due to family-related factors such as childcare (see, e.g., Goldin, 2014; Kleven et al., 2019), an analysis of the household context is necessary for a more comprehensive understanding of the underlying drivers of gender differentials in lifetime earnings.

This study uses the Socio-Economic Panel (SOEP) to shed light on the role of women's family backgrounds in gender differences, from both a cross-sectional and a lifetime perspective. Using an Oaxaca Blinder decomposition, we show that the cross-sectional gender gap can largely be explained by both the extensive and intensive margins of labor. On average, women have less work experience and work fewer hours, which has a strong negative effect on women's earnings.

To further take advantage of the detailed socioeconomic and family background information in the SOEP survey compared to administrative data sources, we use a dynamic microsimulation model to obtain full employment biographies, and subsequently lifetime earnings data. This approach leads to a more comprehensive sample than the ones of earlier studies (see Bönke et al., 2015; Boll et al., 2017) for Germany as we are, for the first time, able to include self-employed individuals, civil servants and women with longer unemployment or labor market inactivity spells. Our estimates show that women accumulate on average around 51.5% less than men in terms of lifetime earnings up to age 60. The unadjusted gender gap in lifetime earnings correlates largely with the number of children and ranges from 17.3% for childless women to 68.0% for women with three children or more.

To investigate which part of the observed gender gap in lifetime earnings can be associated with differences in the distribution of characteristics (e.g. work experience, level of education) across gender and which part is due to differences in labor market returns to characteristics, we estimate women's counterfactual lifetime earnings. We find that around 80% of the observed lifetime earnings gap can be explained by different characteristics across men and women, leading to an adjusted gender lifetime earnings gap of 10%. Contrary to the unadjusted gap, motherhood does not play a crucial role for the adjusted gender lifetime earnings gap. The adjusted gender gaps in lifetime earnings for childless women and women with three or more children only differ by around 2 percentage points.

Our paper is related to three different strands of literature. First, it contributes to the extensive literature on the gender gap in pay and its drivers. Existing studies show that a large extent of the pay gap can be attributed to fewer hours worked and higher discontinuity of female employment biographies (e.g., Bertrand et al., 2010; Blau and Kahn, 2017).[16] The persistence of this gender earnings inequality is mainly due to different effects of parenthood on men's and women's labor market behavior, and consequently their earnings (see, e.g., Waldfogel, 1998; Angelov et al., 2016; Kleven and Landais, 2017). In line with previous studies (e.g., Goldin, 2014; Juhn and McCue, 2017; Gallen et al., 2019), we confirm that gender differences in annual earnings increase during the period of family formation, peak around age 40 and slowly decrease until retirement, leading to an inverse u-shape of the gender annual earnings gap over the work life.

[16] Past studies in this field focused on gender differences in human-capital accumulation and discrimination as the main drivers of gender inequalities in labor markets. Altonji and Blank (1999) give an overview of the early literature in this field.

Studies for Germany show that the cross-sectional earnings gap between mothers and non-mothers are largely driven by domestic work and childcare duties (e.g., Beblo and Wolf, 2002; Ejrnæs and Kunze, 2013). Strikingly, child penalties on women's pay are high in Germany compared to other countries (see, e.g., Kleven et al., 2019). This is often attributed to longer maternal leave entitlement and a higher rate of part-time work for women in Germany (see, e.g., Harkness and Waldfogel, 2003; Gangl and Ziefle, 2009). However, more recent studies also stress the influence of relative conservative gender norms in Germany in this context (e.g., Kleven et al., 2019, 2020).

Second, our study adds to the scarce literature on lifetime earnings and specifically to what extent these differ by gender.[17] Using administrative data for the U.S., Guvenen et al. (2021) show that the fraction of women among lifetime top earners is significantly lower than that of men for birth cohorts 1956 to 1958. On average, lifetime top earners in the U.S. tend to be individuals who experience high earnings growth over the first half of their life cycle – the period when the gender gap increases the most, likely due to family-related reasons. In a later study, Guvenen et al. (2022) provide evidence that the large gender lifetime earnings gap is narrowing over time, with women's median lifetime earnings increasing while men's median lifetime earnings decreases for younger birth cohorts. Using administrative data from the German Pension Register (VSKT), Bönke et al. (2015) find evidence that intragenerational lifetime earnings inequality for West German men born between 1935 and 1969 has increased, largely due to losses in the bottom of the lifetime earnings distribution. They also supplement their work with additional results on West German women. However VSKT data only includes women with stable employment biographies. Due to the low labor market participation rate amongst women of older cohorts, the VSKT is not representative for most women and cannot be used to estimate the gender gap in lifetime earnings. Closest to our paper is the study by Boll et al. (2017) analyzing the gender lifetime earnings gap in Germany. Using the administrative Sample of Integrated Labour Market Biographies (SIAB), they estimate an unadjusted gender lifetime earnings gap of 46% for West German birth cohorts 1950 through

[17] Lifetime earnings refer to the sum of individuals' accumulated earnings over their entire work life. Due to their close link to individuals' life chances, lifetime earnings are often seen as the more comprehensive earnings measure in comparison to, for example, cross-sectional annual earnings (see, e.g., Corneo, 2015; Tamborini et al., 2015).

1964. They show that the gender gap widens significantly during the age of family formation and that gender differences in work experience and hours worked explains around two-thirds of this overall gender lifetime earnings gap. However, SIAB data does not offer any information about individuals' family background. Hence, to the best of our knowledge, our study is the first to examine the influence of parenthood on the gender gap in lifetime earnings in Germany.

Third, our study contributes from a methodological point of view to the literature on the implementation of dynamic microsimulation models for the simulation of missing information (e.g., Zucchelli et al., 2012; Li and O'Donoghue, 2013; Levell and Shaw, 2016). A dynamic microsimulation approach refers to a regression-based simulation which predicts the transition probabilities of different units (e.g. individuals or households) for moving from one state to another between two different points in time. Therefore, in contrast to studies using a splicing approach (e.g., Westermeier et al., 2012; Grabka and Goebel, 2017) where sequences of existing biographies are stitched together to construct full life-cycle data, the microsimulation approach typically "ages" the data year by year (Li and O'Donoghue, 2013). We apply a dynamic microsimulation model to SOEP survey data to obtain complete earnings biographies, which facilitates lifetime earnings analyses. Combining simulation models with survey data is a well-established method to deal with missing observations and panel attrition, which often impede using survey data to conduct long-term analyses (see, e.g., Brown et al., 2009; Coronado et al., 2011). For Germany, for example, there are existing studies simulating employment biographies using SOEP data (e.g., Geyer and Steiner, 2014; Bonin et al., 2015; Hanisch and Klos, 2016).

The next section introduces our dataset and starts by analyzing cross-sectional gender differences in hourly wages and annual earnings over the work life by using an Oaxaca Blinder decomposition. Section 2.3 describes our microsimulation approach to obtain full work biographies and presents our estimates for the unadjusted and adjusted gender lifetime earnings gap. Section 2.4 concludes.

2.2 Cross-sectional analysis

The cross-sectional analysis allows us to explore how gender gaps in hourly wages and annual earnings develop with increasing age and to investigate if short-term differences already follow certain patterns across gender. This first step is crucial to subsequently better understand how gender inequalities in labor market characteristics and earnings add up or equalize over the entire work life.

2.2.1 Data and methodology

Our study is based on the German Socio-Economic Panel (SOEP). The SOEP is a representative annual panel survey questioning about 30,000 individuals across 15,000 households since 1984. In contrast to administrative data, the SOEP includes a rich set of socioeconomic variables, detailed labor market information and household background including information on the partner and children.[18]

We restrict our cross-sectional analysis to birth cohorts 1940 to 1979. These are the same birth cohorts used for the underlying regressions of our microsimulation model in Section 2.3. We observe these cohorts at least once between the ages of 38 and 44 in the SOEP. This age restriction is crucial as it is the age frame when individuals' cross-sectional earnings show the highest correlation with lifetime earnings and is therefore needed to successfully simulate life-cycle profiles in Section 2.3 (Björklund, 1993; Bönke et al., 2015). Further, we focus on West German individuals since those born in East Germany were only included in the SOEP after the German reunification in 1990. The poor comparability of the Federal Republic of Germany and the German Democratic Republic with respect to labor market institutions and economic systems does not allow us to simulate missing information for East Germans before 1990.

Section 2.2 focuses on the evolution of cross-sectional hourly wages and annual earnings with increasing age over the work life. This approach sheds light on two main components of the gender gap in lifetime earnings; the gender gap in hourly wages shows the differences in the compensa-

[18] See Goebel et al. (2019) for a detailed overview of the SOEP.

tion between women and men for one hour of their work, while the gap in annual earnings reveals dissimilarities driven by the variation in working hours.

We use an Oaxaca Blinder decomposition (see Oaxaca, 1973; Blinder, 1973) to investigate how much of the difference in the observed gender gap is driven by different characteristics between men and women and how much can be attributed to different returns to characteristics within the labor market.[19] Using this decomposition approach, the gender gap G in the labor market outcome variable L (here: logarithmic hourly wage and logarithmic annual earnings) is defined as:

$$G_x = E(L_{mx}) - E(L_{fx}) \tag{1}$$

Therefore, G is the gender differential between the means of outcome L for men (m) and women (f) at age x. We can then divide the gender gap into two parts: the endowment and the coefficient part. The endowment part is the component of the gender gap which arises due to differences in the distribution of characteristics between men and women. The coefficient part accounts for differences in returns to characteristics. Hence, the coefficient part shows the gender driven difference of the labor market's willingness to pay for the same characteristics obtained by either men or women. However, note that the coefficient part may also include gender differences that remain unexplained in our model due to data and model restrictions. We run the following regression model separately by sex (s) and age (x) for the labor outcome L [20]:

$$L_{s,i,x} = \alpha_{s,i,x} + \beta_{s,i,x} Z_{s,i,x} + \epsilon_{s,i,x}, \quad E(\epsilon_{s,x}) = 0, \quad s \in \{F, M\}, x \in [20, 60] \tag{2}$$

where Z is a vector of control variables including work experience measured as number of working years, full-time or part-time work, work sector, highest education level, marital status and number of children. In addition, we control for cohort and time effects.[21]

[19] A more detailed description of this methodological approach can be found in Subsection 2.5.1 in the Appendix.

[20] For comparability, we only control for variables that we can also use in our analysis of the lifetime gender gap in Section 2.3.

[21] Our pooled sample includes birth cohorts 1940 to 1979. Therefore, we include cohort dummies into our estimation model. We do not find any consistent cohort effects in our analysis. Figure 2.10 in the Appendix also shows that gender gaps in labor market outcomes are generally stable over time in our sample of working women.

2.2.2 Hourly wage

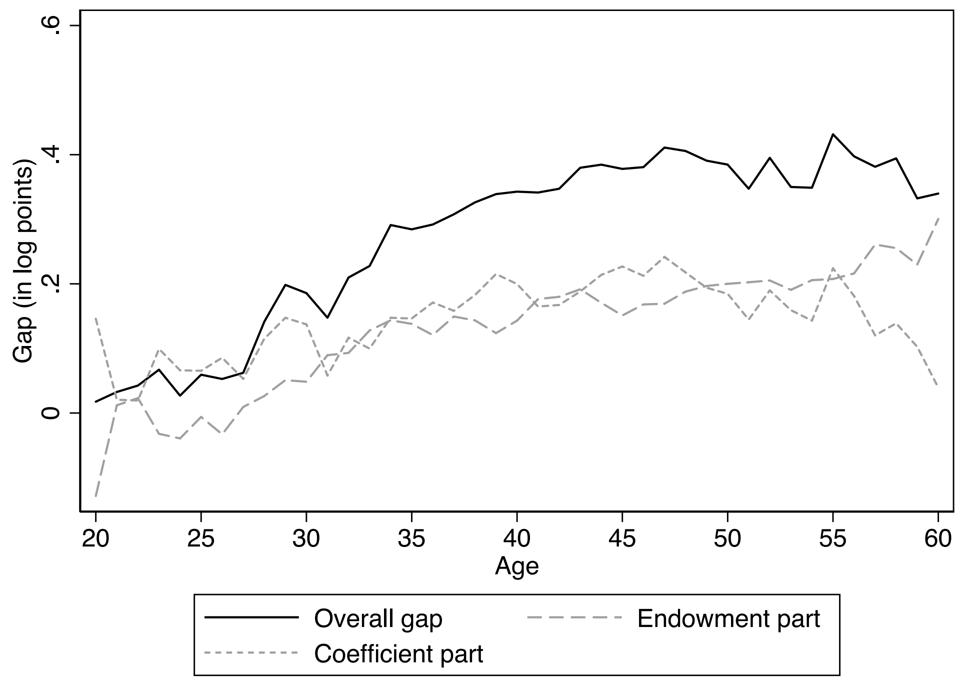
Overall, employed men have significantly higher hourly wages than employed women (see Table 2.3 in the Appendix). At the beginning of their work life at age 20, men earn on average 9.37 euros per hour while women's average wage is only 7.97 euros per hour. In line with results found by the Federal Statistical Office, the average hourly wages of men in our sample then almost triples over the work life to 26.13 euros per hour at age 60 (Statistisches Bundesamt, 2017). In contrast, women's hourly wages only increase to 17.48 euros, already showing significant gender differences in wage growth over the work life.

The solid line in Figure 2.1 shows the evolution of the gender gap in hourly wages in log points from age 20 to 60. Notably, the gender gap remains stable over the early years of work life. At age 25, men's hourly wages are only 0.059 log points higher than women's and the difference is still insignificant (see also Table 2.1). However, during the time of family formation and childcare, this gap drastically widens up to a highly significant difference of 0.378 log points at age 45.[22] Afterwards, the growth of the gender gap in hourly wages slows down and remains relatively stable with a peak at age 55. This finding is consistent for all cohorts (see Figure 2.11 in the Appendix). In line with our findings, previous studies also documented a widening of the gender wage gap over the life cycle (e.g., Anderson et al., 2002; Angelov et al., 2016; Tyrowicz et al., 2018).

The results of the Oaxaca Blinder decomposition are displayed by the grey lines in Figure 2.1 and also in Table 2.1. Visibly, the widening of the gender gap in hourly wages over the work life is driven by the increase in the endowment part, while the coefficient part of the gender gap shapes its overall trend. At younger ages, the different distribution of characteristics does not play a role yet. Therefore, at the beginning of work life all wage differences between men and women are due to different returns to labor market characteristics. Main differences in characteristics such as work experience or family background widen only later in life; after age 25, the high and significant coefficients for work experience in Table 2.1 show that the increase of the endowment

[22] A gender gap of 0.059 log points corresponds to a wage differential of $(e^{0.059} - 1) * 100 = 6.08\%$, while a gap of 0.378 log points corresponds to a wage differential of $(e^{0.378} - 1) * 100 = 45.94\%$.

Figure 2.1. Gender gap in hourly wages



Notes: Only employed individuals are considered. Cohorts 1940-1979, weighted sample. *Source:* Own calculations based on SOEP v35.

part is mainly driven by women's lower gain of work experience with increasing age. By the age of 60, men have accumulated on average 37.32 years of full-time and 1.09 years of part-time work experience, whereas women have accumulated on average only 19.65 years of full-time and 13.32 years of part-time work experience (see Table 2.3 in the Appendix). Our results show that these large differences in work experience are crucial to explaining the gender gap in hourly wages. By the end of the work life, differences in work experience account for 0.309 log points of the overall gender wage gap of 0.340 log points. Hence, around 90% of the overall gender gap of 40.5% in hourly wages can be explained by differences in work experience.

In contrast to the stable growth of the endowment part, the evolution of the coefficient part follows a slight inverse u-shape. At age 20, the gender gap cannot be explained through differences of characteristics across genders, but the coefficient part amounts to 0.126 log points.

This means that even if women and men had the same labor market characteristics, men's wages would be 0.126 log points (13.4%) higher than women's wages at this age. The coefficient part of the gender gap then peaks at 0.247 log points (28.0%) at age 45 and then declines again to a difference of 0.042 log points (4.3%) just before retirement.[23] In contrast to the endowment part, none of the variable groups have a constant significant influence on the overall gender gap, including the constant itself.[24] Therefore, not one individual effect dominates the coefficient part of the overall gender gap, but the coefficient part is instead a combination of many individual influences including those not controlled for in this regression model.

In summary, the gender gap in hourly wages is determined by two factors: first, women have in sum less favorable labor market characteristics compared to men, and second, even if they have the same characteristics, the labor market rewards women worse than men. The influence of differences in characteristics grows significantly with age, mainly through increasing differences in accumulated work experience across gender. Of the observed gender gap of 40.5% (0.340 log points) at age 60, different characteristics account for 87% (0.297 log points). This leads to an adjusted gender gap in hourly wages of 5.3%.

[23] Table 2.4 and Table 2.5 in the Appendix display the separate regression results for men and women which provide the basis for the difference in coefficients displayed in the Oaxaca Blinder regression.

[24] The constant of the coefficient part also includes the effects of gender differences in unobserved predictors such as different occupational choices or differences in employers (Jann, 2008).

Table 2.1. Oaxaca Blinder decomposition of hourly wage gender gap

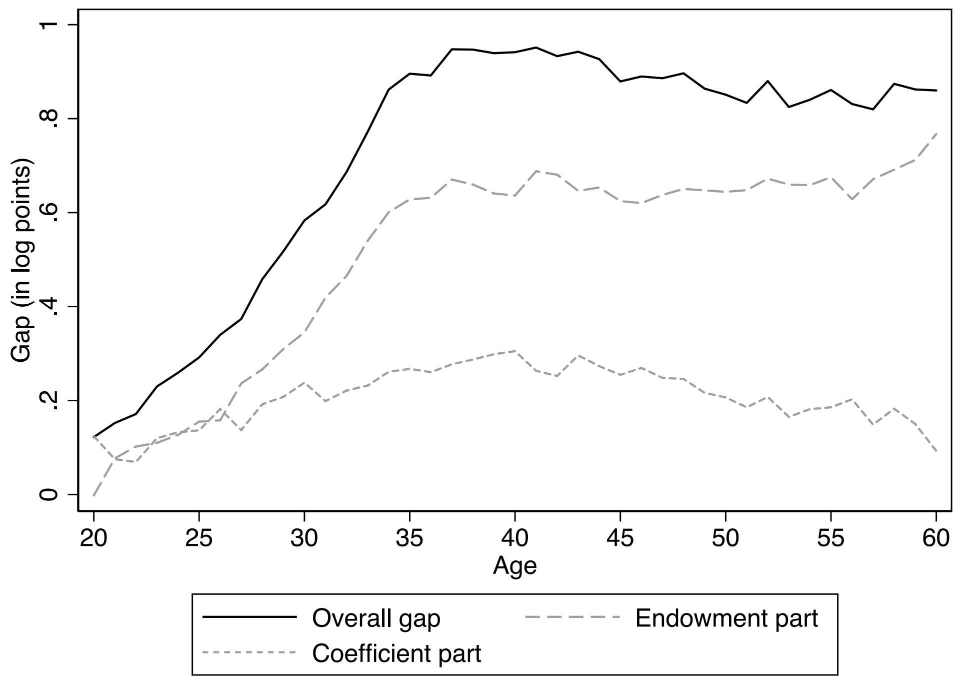
	(1) Age 20	(2) Age 25	(3) Age 30	(4) Age 35	(5) Age 40	(6) Age 45	(7) Age 50	(8) Age 55	(9) Age 60
Overall									
Men	1.963***	2.563***	2.771***	2.912***	2.980***	3.008***	3.019***	3.054***	3.003***
	(0.040)	(0.021)	(0.015)	(0.012)	(0.012)	(0.013)	(0.016)	(0.022)	(0.026)
Women	1.945***	2.503***	2.586***	2.628***	2.637***	2.630***	2.634***	2.622***	2.663***
	(0.033)	(0.024)	(0.019)	(0.017)	(0.016)	(0.017)	(0.017)	(0.020)	(0.031)
Difference	0.018	0.059	0.186***	0.284***	0.343***	0.378***	0.385***	0.432***	0.340***
	(0.052)	(0.031)	(0.024)	(0.021)	(0.020)	(0.021)	(0.024)	(0.030)	(0.041)
Endowment	-0.108**	-0.031	0.033*	0.107***	0.107***	0.131***	0.196***	0.200***	0.297***
	(0.040)	(0.018)	(0.015)	(0.018)	(0.020)	(0.022)	(0.026)	(0.028)	(0.043)
Coefficient	0.126*	0.091**	0.152***	0.177***	0.235***	0.247***	0.189***	0.231***	0.042
	(0.050)	(0.033)	(0.028)	(0.026)	(0.029)	(0.028)	(0.036)	(0.040)	(0.060)
Endowment									
Children	0.003	-0.000	0.001	-0.002	-0.004	-0.009*	-0.015*	-0.014	-0.013
	(0.005)	(0.003)	(0.001)	(0.002)	(0.003)	(0.004)	(0.007)	(0.011)	(0.013)
Married	0.001	-0.001	0.004	0.002	0.003	0.005*	0.000	-0.002	0.010
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.008)
Experience	-0.068*	0.024*	0.084***	0.167***	0.207***	0.224***	0.228***	0.264***	0.309***
	(0.030)	(0.011)	(0.013)	(0.019)	(0.022)	(0.028)	(0.026)	(0.032)	(0.049)
Part time	0.002	-0.041**	-0.027	-0.067***	-0.096***	-0.066***	-0.026	-0.056*	-0.030
	(0.008)	(0.013)	(0.015)	(0.019)	(0.019)	(0.019)	(0.019)	(0.024)	(0.024)
Education	-0.008	-0.019**	-0.009	0.021**	0.019**	0.022***	0.031***	0.030***	0.045***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)	(0.011)
Cohort	-0.001	-0.002	-0.000	0.001	0.003	0.001	0.002	0.003	-0.001
	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Sector	-0.037	0.009	-0.019*	-0.017**	-0.025***	-0.045***	-0.024***	-0.024*	-0.022*
	(0.029)	(0.011)	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)	(0.010)	(0.011)
Coefficient									
Children	0.003	0.030	0.095***	0.063	0.002	0.007	-0.075	-0.048	0.080
	(0.005)	(0.020)	(0.025)	(0.034)	(0.038)	(0.046)	(0.044)	(0.053)	(0.088)
Married	-0.006	0.021	0.041	0.052	0.090*	-0.008	0.100*	0.047	0.020
	(0.010)	(0.027)	(0.031)	(0.034)	(0.038)	(0.041)	(0.045)	(0.056)	(0.074)
Experience	0.243***	0.207	0.067	-0.094	-0.058	0.005	-0.150	0.196	-0.973
	(0.063)	(0.129)	(0.128)	(0.127)	(0.112)	(0.170)	(0.226)	(0.280)	(0.995)
Part time	0.013	0.031	0.008	-0.021	0.032	0.032	0.030	0.145***	0.036
	(0.027)	(0.037)	(0.023)	(0.019)	(0.021)	(0.021)	(0.025)	(0.036)	(0.054)
Education	0.329	-0.144	-0.210	-0.105	-0.564*	0.183	0.568	0.131	0.722
	(0.195)	(0.174)	(0.141)	(0.230)	(0.256)	(0.237)	(0.295)	(0.840)	(0.648)
Cohort	0.083	0.023	0.002	-0.007	0.091	-0.019	0.030	-0.030	0.002
	(0.044)	(0.085)	(0.036)	(0.125)	(0.049)	(0.034)	(0.041)	(0.038)	(0.040)
Sector	0.222	-0.445**	-0.436**	-0.053	-0.066	-0.139	-0.037	-0.085	-0.153
	(0.193)	(0.139)	(0.160)	(0.116)	(0.147)	(0.142)	(0.124)	(0.188)	(0.192)
Constant	-0.762**	0.368	0.587*	0.343	0.708*	0.186	-0.276	-0.125	0.308
	(0.276)	(0.283)	(0.255)	(0.308)	(0.322)	(0.317)	(0.383)	(0.887)	-1.090
N	765	1782	3053	4323	5356	5592	4304	2866	1758

Notes: Standard errors in parentheses; The stars refer to the following significance level: $*p < 0.05, **p < 0.01, ***p < 0.001$. The different drivers are summarized as followed: "Children": Number of children; "Married": Dummy variable on marital status, "Experience": Total years of working full time, part time or being inactive (also squared); "Part time": Dummy variable indicating full time or part time work; "Education": Dummy variables indicating highest level of educational attainment, "Sector": Occupational sector; "Cohort": Cohort dummies. Cohorts 1940-1979, weighted sample. *Source:* Own calculations based on SOEP v35.

2.2.3 Annual earnings

In addition to earning less per hour, women also work on average fewer hours than men do. Therefore, the gender gap in annual earnings might be even wider than the gap in hourly wages due to gender differences in the intensive margin of work.

Figure 2.2. Gender gap in annual earnings



Notes: Only employed individuals are considered. Does not include values of zero annual earnings. Cohorts 1940-1979, weighted sample. *Source:* Own calculations based on SOEP v35.

Figure 2.2 shows the overall gender gap in annual earnings, the part of the gap due to different characteristic across gender (endowment part) and the part of the gender gap due to differences in coefficients (coefficient part). Visibly, the gender gap in annual earnings is significantly higher than the gender gap in hourly wages. At the peak of the gap at age 40 (0.829 log points corresponding to 129.1%), men's average annual earnings are more than twice as high than women's. Similar to the gender gap in hourly wages, the gender gap in annual earnings increases rapidly until age 35 and remains on a constant high level during the years of child rearing. Afterwards, it only declines slightly until retirement. This finding is in line with earlier studies for the U.S. providing evidence for a similar course of the cross-sectional gender gap in annual earnings over the work life (Goldin, 2014; Juhn and McCue, 2017).

When decomposing the overall gender gap in annual earnings, we find that the larger gap (in comparison to the gap in hourly wages) is driven by the significantly higher endowment part. While the gender gap due to differences in coefficients is only slightly higher than in the model for hourly wages, the endowment part has more than tripled.[25] This result underlines the importance of differences in the intensive labor margin across gender.

Table 2.2 shows that the endowment part of the gender gap in annual earnings is also driven by the lesser work experience women accumulate over their life cycle. Moreover, the lower number of hours worked by women per year at all ages influences the gender gap to an even greater extent. These findings are in line with previous studies (e.g., Bertrand et al., 2010; Gallen et al., 2019).

At age 35, women's annual earnings are on average 0.327 log points lower than men's due to their lower number of work hours.[26] In addition, women's earnings are on average 0.203 log points lower than men's due to the lesser work experience they have accumulated up to this age. This means that at this point around half of the overall gap can be explained by the distribution of working hours and around a quarter can be explained by the different distribution of work experience. The effect of work experience steadily increases over the life cycle and peaks at age 60 with 0.351 log points. In contrast, differences in the level of education or family background play a smaller role.

The coefficient part of the gender gap in annual earnings is positive throughout the life cycle. This means that, besides less favorable characteristics, women also face less beneficial coefficients in their wage regression (see Table 2.2, and Tables 2.6 and 2.7 in the Appendix). This is especially pronounced between ages 30 and 45. There are two potential explanations: First, employers could

[25]Please note that since this subsection focuses on the intensive margin of work, we now include the total hours worked per year for this model in contrast to the binary variable (part-time/full-time) used when we were analyzing the gender gap in hourly wages. Consequently, this leads to an even more significant endowment part for the analysis of annual earnings as the total number of work hours is a key driver in the earnings difference across gender.

[26]It is crucial to note that our model does not control for endogenous choice. Hence, we do not differentiate whether women choose to work fewer hours or if they have trouble finding adequate employment. See, for example, Harnisch et al. (2018) and Beckmannshagen and Schroder (2022) for studies on working hours mismatches in Germany.

fear a higher risk of work absence by women due to pregnancy and child rearing, and therefore already include the higher risk of absence in the paid wages of women (Correll et al., 2007). Second, women might opt for less financially rewarding positions in return for higher work flexibility after having children (Goldin, 2014). However, interestingly, for individuals aged 60 the coefficient part of the gender gap is very small in magnitude and no longer statistically significant, indicating that at this point the gender gap in annual earnings is almost entirely driven by differences in endowments.

Table 2.2. Oaxaca Blinder decomposition of the annual earnings gender gap

	(1) Age 20	(2) Age 25	(3) Age 30	(4) Age 35	(5) Age 40	(6) Age 45	(7) Age 50	(8) Age 55	(9) Age 60
Overall									
Men	9.462***	10.155***	10.460***	10.623***	10.695***	10.713***	10.717***	10.693***	10.542***
	(0.041)	(0.024)	(0.017)	(0.012)	(0.013)	(0.015)	(0.017)	(0.022)	(0.030)
Women	9.424***	9.950***	9.923***	9.854***	9.867***	9.915***	9.904***	9.868***	9.775***
	(0.039)	(0.026)	(0.026)	(0.024)	(0.021)	(0.021)	(0.024)	(0.028)	(0.040)
Difference	0.038	0.205***	0.537***	0.769***	0.829***	0.797***	0.812***	0.825***	0.766***
	(0.057)	(0.036)	(0.031)	(0.027)	(0.024)	(0.025)	(0.030)	(0.036)	(0.050)
Endowment	-0.081	0.102***	0.318***	0.538***	0.555***	0.529***	0.609***	0.657***	0.747***
	(0.046)	(0.026)	(0.028)	(0.025)	(0.025)	(0.028)	(0.034)	(0.036)	(0.050)
Coefficient	0.119*	0.103**	0.219***	0.231***	0.274***	0.269***	0.203***	0.168***	0.019
	(0.046)	(0.036)	(0.036)	(0.028)	(0.031)	(0.033)	(0.042)	(0.042)	(0.053)
Endowment									
Children	-0.000	0.001	0.001	-0.001	-0.003	-0.010*	-0.018*	-0.020	-0.012
	(0.005)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)	(0.007)	(0.011)	(0.012)
Married	0.001	0.001	0.005	0.001	0.001	0.001	-0.002	-0.004	0.003
	(0.004)	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.008)
Experience	-0.058	0.033*	0.129***	0.203***	0.244***	0.273***	0.306***	0.334***	0.351***
	(0.030)	(0.014)	(0.015)	(0.018)	(0.022)	(0.026)	(0.028)	(0.033)	(0.040)
Hours worked	0.023	0.082***	0.214***	0.327***	0.313***	0.282***	0.310***	0.331***	0.371***
	(0.018)	(0.015)	(0.024)	(0.022)	(0.021)	(0.023)	(0.025)	(0.029)	(0.034)
Education	-0.003	-0.021**	-0.011	0.023**	0.020**	0.023***	0.032***	0.033***	0.048***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)	(0.012)
Cohort	-0.001	-0.002	0.000	0.001	0.002	0.000	0.002	0.003	-0.002
	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Sector	-0.043	0.008	-0.019*	-0.016*	-0.021**	-0.040***	-0.021**	-0.020	-0.012
	(0.026)	(0.011)	(0.009)	(0.006)	(0.007)	(0.008)	(0.008)	(0.010)	(0.011)
Coefficient									
Children	0.000	0.037*	0.155***	0.069	-0.005	0.025	-0.093	-0.074	0.069
	(0.004)	(0.015)	(0.028)	(0.037)	(0.040)	(0.049)	(0.048)	(0.057)	(0.081)
Married	-0.004	0.033	0.040	0.049	0.092*	-0.012	0.113*	0.075	0.060
	(0.010)	(0.025)	(0.033)	(0.036)	(0.040)	(0.048)	(0.048)	(0.055)	(0.074)
Experience	0.224***	0.146	0.045	-0.139	-0.159	-0.150	-0.169	0.378	-0.964
	(0.063)	(0.139)	(0.146)	(0.156)	(0.121)	(0.177)	(0.269)	(0.423)	(0.966)
Hours worked	-0.348	-0.260	-0.625***	-0.811***	-0.801***	-0.783***	-0.891***	-1.152***	-0.621***
	(0.222)	(0.184)	(0.160)	(0.105)	(0.100)	(0.143)	(0.144)	(0.145)	(0.151)
Education	0.356*	-0.082	-0.240	-0.165	-0.595*	0.229	0.720*	0.932	0.809
	(0.173)	(0.182)	(0.151)	(0.245)	(0.263)	(0.310)	(0.332)	(0.700)	(0.699)
Cohort	0.067	0.002	-0.038	0.028	0.134**	-0.005	0.039	-0.030	0.003
	(0.044)	(0.051)	(0.039)	(0.124)	(0.046)	(0.036)	(0.044)	(0.040)	(0.040)
Sector	0.166	-0.295*	-0.396*	-0.126	-0.055	-0.091	-0.008	-0.120	-0.098
	(0.180)	(0.144)	(0.166)	(0.130)	(0.159)	(0.150)	(0.142)	(0.213)	(0.217)
Constant	-0.344	0.521	1.278***	1.326***	1.663***	1.056*	0.492	0.159	0.759
	(0.330)	(0.304)	(0.310)	(0.358)	(0.343)	(0.413)	(0.465)	(0.834)	-1.112
N	765	1782	3053	4323	5356	5592	4304	2866	1758

Notes: Standard errors in parentheses; The stars refer to the following significance level: $*p < 0.05, **p < 0.01, ***p < 0.001$. The different drivers are summarized as followed: “Children”: Number of children; “Married”: Dummy variable on marital status, “Experience”: Total years of working full time, part time or being inactive (also squared); “Hours worked”: Hours worked per year; “Education”: Dummy variables indicating highest level of educational attainment, “Sector": Occupational sector; “Cohort”: Cohort dummies. Cohorts 1940-1979, weighted sample. *Source:* Own calculations based on SOEP v35.

2.3 Microsimulation and lifetime analysis

The previous section gave an analysis of the cross-sectional gender gaps in hourly wages and annual earnings, their development with increasing age and drivers. In this section, we investigate how gender earnings differentials might accumulate or balance out over the complete work life by looking at lifetime earnings. This allows us to shed light on the biographical dimension of the gender earnings gap.

2.3.1 Data and methodology

We continue to use the SOEP as it offers panel data containing not only detailed labor market but also family background information, which administrative data cannot offer. However, the SOEP suffers from panel attrition. Only around 10% of the participants have been observed for at least 20 years or more, with an average participation period of 9.36 years see Figure 2.12 in the Appendix). To investigate lifetime earnings for a larger sample, we implement a dynamic microsimulation approach to fill in the missing data of non-observed years during an individual's work life. This approach yields complete earnings data for the observation period which we can combine with the rich set of socioeconomic characteristics and family information in the SOEP.

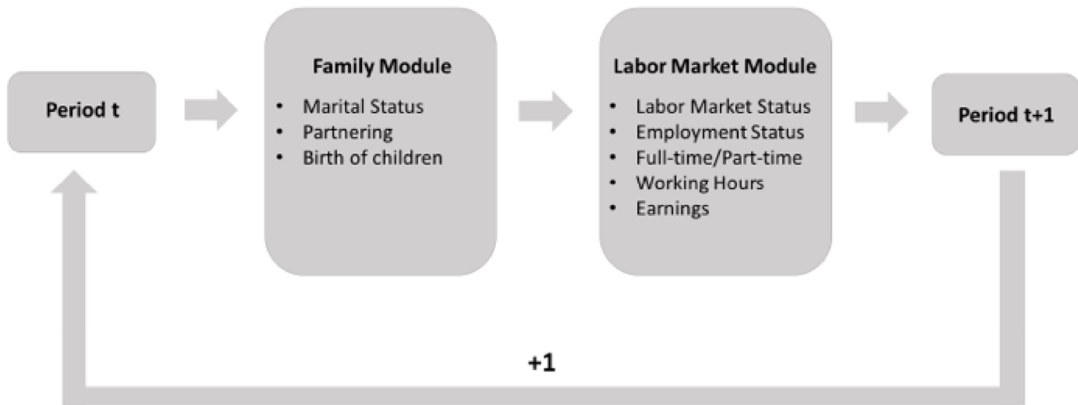
To implement our dynamic microsimulation model successfully, we need to add the following restrictions to our cross-sectional sample: First, our lifetime earnings investigation focuses on birth cohorts 1964 to 1972 only. This approach gives us the opportunity to observe the cohorts starting at age 20 until at least age 45. This restriction is important as we know in the German context that only lifetime earnings up to age 45 and older are sufficient proxies for complete lifetime earnings up to age 60 (Bönke et al., 2015). Second, we exclude individuals who were only observed prior to turning 30 since labor market patterns of individuals in their twenties are very unstable and could yield a life-cycle bias (see, e.g., Haider and Solon, 2006; Brenner, 2010; Bönke et al., 2015). Further, the probability of observing the highest educational attainment accurately increases significantly with age 30 and older (see Autorengruppe Bildungsberichterstattung, 2018) and observing the true educational attainment is crucial as education levels and earnings patterns over the work life are highly correlated (see, e.g., Bhuller et al., 2011; Bönke et al., 2015; Brunello et al., 2017). Third, we also exclude individuals without at least two consecutive observation years in the SOEP. Otherwise, no panel information is available and a distinction between individual short- and long-term labor shocks would not be possible. After eliminating those observations, we are left with a sample of 3,315 women and 3,212 men across birth cohorts 1964 to 1972 (see Table 2.8 in the Appendix) for the dynamic microsimulation.

2.3.1.1 Dynamic microsimulation model

We apply a dynamic microsimulation model to fill in missing information in non-observed years based on the individual's employment biography and socioeconomic characteristics. The general idea and structure of our microsimulation approach follows the approach proposed by Levell and Shaw (2016). To exploit our data to its fullest extent, we use both forward- and backward-looking simulations. The simulation starts either at an individual's first or last observed year in the data. As shown in Figure 2.3, we impute the missing variables in time $t+1$ or $t-1$ by running the regressions for our dynamic microsimulation in two consecutive steps: First, missing observations of marital status, fertility (i.e. number of children) and partners are simulated in the Family Module (Module 1). Second, the obtained information from Module 1 is used in addition to other provided data to simulate individuals' labor market information in the Labor Market Module (Module 2). Completing both modules yields the successful imputation of all relevant information in time $t+1$ or $t-1$. Afterwards, the process moves forward to the simulation of the next years, i.e. $t+2$ or $t-2$, $t+3$ or $t-3$, and so on. The simulation ends after reaching 1984 in the backward looking and 2017 in the forward-looking process. We obtain a full dataset without any missing earnings or family information between 1984 and 2017.

In addition, investigating complete lifetime patterns for our sample requires us to extend our simulation for 15 additional years until 2032, when the youngest birth cohort 1972 turns 60. The prediction of employment biographies after 2017 is based on regression parameters of observed

Figure 2.3. Dynamic microsimulation model



Source: Own diagram.

individuals from older cohorts, while we assume that general labor market characteristics (e.g., unemployment rate) remain stable after 2017. We also account for differences in trends using cohort and age fixed effects in our regressions. Nevertheless, this prediction comes naturally with a certain level of uncertainty due to the assumption that trends remain stable - an assumption that neglects, for example, labor market effects related to the COVID-19 pandemic. The simulation ends when all missing information between 1984 and 2032 is simulated.

Within each module, the simulation of variables is based on estimating transition probabilities between two years, e.g., if marital status changes from year t to $t+1$. The estimation of a change of a variable j between two periods is then implemented by using a random process (see, e.g., Neufeld, 2000; Plümper and Troeger, 2007; Zucchelli et al., 2012): For each individual observation i we simulate the transition probability from time t to $t+1$ or $t-1$ and then draw a random number N_{it} from a uniform $[0, 1]$ distribution. If the calculated transition probability P_{it} is larger than the drawn random number N_{it} $(P_{it} > N_{it})$, a transition occurs. In contrast, no transition takes place if $P_{it} \leq N_{it}$. Therefore, high transition likelihoods do not always induce actual transitions and even low transition probabilities may still lead to transitions. This approach helps to account for the uncertainty that comes with a simulation. Additionally, we use a Monte Carlo simulation approach to test the robustness of our results (see Figures 2.14 and 2.15 in the Appendix). The results of the Monte Carlo simulation confirm the reliability and robustness of our simulation outcomes.

Next, we will give brief summaries about both simulation modules. Detailed information on the regression models used in each simulation step can be found in Table 2.9 in the Appendix.

2.3.1.2 Module 1: Family module

Empirical evidence shows that family background strongly influences women's labor market behavior (e.g., Kleven and Landais, 2017). Therefore, we need information on individual's family background before simulating earnings for non-observed years. All individuals in our sample completed entry questionnaires including questions on marital status and, if applicable, birth years of children before entering the survey; this allows us to reconstruct full family histories. Consequently, missing data occurs exclusively after individuals left the survey. This eliminates the necessity of the backward looking simulation component in this module. In addition, we also observe most women at older ages so only around 20% of child information must be simulated.

The Family Module then consists of two steps: predicting marital status, including a partnering module when necessary, and predicting births of children for individuals with missing information. First, we run logistic regressions separately by gender s (Female or Male) and marital status m (Single or Partnered) in year t to predict the individual transition probability $p^{married}$ to change the marital status from year t to the missing year $t+1$:

$$p^{married}_{m,s,t+1} = \beta_0 + \beta_1 X_{m,s,t} + \epsilon_{m,s,t}, \quad E(\epsilon_{m,s,t}) = 0, m \in \{S, P\}, s \in \{F, M\}, t \in [1984, 2017] \quad (3)$$

The regression consists of a set of explanatory variables X_t including socioeconomic characteristics (e.g., education, age, migration background) and labor market behavior (e.g., employment status). In addition, we control for the number of years that an individual's marital status has remained unchanged until year t. Table 2.9 in the Appendix gives a detailed overview about all covariates included in each regression-based simulation step.

Recall that if $P_{it} \leq N_{it}$, the marital status stays the same and if $P_{it} > N_{it}$, the marital status changes. Therefore, this simulation step has four possible outcomes: First, a person who is single in year t can remain single in $t+1$. Second, married individuals can stay married. Here we assume that their partners remain the same. Third, married individuals in period t can get divorced and become single in $t+1$.[27] And fourth, singles in year t can get married in $t+1$. In this last case, we run a Partner Module to assign a partner.[28] This allows us to account for partners' characteristics when simulating family and labor market decisions. Using Mahalanobis distance matching (see Mahalanobis, 1936) we five "best" partners based on age, education and region for each observation. We then randomly assign one of the five potential partners to the individual. Our matching procedure is not unique, i.e., one individual can serve multiple times as a "donor" for partner characteristics. In this way, we ensure a sufficient pool of potential partners.

Next, we simulate whether a woman will give birth to a child in the next non-observed period $t+1$ by marital status m:

$$p^{birth}_{m,t+1} = \beta_0 + \beta_1 X_{m,t} + \epsilon_{m,t}, \quad E(\epsilon_{m,t}) = 0, m \in \{S, P\}, t \in [1984, 2017]. \tag{4}$$

Again, X_t represents a set of explanatory variables including socioeconomic characteristics like information on existing children and labor market information. The simulation is similar to the approach described in the simulation of the marital status. Afterwards, the information on an individual's number of children is updated accordingly. In contrast to our marriage simulation, births are only simulated for women. Children are then attached to men depending on women's family background.

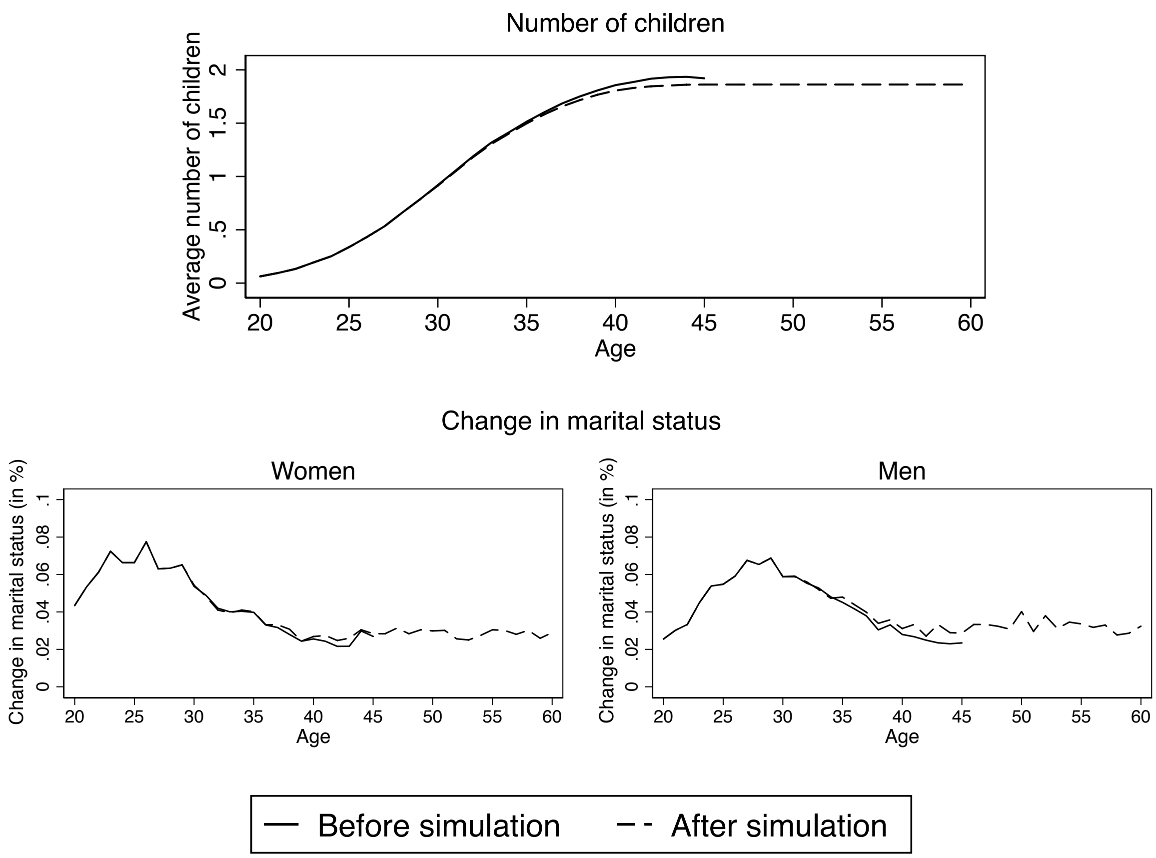
Since we estimate transition likelihoods for $t+1$ by using information available in period t, the likelihood of a change of the marital status or a childbirth in $t+1$ do not influence the transition probability of one another. Therefore, the order in which we implement fertility and marital

[27] In this case we assume that the children stay with the mother. Empirical evidence by the Statistisches Bundesamt (2018) supports this assumption: The share of single fathers in the period since 1997 is only 10 to 13%.

[28] For a few married individuals in our data, we cannot observe partner information since the partner did not participate in the survey, e.g., because they refused. In those cases, we also run the Partner Module as a preparation step before starting the Family Module.

transitions is irrelevant and does not alter our results.

Figure 2.4. Family information before and after simulation



Notes: Panel A shows the average number of children of women by age before and after the simulation. Panel B demonstrates the share of individuals in our sample changing their marital status before and after the simulation. *Source:* Own calculations based on SOEP v35.

Completing the Family Module for years 1984 to 2032 results in a sample with full information on family characteristics. Figure 2.4 shows that our simulated data (dashed line) replicates the initial distributions before the simulation (solid line) very accurately. In Panel A, the women's average number of children increases strongly until age 35. Then, the growth rate slows down and comes to a natural stop between ages 40 and 45 due to biological reasons. Panel B displays the percentage change in marital status by age. Obviously, both men and women follow the same trend over the life cycle. Most changes in marital status happen in the beginning of life.

2.3.1.3 Module 2: Labor market module

The Labor Market Module generates complete information on an individual's employment biography through five stages: labor market participation, employment status, type of work arrangement (full-time or part-time), annual working hours and annual earnings. In this module, we use both forward and backward simulation as the introductory survey questionnaires do not allow us to construct sufficient work histories. Our model description will focus on the forward-looking simulation component. However, the backward-looking part of the simulation follows the same methodology.

In general, the logic and structure of this module is very similar to our approach in the Family Module. We start with the estimation of $p^{lmp}_{(m,t+1)}$, the probability for an individual of marital status m to change the labor market participation lmp from year t to year $t+1$. The labor market participation dummy variable is equal to 1 if individuals are unemployed or employed and equal to 0 if they are not attached to the labor market (e.g., due to parental or sick leave). We run the estimation separately by gender s and marital status m:

$$p^{lmp}_{s,m,t+1} = \beta_0 + \beta_1 p^{lmp}_{s,m,t} + \beta_2 p^{lmp}_{s,m,t-1} + \beta_3 X_{s,m,t} + \epsilon_{s,m,t},$$

$$E(\epsilon_{s,m,t}) = 0,\ s \in \{F, M\},\ m \in \{S, P\},\ t \in [1984, 2017]. \tag{5}$$

$X_{(s,m,t)}$ is again a vector of control variables with socioeconomic characteristics like marital status, partner's earnings and their own labor market information. Further, we include lagged dependent variables to account for path dependencies over the work life while still modelling a dynamic data generating process.[29] If individuals are recorded as not participating in year $t+1$, we directly record their earnings as zero for $t+1$ and do not include them in the subsequent steps. For individuals who are active in the labor market, we next run a regression to estimate the probability to change their employment status $p^{emp}_{(s,m,e,t+1)}$ (employed/unemployed) from year t to

[29] For this estimation strategy, we are only able to include individuals that have at least two observation years in the SOEP. Including additional lags would result in a reduced sample size since it would impose stricter sample restrictions (surveyed for at least three years in the SOEP).

year $t + 1$. The following model is run separately by gender s, marital status m and employment status e:

$$p^{emp}_{s,m,e,t+1} = \beta_0 + \beta_1 p^{emp}_{s,m,e,t} + \beta_2 p^{emp}_{s,m,e,t-1} + \beta_3 X_{s,m,e,t} + \epsilon_{s,m,e,t},$$

$$E(\epsilon_{s,m,e,t}) = 0,\ s \in \{F, M\},\ m \in \{S, P\},\ e \in \{0, 1\},\ t \in [1984, 2017]. \tag{6}$$

Once more, the regression contains a set of explanatory variables $X_{(s,m,e,t)}$ including information on family and the socioeconomic background. Also included in the control vector is the work history of individuals. To this end, we measure work experience by years of full-time work, part-time work and years without any work until year t to account for the different levels of labor market experience.

Individuals recorded as unemployed in year $t + 1$ after this first regression step receive zero earnings in $t + 1$ and are excluded from further estimations. For all employed individuals, the dynamic microsimulation moves forward with a logistic regression simulating if individuals worked full- or part-time in year $t + 1$. In the next step, we estimate the probability of changing full-time or part-time arrangements from year t to year $t + 1$:

$$p^{wt}_{(s,m,t+1)} = \beta_0 + \beta_1 p^{wt}_{s,m,t} + \beta_2 p^{wt}_{s,m,t-1} + \beta_3 X_{s,m,t} + \epsilon_{s,m,t},$$

$$E(\epsilon_{s,m,t}) = 0,\ s \in \{F, M\},\ m \in \{S, P\},\ t \in [1984, 2017]. \tag{7}$$

Again, $X_{(s,m,t)}$ includes the usual control variables in addition to the labor market history. We can now move on to estimate the precise number of annual working hours in $t + 1$ separately for part-time and full-time workers. We use an OLS regression model following the same logic as the earnings regression model as introduced in Equation (2.8).[30]

Finally, we use an earnings regression to estimate the annual earnings $y_{(s,m,t+1)}$ by gender s

[30]Again, see Table 2.9 in the Appendix for more detailed information.

and marital status m:

$$y_{(s,m,t+1)} = \beta_0 + \beta_1 y_{s,m,t} + \beta_2 y_{s,m,t-1} + \beta_3 X_{s,m,t} + \epsilon_{s,m,t},$$

$$E(\epsilon_{s,m,t}) = 0,\ s \in \{F, M\},\ m \in \{S, P\},\ t \in [1984, 2017]. \tag{8}$$

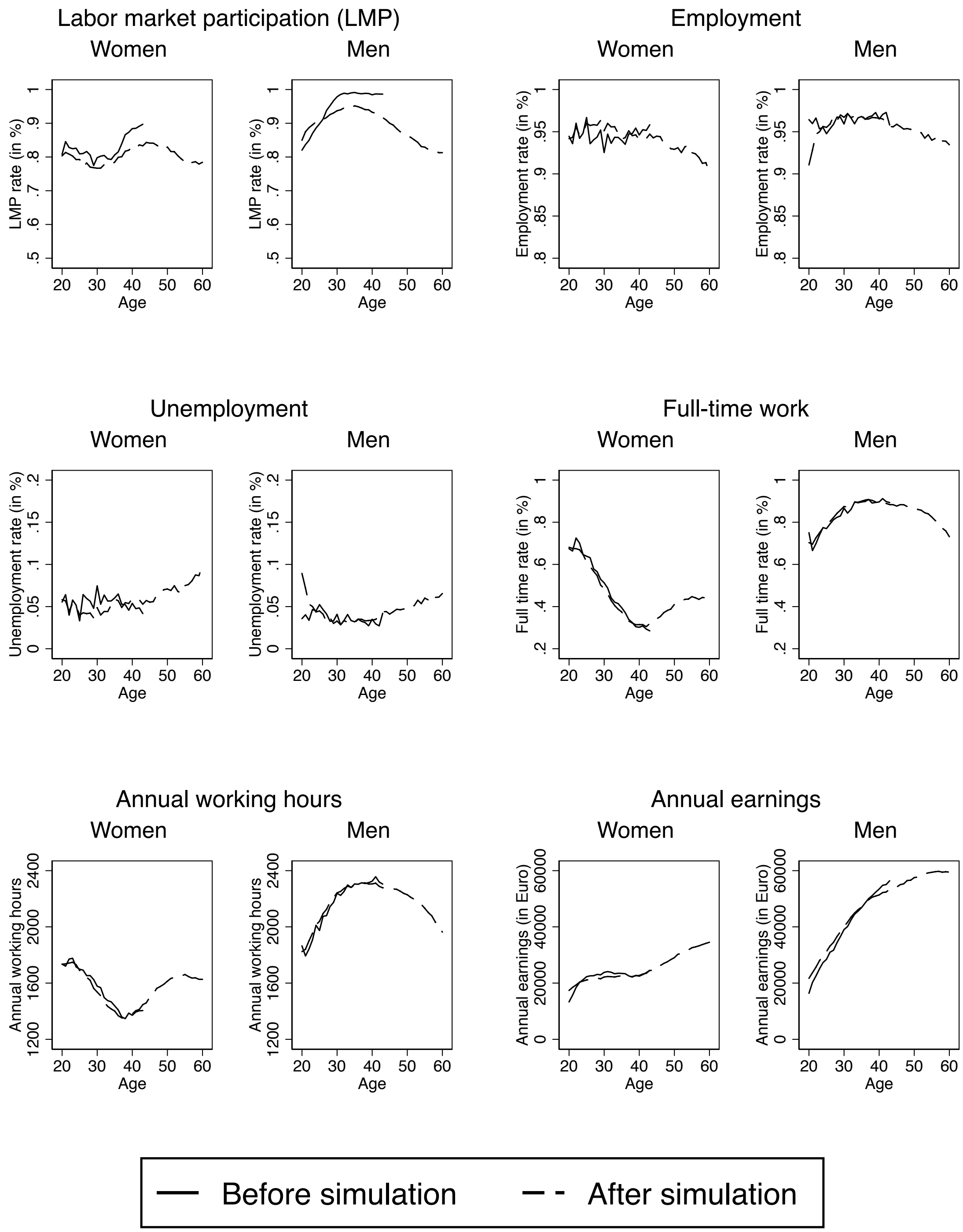
$X_{(s,m,t)}$ now includes information about the work history in years of full-time work, part-time work or unemployment, working hours in t and, if applicable, partner and child information. All earnings are price-adjusted and presented in 2015 euros. The simulation then moves to the next year, e.g., $t+2$ or $t-2$. After completing all five steps of the Labor Market Module between 1984 and 2017, all individuals have complete employment and earnings information for previously unobserved years. Afterwards, we continue the simulation until 2032 to obtain complete biographical data up to age 60.

Figure 2.5 shows that our simulated data (dashed line) replicates the original SOEP data (solid line) well, particularly for Panel D (Full-time work), Panel E (Working hours) and Panel F (Earnings). Panel A (Labor Market Participation), Panel B (Employment) and Panel C (Unemployment) show small deviations. Most of these differences occur in the beginning of the work life. These differences do not necessarily diminish the quality of our microsimulation for the following two reasons: First, our sample restriction to individuals observed at least once at age 30 or older leads to fewer observations in individuals' early twenties. As a result, our SOEP sample before the simulation is not very reliable for this age range due to a small sample size, and therefore comparisons may be misleading. Second, as depicted in Figure 2.5, earnings are on average relatively low at the beginning of an individuals work life and they increase over their careers. Consequently, earnings at young age only account for a small share of lifetime earnings.

After the completion of both modules of our dynamic microsimulation model, we obtain all relevant labor market and household information for birth cohorts 1964 to 1972 from age 20 to 60 to proceed with our lifetime analysis.[31]

[31]Our sample after the microsimulation is significantly different from our original SOEP sample. Therefore, we cannot use the longitudinal weights initially provided by the SOEP. To maintain representativeness, we therefore use census

Figure 2.5. Labor market information before and after simulation



Notes: Only employed individuals are considered. Does not include values of zero annual earnings. Cohorts 1940-1979, weighted sample. *Source:* Own calculations based on SOEP v35.

data (Mikrozensus) to reweight our sample with regard to cohort, age, family and labor market information. The Mikrozensus is considered highly representative for Germany, covering about 1% of the entire German population through mandatory participation.

Overall, the simulated data mirrors the data patterns before simulation and our simulation results are robust. Additional robustness checks based on a Monte Carlo simulation approach and the simulation of pseudo-missings can be found in the Appendix.

2.3.2 Lifetime analysis

We know that women face lower hourly wages and annual earnings than men, but the cross-sectional analysis only shows a snapshot of an individual's employment biography and does not reveal how the gender gap adds up or balances out over the life cycle. For a better understanding of when and how in life the gender gap develops, we investigate differences in accumulated earnings over the life cycle for birth cohorts 1964 to 1972 using their complete biography data from age 20 to 60 obtained from our microsimulation. To analyze the accumulation of earnings over the work life, we follow Bönke et al. (2015) and use the "up-to-age-X" (UAX) concept. UAX earnings refer to accumulated gross annual earnings in 2015 prices up to a certain age X. In line with the study by Bönke et al. (2015), we define lifetime earnings as UA60 earnings.

2.3.2.1 Gender gap in lifetime earnings

To analyze the gender gap in lifetime earnings, we now focus on nonlogarithmic incomes rather than logarithmic incomes as used in the Oaxaca Blinder decomposition in Section 2.2.[32] Using logarithmic incomes would lead to the exclusion of zero earnings and, thus, periods of inactivity.[33] Since especially women accumulate periods of inactivity over life through motherhood and child rearing, those parts of their employment biographies without any earnings play a crucial role for the gender lifetime earnings gap and need to be included in this analysis.

The gender gap G in the labor market outcome variable L (here: hourly wages, annual earn-

[32] As stated in Section 2.2, the Oaxaca Blinder decomposition is based on an OLS regression model using log hourly wage and log annual earnings.

[33] The inverse hyperbolic sign (ihs) transformation represents an alternative concept. In contrast to the logarithmic transformation, it is also defined for negative and zero values (see, e.g., Burbidge et al., 1988; Pence, 2006). Due to these advantages, it is primarily used in the literature on wealth distributions (e.g., Pence, 2006; Grabka et al., 2015; Sierminska et al., 2018). However, we refrain from using this transformation as it is not easily interpretable and not a very commonly used concept in the literature on gender earnings gaps.

ings, UAX earnings) in percent for men m and women f at age x is now defined as:

$$G_x = [(\overline{L}_{m,x} - \overline{L}_{f,x})/\overline{L}_{m,x}] \times 100 \, . \tag{9}$$

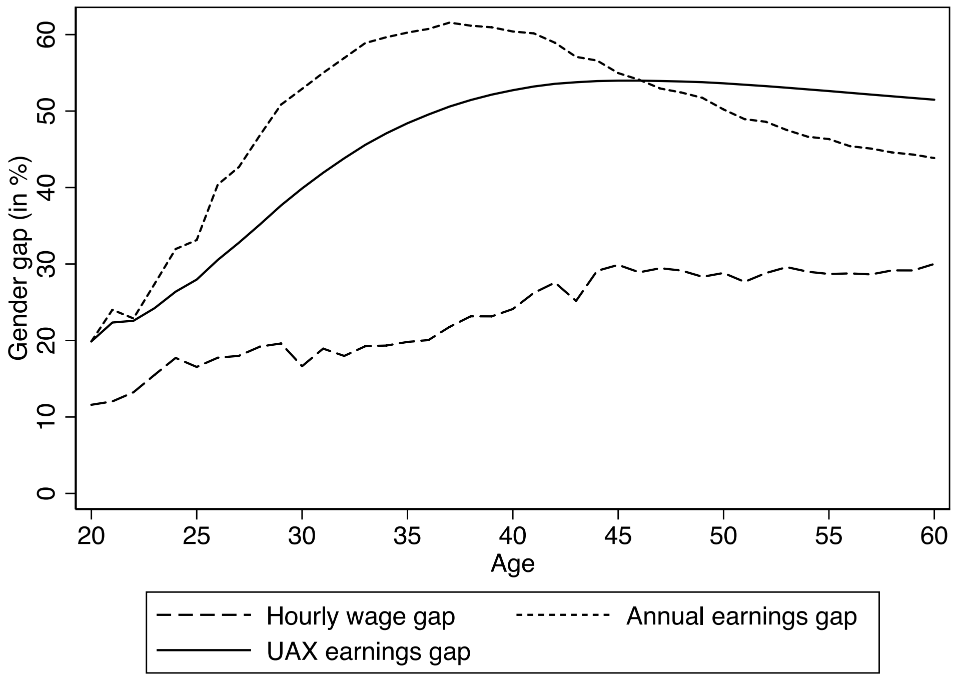
Based on our new sample obtained from the microsimulation, Figure 2.6 shows the gender gaps in hourly wages, annual earnings and UAX earnings for ages 20 to 60 for birth cohorts 1964 through 1972. As expected, despite the same trend, we see several differences when we compare the gender gaps in hourly wages and annual earnings using this microsimulation sample to our results based on the cross-sectional sample discussed in Section 2.2.

At early ages, the gender gap in hourly wages rather low but then increases steadily until retirement. However, we can observe differences in levels which are driven by the more confined cohort restriction in our microsimulation sample and the varying definition of the gender gap (logarithmic vs. non-logarithmic income). Comparing the gender gaps in annual earnings reveals more pronounced differences between the cross-sectional and lifetime approach. First, the inversely U-shaped gender gap in annual earnings in Figure 2.6 is significantly larger than the gender gap shown in Figure 2.2. This difference is largely driven by the inclusion of inactive labor periods with zero earnings in this lifetime analysis, while we excluded those in our cross-sectional analysis in Section 2.2.[34] Including periods with zero earnings leads to a decline in women's average earnings, and thus to an increase in the gender gap. Naturally, this difference is especially pronounced in the years of family formation when women, on average, have longer spells of labor market inactivity due to child rearing. Second, in contrast to the gender gap estimated using the cross-sectional sample, Figure 2.6 shows a pronounced decline of the gender gap in annual earnings between ages 40 and 60. Again, this difference is driven by the different composition of our two samples. While the cross-sectional sample includes all birth cohorts 1940 to 1979, the lifetime sample is restricted to younger cohorts. Due to the higher labor market participation rates for women of younger cohorts, the gender gap in annual earnings declines again before retirement once we re-

[34] See Figure 2.16 for a direct comparison of the gender gap in annual earnings when including or excluding individuals with zero earnings.

strict our sample to younger cohorts, because more women reenter the labor market after times of inactivity during family formation.

Figure 2.6. Gender gaps in wages, annual earnings and UAX earnings over the life cycle



Notes: Individuals with zero UAX earnings are included in the calculation. For annual earnings, employed and unemployed individuals are considered. For hourly wages, only employed individuals are considered. Cohorts 1964-1972. *Source:* Own calculations based on SOEP v35.

Finally, the solid line in Figure 2.6 shows the gender gap in UAX earnings as the sum of the annual earnings up to age X. Ultimately, the UA60 earnings coincide with our definition of lifetime earnings. Hence, the higher the age X, the closer UAX earnings are to lifetime earnings. At the beginning of the work life, women earn on average 20% less than men do. The difference in earnings accumulates over the life course and increases to a gender gap in UA40 earnings of 52.7%. After that, the gap remains stable, which results in a gender gap in lifetime earnings of 51.5% (UA60). At this point in life, women have earned on average around 732,000 euros — slightly less than half of the average income that men were able to accumulate (1,510,000 euros).[35]

The evolution of the gender gap in UAX earnings is by construction driven by the gender gap in the annual earnings curve. UAX earnings are less volatile since the marginal effect of adding an

[35] Compare Figure 2.17 and Figure 2.18 for the distribution of annual earnings and UAX earnings by men and women over the work life.

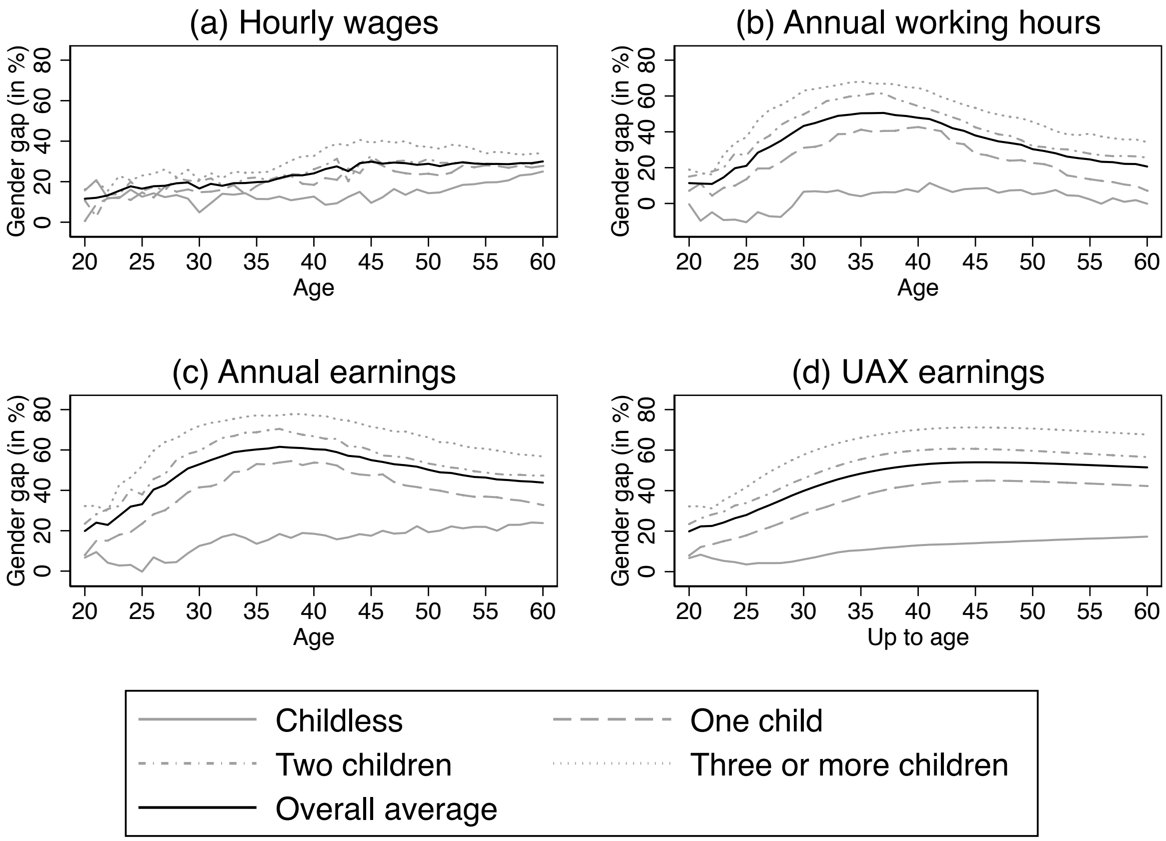
additional year of annual earnings to the UAX earnings decreases with increasing age. Hence, the gender gaps in annual and UAX earnings both experience large growth until age 40, but when the gender gap in annual earnings declines again, the UAX gender gap remains at its high level.

The profound difference in lifetime earnings is largely the result of differences in the extensive and intensive margin of labor supply of women over their lives. One can discuss how labor supply is influenced by own decisions or forced by personal and social circumstances. Previous studies have shown a strong relationship between gender gaps in income and children (e.g., Angelov et al., 2016; Kleven and Landais, 2017; Adda et al., 2017). This can be partially explained by the close connection between women's labor market decisions and the number of children they have (Kuhhirt and Ludwig, 2012; Ejrnæs and Kunze, 2013). In line with these studies, we also find that mothers face higher earning losses with every additional child, while fatherhood does not seem to affect men's earnings. Hence, observed earnings differences between childless women and men are smallest and grow wider with every additional child (see Figure 2.17 in the Appendix). This observation also holds true when we analyze the evolution of UAX earnings by number of children (Figure 2.18 in the Appendix).

Figure 2.7 shows the gender gap in hourly wages (Panel A), the gender gap in hours worked (Panel B), the gender gap in annual earnings (Panel C) and the gender gap in UAX earnings (Panel D) over the life cycle by number of children. In the beginning, the gender gap in hourly wages shows only small gender differences for men and women with and without children but widens over the life cycle. In Section 2.2, we have shown that this is mainly explained by the lesser work experience women with children gain over their life courses. The gender gap in annual earnings clearly differs by the number of children throughout the entire life cycle (see Figure 2.7, Panel C), exacerbating the gap in hourly wages mainly due to mother's lower intensive margin of work (see Figure 2.7, Panel B).

The gender gap in lifetime earnings also increases with the number of children. While childless men and women experience a gender gap of 17.3%, the gap is significantly higher for men and women with three or more children (68.0% at age 60). The significant widening of the gender gap

Figure 2.7. Gender gaps over the life cycle by children



Notes: Number of children refers to the total number at age 60. Gender gaps in accumulated earnings are earnings up to a given age. Individuals with zero annual and UAX earnings are included in the calculation. *Source:* Own calculations based on SOEP v35.

between UA20 and UA35 earnings thereby coincides with the increase in the cross-sectional gender gaps in annual hours worked, and consequently annual earnings. These results are in line with existing studies finding evidence for motherhood penalties and fatherhood premiums (e.g., Budig and England, 2001; Killewald and Gough, 2013; Killewald and García-Manglano, 2016). Therefore, descriptive evidence clearly hints that motherhood might be a key driver of gender earnings inequality over the life cycle.

2.3.2.2 Counterfactual analysis

In the last step, we want to determine which part of the observed gender gap in lifetime earnings can be associated with differences in the distribution of characteristics across gender and which part is associated with differences in returns to characteristics. To investigate this issue further, we will predict counterfactual lifetime earnings for women in the following two steps.

First, we take the earnings regression results from our microsimulation model, estimated for male M and female F individuals separately:

$$\hat{y}_{s,t+1} = \hat{\beta}_{0,s} + \hat{\beta}_{1,s} y_{s,t} + \hat{\beta}_{2,s} y_{s,t-1} + \hat{\beta}_{3,s} X_{s,t}, \quad s \in \{F, M\} \text{ and } t \in [1984, 2017] \tag{10}$$

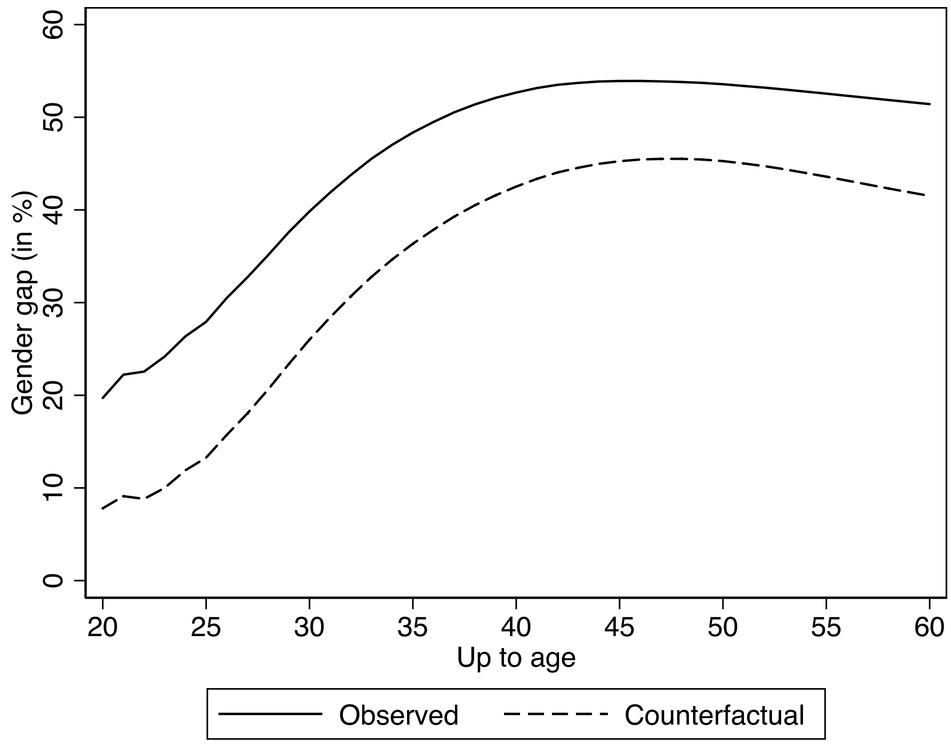
Second, we then estimate women's counterfactual annual earnings $\hat{y}_f^C$ by using the coefficients obtained from the male regression model in the women's Mincer earnings regression:

$$\hat{y}_{f,t+1} = \hat{\beta}_{0,m} + \hat{\beta}_{1,m} y_{f,t} + \hat{\beta}_{2,m} y_{f,t-1} + \hat{\beta}_{3,m} X_{f,t}, \quad t \in [1984, 2017] \tag{11}$$

Women's counterfactual annual earnings in year t then represent the salary women would have earned if their characteristics were rewarded the same as men's. Adding up the counterfactual annual earnings for each woman over the life course then yields women's counterfactual UAX earnings. As a result, all differences displayed in the counterfactual gender lifetime earnings gap are solely based on different characteristics for men and women and not by different returns to characteristics.

Figure 2.8 compares the observed and counterfactual gender gaps in UAX earnings. That means the difference between the truly observed and the counterfactual gender gap can be interpreted as the unexplained part of the gender gap in UAX earnings (adjusted gender gap). In the beginning of the work life, the difference between both gaps shown in Figure 2.8 is 12.1 pp. Therefore, in early years, approximately half of the gender gap in UAX earnings is due to a different allocation of characteristics and half is due to a different reward or payment of characteristics. The adjusted gender gap then increases to about 14.8% for UA30 earnings and declines afterwards to 10% for lifetime earnings (UA60). Thus, until the years of family formation, the unexplained difference between women's and men's pay grows, whereas it declines towards retirement. Overall, 80% of the observed gender lifetime earnings gap of 51.5% at age 60 can be explained by a dif-

Figure 2.8. Counterfactual estimation of the lifetime earnings gap

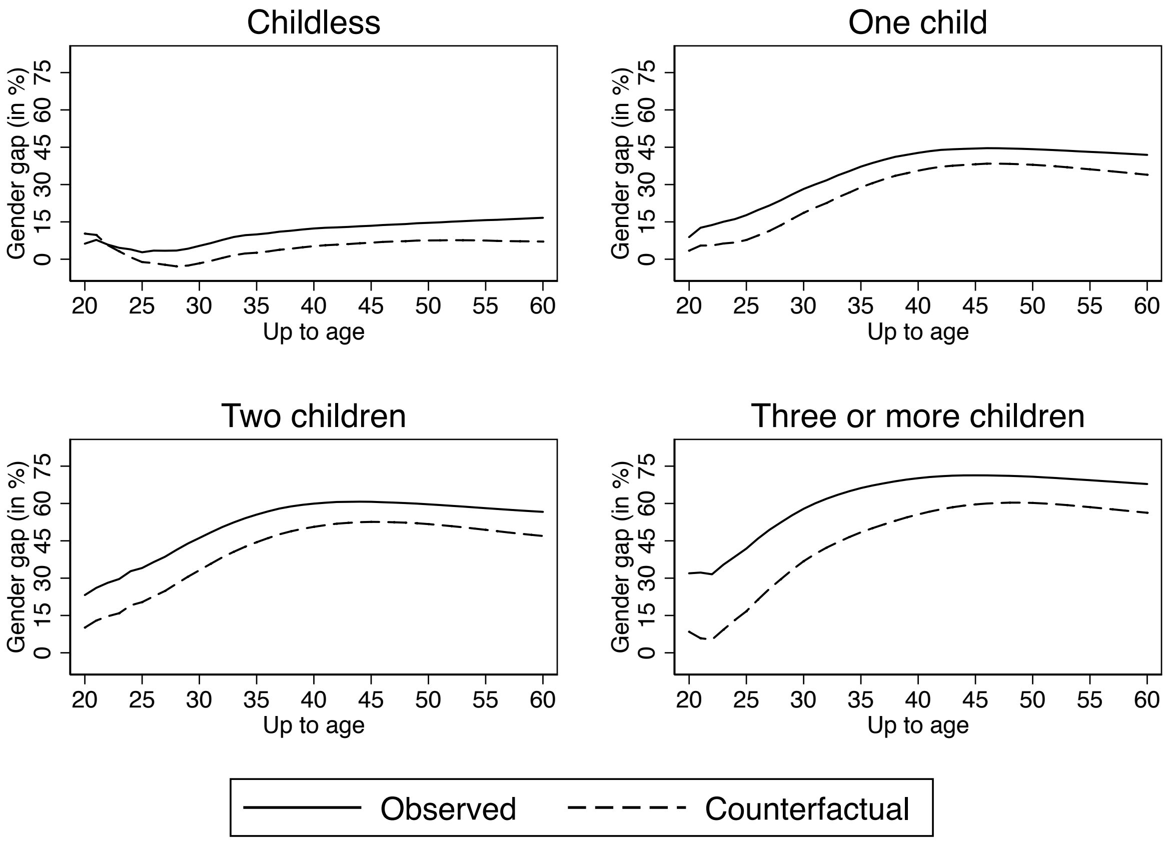


Notes: Estimated and counterfactual gender gap in UAX earnings. Gender gaps in accumulated earnings are earnings up to a given age. Individuals with zero UAX earnings are included in the calculation. *Source:* Own calculations based on SOEP v35.

ferent distribution of labor market characteristics of men and women. Consequently, one fifth of the observed gender lifetime earnings gap of 51.5% at age 60 is due to a less favorable reward for women's labor market characteristics, leading to an overall adjusted gender lifetime earnings gap of around 10%. The evolution of the adjusted gender gap indicates that rewards are least favorable for women in the first half of their work life. As this is the main time for family formation, this might be due to either a sorting of women into worse positions to gain more flexibility or the labor market rewarding women less favorably during this time due to the higher risk of inactivity periods.

Next, we want to investigate how motherhood influences the adjusted gender gap in lifetime earnings. Hence, Figure 2.9 compares the observed and counterfactual gender gaps by the number of children. As already shown in Figure 2.7 (Panel D), the observed gender gap in lifetime earnings is lowest for childless women and increases strongly with the number of children women

Figure 2.9. Counterfactual estimation of the lifetime earnings gap by number of children



Notes: Estimated and counterfactual gender gaps in UAX earnings. Gender gaps in accumulated earnings are earnings up to a given age. Individuals with zero UAX earnings are included in the calculation. *Source:* Own calculations based on SOEP v35.

have. But how much of the observed gender gap in lifetime earnings of women with and without children can be explained by a different distribution of characteristics, and what is the influence of the role of motherhood on the adjusted gender gap in lifetime earnings?

Using German data, this paper shows for the first time that in stark contrast to the observed gender gap in UAX earnings, the adjusted gender gap only slightly differs by the number of children women and men have. The difference between childless women and women with three or more children amounts to only 3 pp, with mothers of three or more children facing the highest adjusted gender gap in lifetime earnings with 11.4%. Hence, the large differences in the observed gender gaps of women with and without children are mainly driven by the different accumulation of characteristics rather than an additional unexplained penalty of motherhood.

Overall, we show that the difference in the gender gap in lifetime earnings by motherhood is largely driven by different characteristics women accumulate over their work life. Our results in Section 2.2 and Figure 2.7 (Panel B) indicated that these differences are primarily due to fewer working hours and less work experience which women with children accumulate over their work life. Nevertheless, at the end of the work life women on average face an adjusted gender gap in lifetime earnings of around 10%.

2.4 Conclusion

This paper underlines the importance of accounting for the biographical dimension when analyzing gender inequalities. First, our results show that cross-sectional gender differences are persistent over the work life. Comparing multiple dimensions of cross-sectional gender differences, we find that the gender gap in hourly wages is substantially smaller (less than half the size) than the gender gap in annual earnings. Using an Oaxaca Blinder decomposition, we show that the gender gap in annual earnings can largely be explained by the extensive and intensive margin of labor, with women accumulating less work experience and working fewer hours.

We then applied a dynamic microsimulation model to obtain full lifetime earnings data including family background information. Using our simulated data, we observe a gender gap in lifetime earnings of 51.5%. Further, we show that the unadjusted gender gap in lifetime earnings increases with the number of children women have. While childless women face an average gender gap in lifetime earnings of 17.3%, mothers with three or more children experience a gap of 68.0%. Furthermore, we used the coefficients from the male earnings regression simulation model to estimate women's counterfactual earnings. As a result, all differences remaining were solely based on different characteristics of men and women and not by different returns to characteristics. The difference between the truly observed gender gap and the counterfactual gap then yielded the adjusted gender gap in lifetime earnings of 10%. This means that women earn on average 10% less than men over their lifetime due to a different reward for their characteristics in comparison to men. We find that in stark contrast to the observed gender gap in UAX earnings, the adjusted gender gap only differs slightly by the number of children women and men have.

The documented gender inequalities in lifetime earnings are high and therefore concerning for a variety of social and economic reasons. For example, fewer financial opportunities for women, and especially mothers, might create unhealthy dependency structures within households (Kalmuss and Straus, 1982). Furthermore, lower lifetime earnings result in significantly lower pensions and consequently a higher risk of poverty among elderly women (see, e.g., Fasang et al., 2013; Grabka et al., 2017). Against this background, it is of high importance to create the right conditions for women to have the opportunity and incentive to increase their labor market participation. One promising suggestion on how to increase work incentives for women in Germany is, for example, a reform of *Ehegattensplitting*, the joint taxation of married couples or civil partners (Bach et al., 2017). Furthermore, the influential study by Olivetti and Petrongolo (2017) stresses the importance of the availability of childcare in this context. For Germany specifically, there is evidence that more extensive provision of adequate childcare would potentially positively influence mothers' labor market participation (e.g., Bauernschuster and Schlotter, 2015; Muller and Wrohlich, 2020). More broadly, fundamental changes in norms regarding the household division of labor are necessary as women still conduct the majority of housework and care-related tasks (Samtleben, 2019). Additionally, employers should offer more flexible work arrangements in order to foster the compatibility of work and family. Indeed, recent studies indicate that such factors might have the potential to foster an increase in women's labor market participation as a considerable share of women who are currently working part-time have the (unrealized) desire to increase their working hours (e.g., Harnisch et al., 2018; Beckmannshagen and Schroder, 2022).

2.5 Appendix

2.5.1 Supplementary material for cross-sectional analyses

Oaxaca Blinder decomposition The Oaxaca Blinder decomposition was simultaneously introduced by Oaxaca (1973) and Blinder (1973) and divides the gender differential in labor market outcomes (here: hourly wage or annual earnings) into an *endowment part* and a *coefficient part*. The endowment part of the gender differential accounts for the part of the gap which can be attributed to differences in the allocation of characteristics (e.g., working hours, highest level of education) between men and women. In contrast, the coefficient part captures the gender differences in labor market returns to characteristics, and therefore in their coefficients. In other words, it states the gender differences of what the labor market is willing to pay for the same characteristics. This part is also called the raw or adjusted gender wage/earnings differential. This adjusted gap, however, also contains the effects of gender differences in unobserved predictors (Jann, 2008). The Oaxaca-Blinder decomposition approach enables us to analyze whether the gender gap in wages/earnings is mainly driven by the different distributions of productivity characteristics or by different rewards for these characteristics by gender.

The gender gap G_x is defined as the difference between the means of the labor market outcomes L at age x of men m and women f:

$$G_x = E(L_{mx}) - E(L_{fx}) \tag{12}$$

L_s for either sex (s) is based on the linear model

$$L_{sx} = Z'_{sx}\beta_{sx} + \epsilon_{sx}, \quad E(\epsilon_{sx}) = 0,\ S \in \{f, m\}, \tag{13}$$

where the vector Z includes all relevant characteristics, β is the estimation vector and ϵ is the error term. Inserting Equation (2.13) into Equation (2.12), the earnings differential can also be written as:

$$G_x = E(Z_{mx})'\beta_{mx} - E(Z_{fx})'\beta_{fx}. \tag{14}$$

For the decomposition of the results, a non-discriminatory coefficient vector is needed, called β^*. Following Neumark (1988), the vector is determined as a pooled regression over both sexes. The gender gap can then be rewritten as:

$$G_x = \underbrace{[E(Z_{mx}) - E(Z_{fx})]'\beta_x^*}_{\text{Endowment part}} + \underbrace{[E(Z_{mx})'(\beta_{mx} - \beta_x^*) + E(Z_{fx})'(\beta_x^* - \beta_{fx})]}_{\text{Coefficient part}} \tag{15}$$

where the first part of Equation (2.15) is the endowment part and the second part is the coefficient component of the gender gap in the labor market outcome.

Supplementary tables and figures

Table 2.3. Descriptive statistics - means by age

Men	Age								
	20	25	30	35	40	45	50	55	60
Annual earnings	15748.13 (10972.17)	27727.89 (13306.99)	37925.13 (18571.57)	45217.80 (24095.07)	51615.70 (31182.61)	54204.14 (38951.27)	54747.55 (35380.01)	53969.63 (33505.90)	51535.02 (50496.35)
Hourly wage	9.37 (7.72)	15.13 (18.11)	18.12 (20.76)	20.72 (16.32)	23.06 (16.25)	23.95 (17.91)	24.24 (14.47)	25.83 (31.96)	26.13 (28.33)
Hours worked per week	34.55 (13.42)	38.29 (14.48)	42.81 (12.47)	43.49 (11.38)	44.39 (11.01)	44.10 (10.61)	43.50 (11.17)	42.65 (12.13)	39.34 (14.38)
Years in full-time work	1.20 (1.28)	4.75 (2.60)	8.54 (3.77)	12.97 (4.37)	17.71 (4.85)	22.58 (5.31)	27.43 (5.71)	32.69 (5.81)	37.32 (5.74)
Years in part-time work	0.14 (0.47)	0.33 (0.98)	0.55 (1.56)	0.56 (1.64)	0.61 (1.93)	0.65 (2.10)	0.75 (2.44)	0.68 (2.46)	1.09 (2.90)
Years in unemployment	0.13 (0.38)	0.31 (0.70)	0.39 (0.98)	0.43 (1.21)	0.45 (1.37)	0.47 (1.64)	0.51 (1.85)	0.49 (1.78)	0.45 (1.65)
Years of education	8.97 (3.86)	10.61 (3.03)	11.84 (3.25)	12.44 (3.17)	12.62 (3.03)	12.65 (2.96)	12.67 (2.92)	12.57 (2.84)	12.73 (2.92)
Women	Age								
	20	25	30	35	40	45	50	55	60
Annual earnings	12773.34 (8683.31)	21115.69 (12332.56)	22975.43 (16720.75)	21925.18 (19512.82)	22944.75 (18626.65)	24975.61 (20497.00)	26705.30 (21713.56)	26475.69 (25559.13)	24659.61 (21236.77)
Hourly wage	7.97 (6.58)	12.87 (9.59)	15.19 (12.19)	15.63 (13.18)	16.23 (12.02)	16.23 (10.88)	16.82 (12.49)	16.54 (13.18)	17.48 (14.99)
Hours worked per week	31.75 (13.02)	32.28 (14.34)	29.91 (15.60)	26.68 (15.26)	27.38 (14.29)	28.87 (13.99)	30.09 (13.98)	29.42 (13.64)	26.97 (14.49)
Years in full-time work	1.20 (1.23)	4.36 (2.71)	6.73 (4.12)	8.04 (5.23)	9.63 (6.46)	11.61 (7.99)	14.00 (9.69)	16.70 (11.75)	19.65 (13.99)
Years in part-time work	0.21 (0.55)	0.82 (1.61)	1.91 (2.60)	3.81 (3.76)	5.69 (4.87)	7.60 (6.16)	9.45 (7.75)	11.66 (9.77)	13.32 (11.79)
Years in unemployment	0.17 (0.40)	0.28 (0.73)	0.40 (0.95)	0.50 (1.19)	0.56 (1.52)	0.58 (1.60)	0.64 (1.77)	0.71 (1.99)	0.57 (1.86)
Years of education	9.17 (3.91)	11.17 (2.98)	12.07 (3.31)	12.42 (3.00)	12.48 (2.89)	12.39 (2.91)	12.34 (2.78)	12.11 (2.59)	12.02 (2.71)

Notes: Only employed individuals with hourly wages and annual earnings greater than zero were included. Cohorts 1940-1979, weighted sample. Annual earnings and hourly wages are price-adjusted and presented in 2015 euros. Standard errors in parentheses. *Source:* Own calculations based on SOEP v35.

Table 2.4. Regression results for hourly wages - women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	20	25	30	35	40	45	50	55	60
One child	-0.019	-0.061	-0.159***	-0.023	-0.003	0.075**	0.068*	0.104**	-0.058
	(0.158)	(0.055)	(0.046)	(0.036)	(0.038)	(0.034)	(0.040)	(0.048)	(0.070)
Two children	-0.461	-0.234**	-0.154***	-0.058	-0.000	0.073**	0.138***	0.088*	-0.014
	(0.501)	(0.107)	(0.058)	(0.041)	(0.039)	(0.036)	(0.040)	(0.048)	(0.071)
3 or more children		-0.171	-0.111	-0.167***	-0.030	0.036	0.129***	0.103*	-0.051
		(0.195)	(0.093)	(0.055)	(0.050)	(0.043)	(0.048)	(0.058)	(0.083)
Married	0.033	-0.038	0.054	0.008	0.004	0.068**	-0.052*	-0.031	0.055
	(0.100)	(0.036)	(0.034)	(0.030)	(0.029)	(0.027)	(0.029)	(0.035)	(0.048)
Years FT	0.445***	0.055**	0.059***	0.028***	0.035***	0.026***	0.027***	0.014**	0.030***
	(0.061)	(0.022)	(0.014)	(0.009)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)
Years FT (sq)	-0.054***	-0.003	-0.002***	0.000	-0.001*	-0.000	-0.000	-0.000	-0.000**
	(0.016)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years PT	-0.023	-0.039	-0.028	-0.019*	-0.013	-0.020***	-0.002	-0.001	-0.011
	(0.103)	(0.029)	(0.017)	(0.011)	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)
Years PT (sq)	0.012	0.001	0.003*	0.002**	0.001**	0.001***	0.000*	0.000	0.000**
	(0.028)	(0.004)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years UE	-0.689***	-0.101**	-0.174***	0.013	-0.062***	-0.096***	-0.076***	-0.058***	-0.044*
	(0.209)	(0.043)	(0.039)	(0.021)	(0.018)	(0.018)	(0.018)	(0.017)	(0.024)
Years UE (sq)	0.236*	-0.000	0.034***	-0.005**	0.004**	0.007***	0.004**	0.001	0.001
	(0.140)	(0.006)	(0.009)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Part-time	0.244***	0.272***	0.110***	0.182***	0.161***	0.102***	0.023	-0.068*	0.069
	(0.081)	(0.049)	(0.042)	(0.032)	(0.031)	(0.027)	(0.031)	(0.039)	(0.054)
Education	-0.068***	0.007	-0.033**	-0.063***	0.018	0.008	-0.023	0.012	-0.052
	(0.024)	(0.017)	(0.015)	(0.015)	(0.023)	(0.015)	(0.021)	(0.029)	(0.036)
Education (sq)	0.004*	0.001	0.003***	0.006***	0.002***	0.003***	0.004***	0.002**	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.241***	1.714***	1.233***	1.700***	1.825***	1.508***	1.033***	1.614***	1.898***
	(0.770)	(0.266)	(0.211)	(0.222)	(0.199)	(0.161)	(0.313)	(0.373)	(0.463)
Obs.	382	882	1307	1859	2493	2653	2043	1320	778
R-squared	0.323	0.127	0.187	0.240	0.192	0.219	0.205	0.213	0.248
Cohort-FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector-FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses; The stars refer to the following significance level: $*p < 0.1, **p < 0.05, ***p < 0.01$. *Source:* Own calculations based on SOEP v35.

Table 2.5. Regression results for hourly wages - men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	20	25	30	35	40	45	50	55	60
One child	0.160	0.089	-0.017	-0.017	0.007	0.029	-0.043	0.026	0.053
	(0.349)	(0.055)	(0.031)	(0.024)	(0.022)	(0.024)	(0.029)	(0.040)	(0.053)
Two children	-0.952	0.134*	0.065*	0.069***	0.033	0.103***	-0.000	0.034	-0.010
	(0.751)	(0.079)	(0.035)	(0.024)	(0.022)	(0.023)	(0.027)	(0.037)	(0.049)
3 or more children	-0.006	0.139*	-0.024	0.015	0.050*	0.049*	-0.013	0.075	0.203***
	(0.173)	(0.075)	(0.045)	(0.033)	(0.028)	(0.029)	(0.035)	(0.049)	(0.067)
Married	-0.026	0.015	0.164***	0.085***	0.101***	0.069***	0.084***	0.020	0.105**
	(0.166)	(0.041)	(0.027)	(0.023)	(0.021)	(0.023)	(0.026)	(0.035)	(0.048)
Years FT	0.737***	0.164***	0.105***	0.058***	0.053***	0.045***	0.032***	0.040***	-0.030
	(0.061)	(0.023)	(0.013)	(0.008)	(0.007)	(0.008)	(0.009)	(0.012)	(0.036)
Years FT (sq)	-0.108***	-0.012***	-0.006***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001**	0.001
	(0.015)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Years PT	0.225	-0.197***	-0.074***	-0.020*	-0.056***	-0.038***	-0.069***	-0.070***	-0.057***
	(0.181)	(0.036)	(0.018)	(0.012)	(0.010)	(0.011)	(0.010)	(0.014)	(0.017)
Years PT (sq)	-0.079	0.021***	0.006***	0.001	0.003***	0.003***	0.003***	0.003***	0.001*
	(0.071)	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years UE	-0.279	-0.108**	-0.178***	-0.113***	-0.117***	-0.105***	-0.094***	-0.069***	-0.094***
	(0.195)	(0.050)	(0.029)	(0.015)	(0.013)	(0.012)	(0.014)	(0.019)	(0.036)
Years UE (sq)	0.099	-0.005	0.023***	0.004***	0.006***	0.006***	0.004***	0.002**	0.006
	(0.101)	(0.014)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
Part-time	0.271***	0.422***	0.257***	0.173***	0.336***	0.251***	0.189***	0.389***	0.201***
	(0.075)	(0.054)	(0.043)	(0.034)	(0.031)	(0.031)	(0.039)	(0.045)	(0.054)
Education	-0.031	-0.038***	-0.071***	-0.039***	-0.051***	0.040*	0.060***	0.002	0.020
	(0.030)	(0.013)	(0.010)	(0.010)	(0.013)	(0.022)	(0.023)	(0.055)	(0.067)
Education (sq)	0.003	0.003***	0.005***	0.003***	0.004***	0.001*	0.000	0.002	0.002
	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)
Constant	1.996***	1.591***	2.263***	2.331***	2.519***	1.703***	1.673***	1.875***	1.318
	(0.504)	(0.163)	(0.183)	(0.172)	(0.173)	(0.187)	(0.231)	(0.437)	(0.926)
Obs.	383	900	1746	2464	2863	2939	2261	1546	980
R-squared	0.449	0.231	0.185	0.229	0.277	0.283	0.252	0.184	0.208
Cohort-FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector-FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors in parentheses; The stars refer to the following significance level:
$*p < 0.1, **p < 0.05, ***p < 0.01.$

Source: Own calculations based on SOEP v35.

Table 2.6. Regression results for annual earnings - women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	20	25	30	35	40	45	50	55	60
One child	0.113	-0.033	-0.130***	-0.008	-0.005	0.101***	0.059	-0.086	-0.044
	(0.150)	(0.051)	(0.045)	(0.036)	(0.037)	(0.034)	(0.039)	(0.047)	(0.071)
Two children	-0.485	-0.234**	-0.205*****	-0.044	0.007	0.092***	0.131***	0.066	-0.024
	(0.486)	(0.100)	(0.059)	(0.041)	(0.039)	(0.035)	(0.039)	(0.048)	(0.071)
3 or more children		-0.056	0.174*	-0.160***	-0.011	0.081*	0.132***	0.079	-0.034
		(0.183)	(0.093)	(0.056)	(0.049)	(0.043)	(0.047)	(0.058)	(0.083)
Married	0.040	-0.062*	0.038	0.044	-0.004	0.102***	-0.036***	-0.013	0.048**
	(0.096)	(0.034)	(0.034)	(0.031)	(0.029)	(0.026)	(0.028)	(0.035)	(0.048)
Years FT	0.466***	0.098***	0.065***	0.031***	0.036***	0.025***	0.023***	0.009*	0.031***
	(0.060)	(0.021)	(0.014)	(0.009)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)
Years FT (sq)	-0.059***	-0.006***	-0.003***	-0.000	-0.001**	-0.000	-0.000	0.000	-0.000**
	(0.015)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years PT	-0.099	-0.033	-0.005	-0.001	-0.002	-0.010*	0.002	-0.001	-0.011
	(0.103)	(0.027)	(0.016)	(0.011)	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)
Years PT (sq)	0.034	0.002	0.001	0.001	0.001	0.001***	0.000	0.000	0.000**
	(0.028)	(0.004)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years UE	-0.524***	-0.076*	-0.174***	-0.010	-0.075***	-0.097***	-0.079***	-0.050***	-0.047*
	(0.197)	(0.040)	(0.039)	(0.021)	(0.018)	(0.018)	(0.018)	(0.017)	(0.024)
Years UE (sq)	0.141	-0.002	0.033***	-0.006**	0.005***	0.007***	0.004**	0.001	0.001
	(0.134)	(0.006)	(0.009)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Weekly hours	0.066***	0.054***	0.081***	0.093***	0.091***	0.087***	0.105***	0.113***	0.093***
	(0.009)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)
Weekly hours (sq)	-0.001***	-0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.046**	0.002	-0.034**	-0.071***	0.013	0.007	-0.024	0.012	-0.051
	(0.023)	(0.016)	(0.015)	(0.015)	(0.023)	(0.015)	(0.020)	(0.028)	(0.036)
Education (sq)	0.002	0.001	0.003***	0.006***	0.003***	0.003***	0.004***	0.002**	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	7.583***	8.273***	8.012***	7.637***	7.141***	7.141***	7.140***	6.986***	7.550***
	(0.197)	(0.137)	(0.130)	(0.126)	(0.169)	(0.119)	(0.153)	(0.213)	(0.277)
Obs.	382	882	1307	1859	2493	2653	2043	1320	778
R-squared	0.573	0.540	0.627	0.663	0.578	0.599	0.674	0.681	0.660
Cohort-FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector-FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

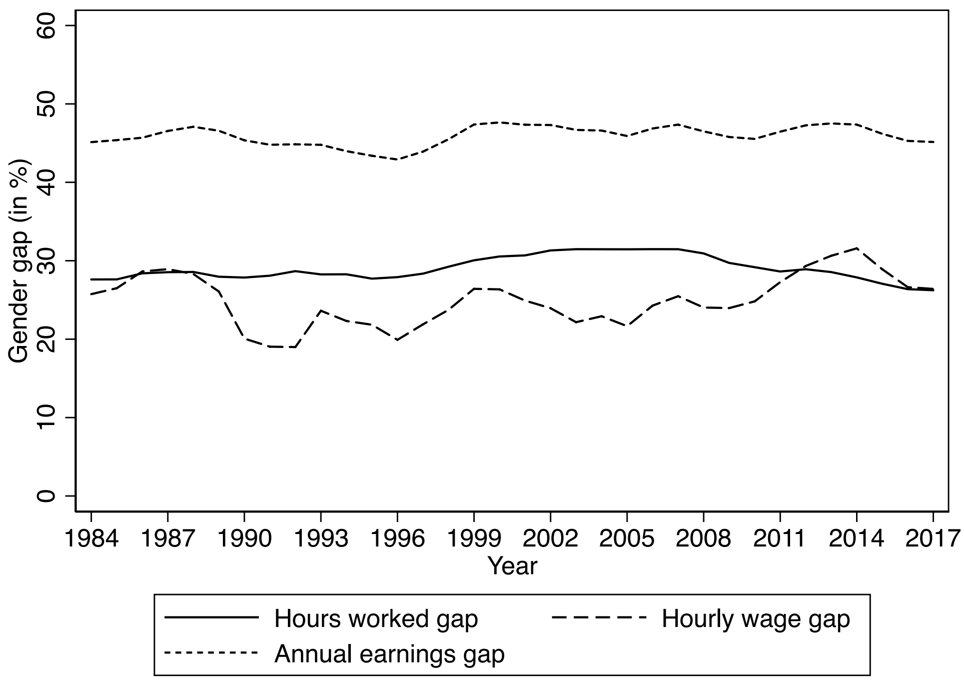
Notes: Standard errors in parentheses; The stars refer to the following significance level: $*p < 0.1, **p < 0.05, ***p < 0.01$. *Source:* Own calculations based on SOEP v35.

Table 2.7. Regression results for annual earnings - men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	20	25	30	35	40	45	50	55	60
One child	0.189	0.061	-0.008	-0.014	0.014	0.028	-0.042	-0.003	0.073
	(0.332)	(0.052)	(0.028)	(0.023)	(0.021)	(0.024)	(0.028)	(0.038)	(0.051)
Two children	-1.006	0.139*	0.066**	0.067***	0.026	0.091***	-0.008	0.019	0.015
	(0.714)	(0.075)	(0.032)	(0.023)	(0.021)	(0.022)	(0.026)	(0.036)	(0.047)
3 or more children	-0.008	0.128*	-0.026	0.025	0.050*	0.051*	0.013	0.100**	0.157**
	(0.164)	(0.071)	(0.041)	(0.032)	(0.026)	(0.028)	(0.034)	(0.047)	(0.065)
Married	0.017	0.021	0.121***	0.078***	0.089***	0.054**	0.091***	0.028	0.099**
	(0.158)	(0.039)	(0.025)	(0.022)	(0.020)	(0.022)	(0.025)	(0.034)	(0.046)
Years FT	0.731***	0.179***	0.094***	0.058***	0.045***	0.043***	0.031***	0.052***	-0.033
	(0.058)	(0.022)	(0.012)	(0.008)	(0.006)	(0.008)	(0.009)	(0.012)	(0.035)
Years FT (sq)	-0.106***	-0.013***	-0.005***	-0.002***	-0.001***	-0.001***	-0.001**	-0.001***	0.001
	(0.014)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years PT	0.095	-0.191***	-0.044***	-0.020*	-0.060***	-0.042***	-0.057***	-0.079***	-0.056***
	(0.174)	(0.034)	(0.016)	(0.011)	(0.010)	(0.011)	(0.010)	(0.013)	(0.015)
Years PT (sq)	-0.051	0.024***	0.003	0.000	0.003***	0.003***	0.003***	0.003***	0.001*
	(0.067)	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years UE	-0.204	-0.107**	-0.188***	-0.110***	-0.118***	-0.101***	-0.091***	-0.109***	-0.122***
	(0.186)	(0.047)	(0.026)	(0.014)	(0.012)	(0.012)	(0.014)	(0.018)	(0.035)
Years UE (sq)	0.040	-0.005	0.023***	0.004***	0.006***	0.005***	0.004***	0.004***	0.008**
	(0.097)	(0.014)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
Weekly hours	0.044***	0.049***	0.070***	0.052***	0.037***	0.054***	0.077***	0.053***	0.071***
	(0.009)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Weekly hours (sq)	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.018	-0.040***	-0.076***	-0.041***	-0.057***	0.039*	0.053**	0.091*	0.019
	(0.028)	(0.012)	(0.009)	(0.009)	(0.012)	(0.021)	(0.023)	(0.053)	(0.065)
Education (sq)	0.003	0.004***	0.005***	0.004***	0.004***	0.002**	0.001	-0.001	0.002
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)
Constant	7.710***	8.367***	8.434***	8.715***	9.163***	7.965***	7.506***	7.527***	8.427***
	(0.195)	(0.113)	(0.099)	(0.103)	(0.115)	(0.174)	(0.201)	(0.394)	(0.730)
Obs.	383	900	1746	2464	2863	2939	2261	1546	980
R-squared	0.542	0.539	0.481	0.394	0.409	0.417	0.437	0.400	0.522
Cohort-FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector-FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

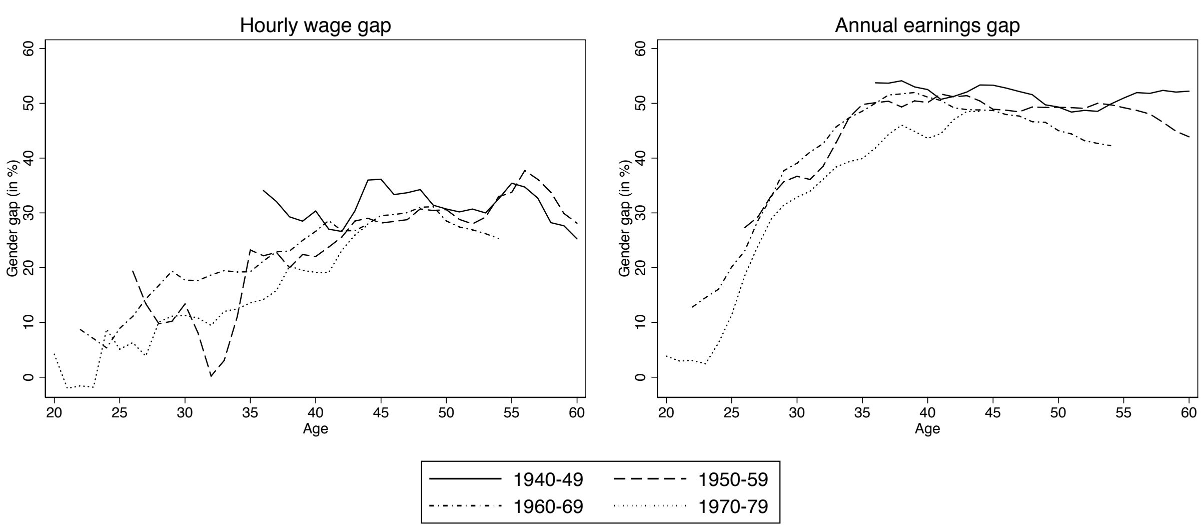
Notes: Standard errors in parentheses; The stars refer to the following significance level:
$*p < 0.1, **p < 0.05, ***p < 0.01$. *Source:* Own calculations based on SOEP v35.

Figure 2.10. Gender gaps in labor market outcomes by survey year



Notes: Only employed individuals are considered. Does not include values of zero annual earnings. Cohorts 1940-1979, weighted sample. *Source:* Own calculations based on SOEP v35.

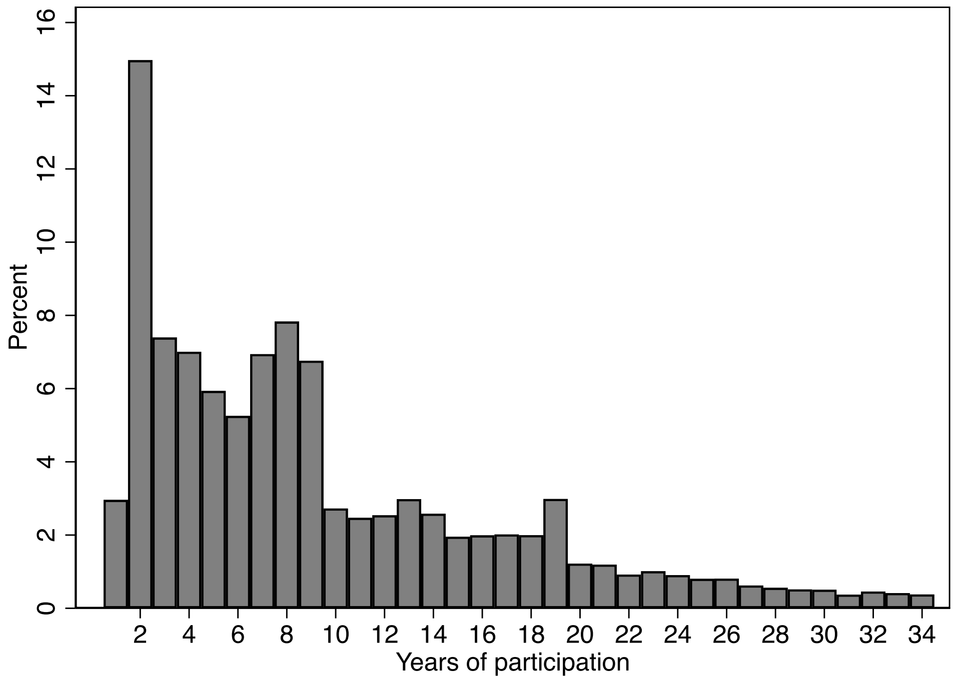
Figure 2.11. Gender gaps in hourly wages and annual earnings by cohort



Notes: Only employed individuals are considered. Does not include values of zero hourly wages or annual earnings. Cohorts 1940-1979, weighted sample. *Source:* Own calculations based on SOEP v35.

2.5.2 Supplementary material for lifetime analyses

Figure 2.12. Distribution of participation years in the SOEP



Notes: Refers to participation years of the SOEP sample used in 2.2 of this paper. Restrictions for the microsimulation in Section 2.3 are not applied here. *Source:* Own calculations based on SOEP v35.

Table 2.8. Distribution of cohorts by gender

Birth Cohort	Number of Men	Number of Women	Total
1964	382	324	706
1965	373	383	756
1966	404	425	829
1967	385	401	786
1968	378	385	763
1969	388	387	775
1970	311	364	675
1971	303	342	645
1972	288	304	592
Total	3212	3315	6527

Source: Own calculations based on SOEP v35.

Table 2.9. Overview regression models of the dynamic microsimulation

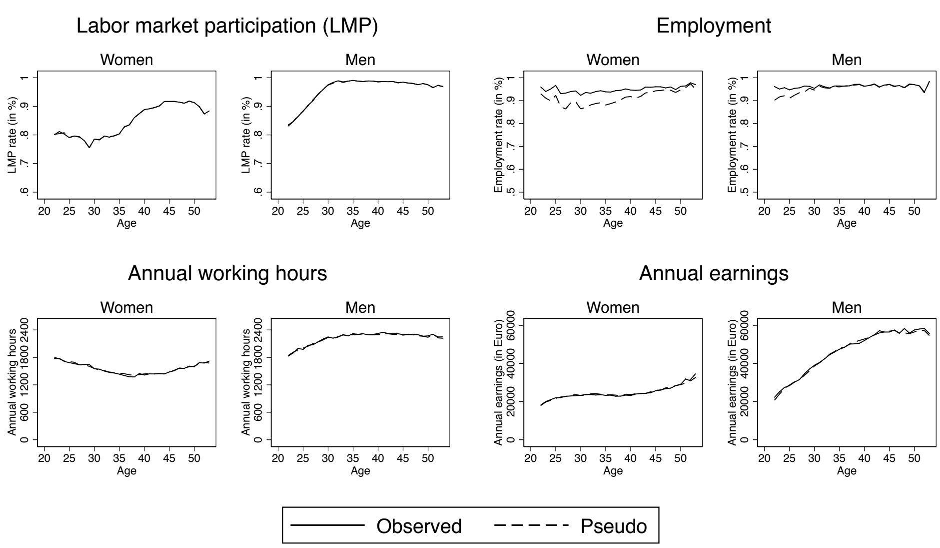
Dependent Variables	Explanatory Variables
Child birth in t+1 (Logit)	Number of children, age of youngest child, earnings; Additionally, for married women: partner's age, highest level of education and earnings; Run separately for married women and single women
Change in marital status (married/single) in t+1 (Logit)	Marriage duration term interacted with age, number of children; Additionally, for women: age of youngest child; Additionally, for married individuals: Partner's age and highest level of education; Run separately for men and women for each respective marital status
Change in labor force status in t+1 (Logit)	Labor force status in t and t-1, labor market history (years in full-time, part-time, unemployment), number of children (not for unmarried men); Additionally, for women: number of years since birth of last child; Additionally, for married individuals: partner's labor force status and earnings in t; Run separately for men and women for each respective marital status
Change in employment status (working/ unemployed) in t+1 (Logit)	Employment status in t-1, labor market history (years in full-time, part- time, unemployment), number of children (not for unmarried men); Additionally, for women: number of years since birth of last child; Additionally, for married individuals: partner's employment status and earnings of the in t; Run separately for men and women for each possible combination of marital and employment status in t
Transition in employment or unemployment in t+1 after not participating in the labor market in t (Logit)	Employment status in t-1, labor market history (years in full-time, part-time, unemployment), number of children (not for unmarried men); Additionally, for women: number of years since birth of last child; Additionally, for married individuals: partner's employment status and earnings in t; Run separately for men and women for each respective marital status (requirement: participating in the labor market in t+1)
Transition full-time work/ part-time work in t+1 (Logit)	Labor force status in t-1, dummy variable indicating full-time or part- time work in t-1, labor market history (years in full-time, part-time, unemployment), number of children (not for unmarried men); Additionally, for women: number of years since birth of last child; Additionally, for married individuals: partner's employment status and earnings of the partner in t; Run separately for men and women for each possible combination of marital and full-time/ part-time status in t
Transition in full- time work/ part- time work in t+1 after not working in t (Logit)	Labor force status in t-1, dummy variable indicating full-time or part-time work in t-1, labor market history (years in full-time, part-time, unemployment), number of children (not for unmarried men)-, Additionally, for women: number of years since birth of last child; Additionally, for married individuals: employment status and earnings of the partner in t; Run separately for men and women for each respective marital status (requirement: working in t + 1)
Number of working hours in t (OLS)	Annual hours worked in t-1 and t-2, annual earnings in t-1, dummy variable indicating full-time or part-time work in and labor market status t-1, number of children (not for unmarried men); Additionally, for married individuals: earnings of the partner in t-1; Run separately for men and women for each respective marital and work (full-time/part-time) status
Annual earnings in t (OLS)	Annual earnings in t-1 and t-2, annual hours worked in t, t-1 and t-2, labor market history (years in full-time, part-time, unemployment), dummy indicating marital status; Run separately for men and women

Notes: Explanatory variables which are included in every model: highest level of education and year of birth interacted with (quadratic) age, place of residency before 1989 (East or West Germany), immigration background (yes or no). This table depicts forward-looking simulations. Backward-looking simulations function analogously. *Source:* Own calculations based on SOEP v35.

2.5.3 Robustness: Microsimulation

Pseudo missings To test the robustness of our simulation model further, we use the concept of pseudo missings. To that end, we set truly observed information for some part of the sample missing (pseudo missings) and predict their now missing observations again by using our dynamic microsimulation and the regression coefficients previously obtained. As we need a starting point of at least two observations for our models due to the lagged terms, we use the first two truly observed years for everyone before starting to create pseudo missings. Figure 2.13 shows the differences between the simulated pseudo missings (dashed line) and the truly observed information (solid line) for labor force status, employment status, annual working hours and annual earnings. In most graphs, the level of accuracy of the model is so high that it is hard to even tell the solid and dashed line apart. For labor market status, the model predicts 99.9% of all pseudo missings correctly. And even for employment status, where there appear to be bigger differences between pseudo missing and observations at a first glance, overall 97.7% of all cases are simulated correctly. These results further support the robustness of our simulation model.

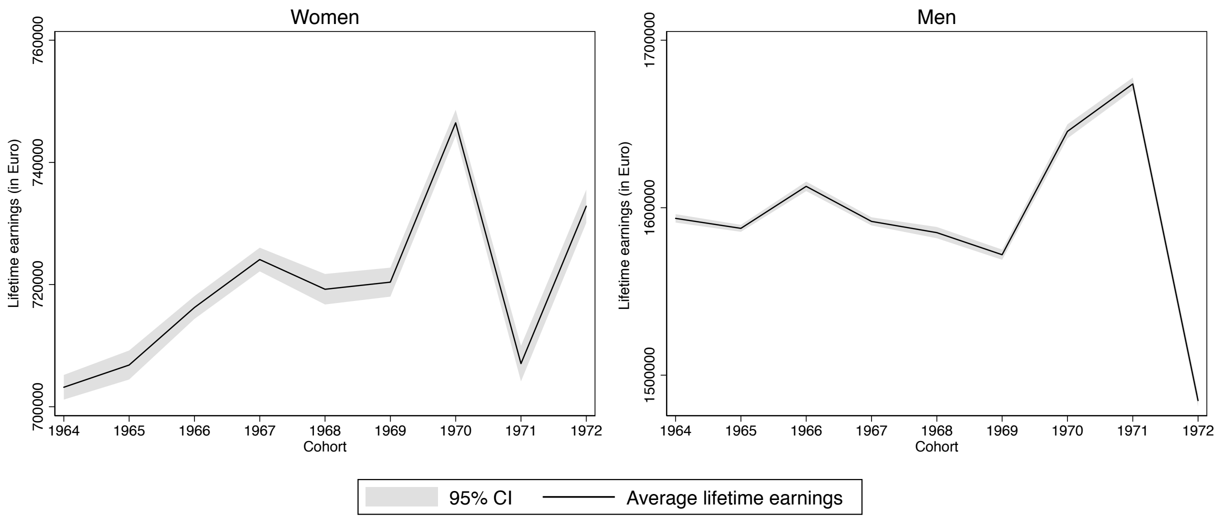
Figure 2.13. Pseudo missings for labor market outcomes



Notes: The graphs comparing truly observed and simulated pseudo information for annual working hours and annual earnings only focus on employed individuals. *Source:* Own calculations based on SOEP v35.

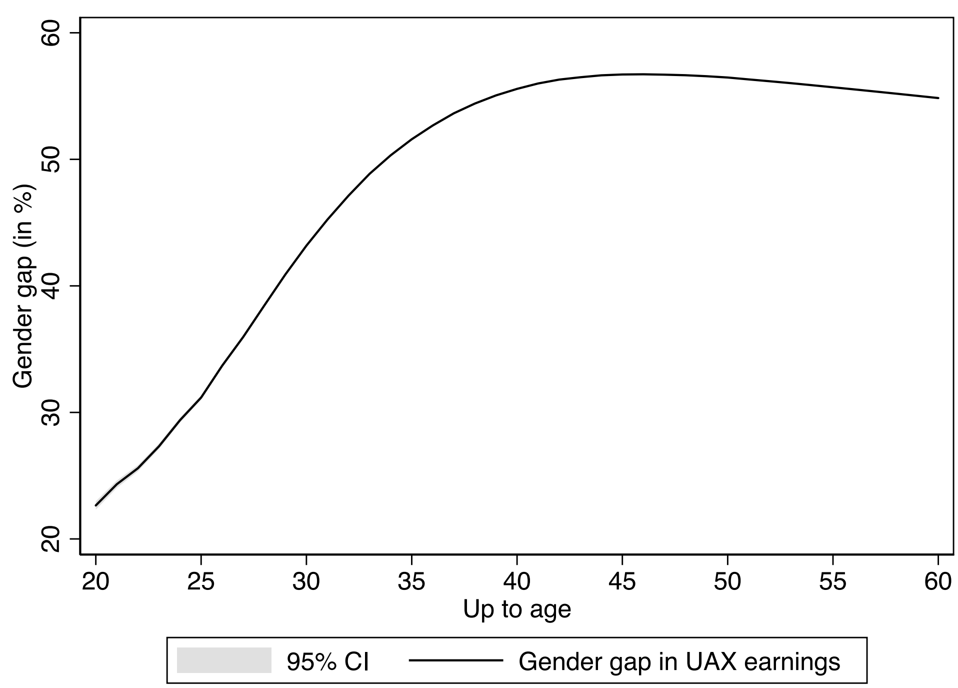
Monte Carlo simulation Another way to validate the robustness of our dynamic microsimulation model is to make use of the underlying random process described in Subsection 2.3.1.1. We implement a Monte Carlo simulation approach by simulating each individual's employment biographies 100 times. By doing so, due to the underlying random process determining transitions in labor market outcome variables between $t-1$ and t, we simulate up to 100 different employment biographies for each individual. However, due to limited computational capacities we only simulate the employment variables (labor market status, employment status, full-time/part-time work, annual working hours and annual earnings) and keep the family information (number of children and marital status) constant for each of the 100 iterations. In the next step, we calculate lifetime earnings for each of the 100 simulated career paths per individual and compute the average lifetime earnings and the resulting UAX earnings gender gap in the population for each of the 100 runs. By deriving the 95% confidence intervals we can analyze whether average lifetime earnings vary significantly for different underlying random processes or whether they are robust. The results are presented in Figures 2.14 and 2.15. Figure 2.14 shows that lifetime earnings by cohorts are very robust. However, lifetime earnings of women vary more strongly than men's. Figure 2.15 provides evidence for a very narrow 95% confidence interval for the gender gap in UAX earnings. Consequently, the results of the Monte Carlo simulation confirm the high robustness of our simulation outcomes.

Figure 2.14. Monte Carlo simulation for earnings



Source: Own calculations based on SOEP v35.

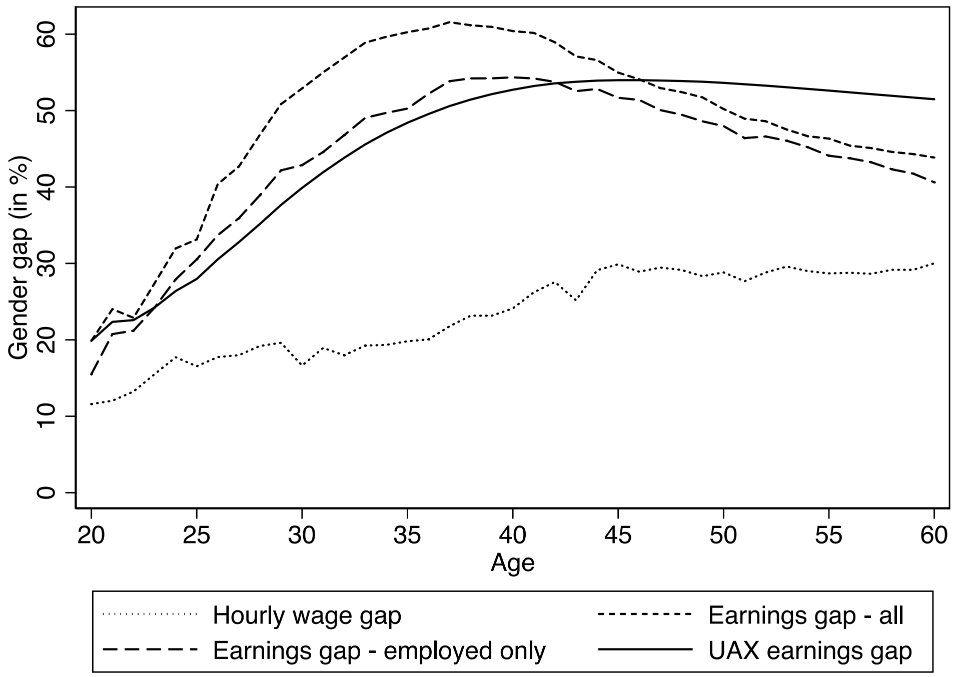
Figure 2.15. Monte Carlo simulation for the gender gap in UAX earnings



Source: Own calculations based on SOEP v35.

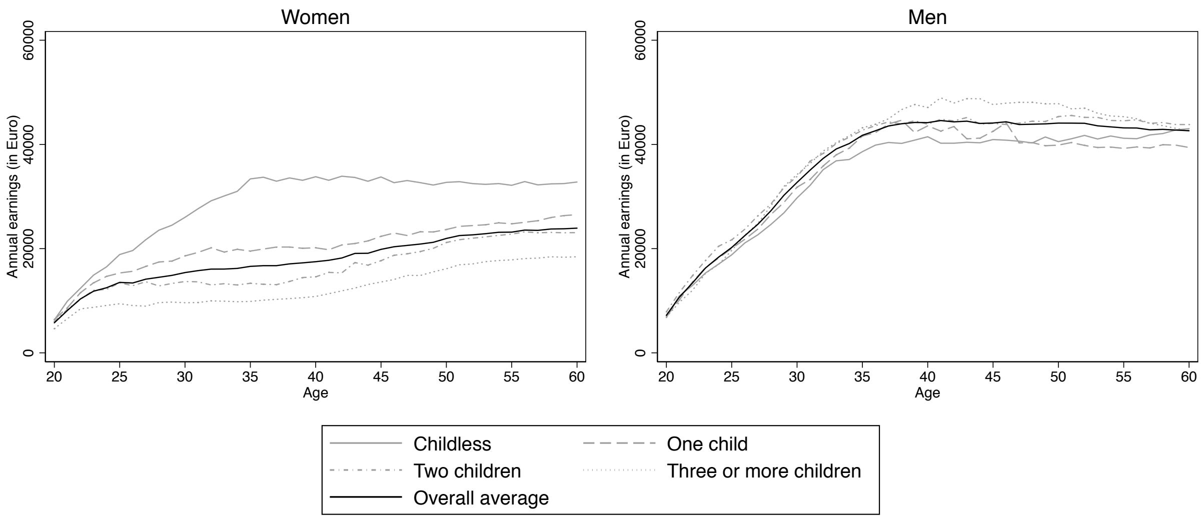
2.5.4 Additional Figures

Figure 2.16. Gender gaps in earnings by different concepts



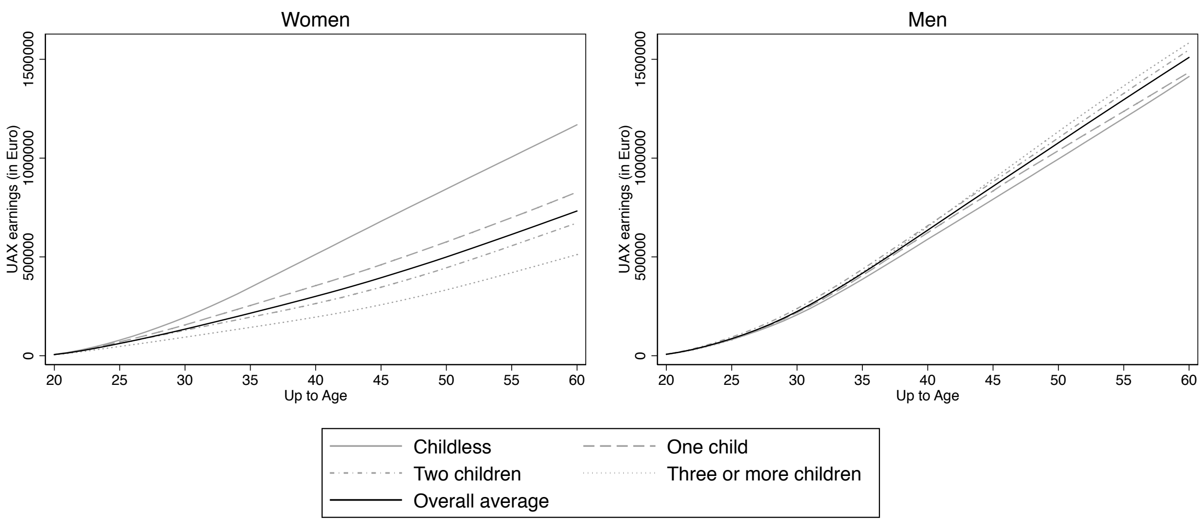
Notes: Individuals with zero UAX earnings are included in the calculation. For annual earnings gap, all employed and unemployed individuals are considered. Cohorts 1964-1972. *Source*: Own calculations based on SOEP v35.

Figure 2.17. Annual earnings by gender and number of children



Notes: Employed and unemployed individuals are considered. Number of children refers to the total number at age 50. Cohorts 1964-1972. *Source:* Own calculations based on SOEP v35.

Figure 2.18. UAX earnings by gender and number of children



Notes: Employed and unemployed individuals are considered. Number of children refers to the total number at age 50. Cohorts 1964-1972. *Source:*

Own calculations based on SOEP v35.

3 The Broken Elevator: Declining Absolute Mobility of Living Standards in Germany

3.1 Introduction

Throughout history parents have sought upward mobility for their children and until recently, this goal seemed within reach. But today, achieving this is arguably harder than ever before. Empirical evidence shows that the fraction of children earning more than their parents declined severely in the U.S. and some other industrial countries (Chetty et al., 2017; Berman, 2022b); the "elevator" to higher living standards for next generations might be broken.

We adopt a concept which allows us to estimate absolute income mobility by combining different data sources where no direct link between parents and their children is required. Absolute income mobility is measured as the fraction of children who earn more than their parents did. Using various German micro data sources, we first estimate detailed cross-sectional income and consumption distributions for children born 1962 through 1988 and their parents. Using transition probabilities from non-parametric copulas, we then create an intergenerational link between the distributions that allows us to estimate absolute income and consumption mobility in postwar Germany for the first time.

We find that the share of children earning more than their parents declined for cohorts 1962 through 1988 from 81 percent to 59 percent. While the decrease was steep for older cohorts with an all-time low of 49 percent for children born in 1978, mean rates of absolute mobility stabilized around 50 percent for cohorts born in the early 1980s and finally increased slightly for the youngest birth cohorts 1986 through 1988. These trends are robust with regard to age, correction for family size, measurement method, copula and data source. Further, we show that this downward trend is similar to the decline in absolute consumption mobility once we exclude the consumption categories of shelter and food.

Across the parental income distribution, children from middle class families were hit hardest with absolute mobility rates declining from 80 to 49 percent. This percentage point drop is higher than for children from all other parts of the income distribution. This adds to the empirical evidence documenting the erosion of the German middle class over time and gives another possible explanation for their fear of falling down the social ladder (e.g., Grabka et al., 2016; OECD, 2021).

A counterfactual analysis reveals that both lower economic growth rates and higher income inequality have driven the strong decline in absolute income mobility. Additionally, there are several long-term societal developments that underlie this shift; these include a trend toward smaller households, particularly among younger generations who are more likely to be living alone, as well as a movement away from the traditional male breadwinner household model. Thus, although younger households may have lower total income than their parents did, resources have to support less household members and therefore the reduction per capita is comparatively less significant.

This paper is linked to several strands of literature. First, it relates to the extensive research on relative intergenerational mobility. These studies investigate how children's outcomes depend on parental ranks, rather than looking at living standards across generations. Studies show that for the US, Germany and many other industrial countries children's outcomes highly depend on their parental background (e.g., Schnitzlein, 2009; Chetty et al., 2014; Bratberg et al., 2017). Most studies place Germany between the US and Scandinavian countries in terms of relative intergenerational mobility (Black and Devereux, 2011; Corak, 2013).

Second, this paper contributes to the scarce literature on absolute mobility. So far only a few studies on this topic have been published due to high data requirements, even though research has shown that people tend to think in absolute rather than in relative terms (Amiel and Cowell, 1999; Ravallion et al., 2018). The most seminal work in this space is from Chetty et al. (2017) which combines U.S. census and CPS data with de-identified tax records and finds that absolute income mobility decreased from 90 percent for children born in 1940 to 50 percent for children born in the 1980s. A study by Berman (2022b) finds that absolute income mobility decreased in eight other advanced economies in the second half of the twentieth century. For Germany, only one study exists that measures absolute social mobility by comparing parents' incomes and children's highest educational attainment (Dodin et al., 2021). The authors find an average five percentage point increase in the share of children obtaining the A-Level with every decile increase in parental income rank for children's birth cohorts 1980 through 1996.

Our paper adds to this literature in several ways. First, this study is the first to compare both parents' and children's incomes in Germany, therefore providing the first true measure of absolute income mobility for Germany. Even though the A-Level completion of children is a first important indication of young adults' labor market opportunities since it is needed to gain college access, there is still a high variation in earnings among college graduates by study field and college performance. Second, our data are more granular than those used in previous studies and allow us to assess measurement methods commonly used in absolute mobility research. Third, we are the first study to also investigate consumption mobility. This is of special interest since consumption is less volatile and better reflects long-term living standards (e.g. Attanasio and Pistaferri, 2016).

The remainder of the paper is structured as follows. Section 3.2 describes the data and the methodology used to estimate absolute mobility. Section 3.3 presents our results on income and consumption mobility. Section 3.4 concludes.

3.2 Data and Methodology

Absolute income mobility is measured as the fraction of children who earn weakly more than their parents. We measure it as the sum of the dichotomous comparison between parent and child income, divided by the number of children N_c in each birth cohort:

$$A_c = \frac{1}{N_c} \sum_i 1\{y_{ic}^k \geq y_{ic}^p\} \tag{16}$$

with y_{ic}^k being the income of child i in birth cohort c and y_{ic}^p being the income of its parents.

Ideally, empirical data on intergenerational mobility includes both true family ties as well as income data for parents and their children at the same age. Measuring absolute income mobility would then be straightforward, but such data is rarely available and only exists for a handful of birth cohorts in Germany. Since this paper aims to investigate German long term trends in absolute mobility for the first time, we use a theorem by Sklar (1959) to overcome this hurdle. The theorem shows that any multivariate cumulative distribution can also be obtained from the corresponding copula and its marginals, allowing us to connect various data sources to estimate rates of absolute mobility.

Following Chetty et al. (2017), we therefore connect parents' and children's marginal income distributions with a copula. In this context, the copula is a $100x100$ transition matrix that captures the probability of a parent in quantile y of the parent income distribution to have a child in quantile x of the child income distribution (e.g., the likelihood of parents in the 50th quantile to have a child in quantile $1, 2, ..., 100$).

We then estimate A_c as the product of the marginal distributions and the copula of parent and child ranks $C_c(r^k, r^p)$. Here, we denote $Q_c^k(r^k)$ and $Q_c^p(r^p)$ as the r^th quantile of child and parent income distributions. Intuitively, Equation (2) now shows the dichotomous comparison of child and parent income quantiles, weighed by the likelihood of occurence of the respective intergenerational quantile combination:

$$A_c = \int 1 \left\{ Q_c^k(r^k) \geq Q_c^p(r^p) \right\} C_c(r^k, r^p) dr^k dr^p \tag{17}$$

The first part of Equation (2) then yields 1 if a child of rank r^k earns weakly more than their parent with rank r^p. Afterwards, the copula weights the pairs by probability of their occurrence leading to an absolute income mobility estimate between 0 (all children earn less than their parents) and 1 (all children earn weakly more than their parents) for children's birth cohort c.

3.2.1 Copula

Empirical data on parent-child links are hard to come by - survey data often suffers from low numbers of observations, while administrative data rarely includes intergenerational links at all. We draw our data on parent-child pairs and their incomes from the German Socio-Economic Panel (SOEP), the only available data source in Germany with information on household incomes of both parents and their children. The SOEP is a highly representative German panel dataset, which follows individuals and their children since 1984 (Goebel et al., 2019). We then take the real average per adult household income to obtain a robust measure for relative income ranks and adjust for household size (Mazumder, 2005). Following Chetty et al. (2017), we use parents' incomes between ages 30 and 60 to obtain their rank within the parental income distribution.[36] For children, we include their incomes between ages 30 and 34.[37] This leaves us with 3,456 parent-child pairs that we use to identify the most likely copula fit. We provide a detailed description of our copula methodology in Appendix 3.5.2, including further robustness checks.

3.2.2 Marginal income distributions

We use the German Mikrozensus (MZ) to construct marginal income distributions for both parents and their statistical children. Starting in 1957, the MZ is the longest German micro data series and due to its mandatory participation the most reliable source of information on households' socio-economic situation.[38] It represents one percent of the entire German population, with 810,000 individuals in 370,000 households reporting information about their household context, educa-

[36] To obtain the rank in the lifetime earnings distribution, using an income measure between mid-thirties and mid-fifties is preferable. At this time in life, correlation between annual and lifetime earnings is highest with around 0.9 (e.g., Björklund, 1993; Bönke et al., 2015).

[37] We apply the same approach to obtain a copula to estimate absolute consumption mobility. Since SOEP data does not include information on consumption but only expenditure, we construct an expenditure copula to estimate absolute consumption mobility. This approach is possible for two main reasons: First, expenditures and consumption are very close in their concepts and should lead to similar copulas. And second, the shape of the copula does hardly influence the estimation process, while the marginal distributions largely determine the rates of absolute mobility (Berman, 2022b). To avoid any confusion, we will refer to this copula as the consumption copula going forward.

[38] The first available data for research purposes starts only with 1962. Hence, our study focuses on birth cohorts 1962 and younger. In addition, data for single years are occasionally missing throughout the past 60 years. Please find a detailed overview of all data sources and data waves we used in this study in Table 3.1 in the Appendix.

tion, labor market situation and disposable income. Disposable income is defined as household income after taxes and benefits and therefore best describes the income that a household truly has available for their consumption. Since this income concept offers a closer approximation of households' living standards than other income concepts such as pre-tax or post-tax incomes, it is best suited for our study to evaluate absolute mobility trends.

The MZ does not provide income as a continuous variable but as tabulated data, including the number of households in each of the up to 24 income categories. To obtain continuous income distributions from the binned data, we use a generalized Pareto estimation (Blanchet et al., 2022). Appendix 3.5.1.2 provides a comprehensive overview of the methodology and its robustness. Still, we cannot eliminate all risk of introducing some measurement noise. Therefore, we also investigate absolute income mobility in Germany using another well-known data source - the Income and Expenditure Survey (*Einkommens- und Verbraucherstichprobe*, EVS), a representative household sample covering 0.1% of the German population.[39] It has been collected in five year intervals by the German Federal Statistical Office since 1962.[40] Despite covering a smaller sample of the German population and relying on voluntary participation, it reports continuous incomes for its participants and provides the opportunity to test the robustness of our results even further. We find that using both the MZ and the EVS yield similar absolute income mobility trends, confirming one more time the reliability of the generalized Pareto estimation in retrieving continuous income distributions.

We construct the marginal income distribution for both parents and children by measuring their real disposable family incomes at age 30. We obtain marginal income distributions for children born 1962 through 1986 directly from each MZ wave since every child in a given cohort turns 30 in the same year. Obtaining the parent's income distribution is not that straightforward. Parents' age at childbirth varies widely and children of the same birth cohort can have very differently aged parents. Still, for comparability we also want to measure the living standard in the parent's

[39] Please see Bönke et al. (2013) for a detailed overview of EVS data and how to harmonize data waves over time.

[40] The EVS lacks waves for 1968 and 1973. Using corresponding MZ waves and the EVS wave 1978, we were able to reconstruct the relevant measures for these years. Our estimates for absolute income mobility using the MZ or EVS yield similar results (see Figure 3B), showing that this approach is successful.

household at age 30. Hence, we need to pool observations from several MZ waves to derive parents' marginal income distributions at age thirty for each child birth cohort.

For example, we construct the parental marginal income distributions for children born in 1982 as follows: First, we use waves 1982 to 1996 and select all parents aged 30 who had a child that was born in 1982. That way we include all income observations at age 30 if the parent had a child of this birth cohort at age 30 or younger. For older parents, we turn to waves 1968 to 1980 and select all individuals aged 30 in each survey year.[41] We assign this group a weight equal to the fraction of individuals aged 31 to 45 in 1982 who gave birth to a child that year. Because it is not possible to identify future parents in waves before 1982, we follow Chetty et al. (2017) and assume that the income distribution of older parents is representative of the general income distribution.

The MZ only includes information on disposable incomes but the EVS also includes data on households' expenditures and consumption. Hence, in addition to testing the robustness of our results on absolute income mobility with a different data source, the EVS also provides the unique opportunity to assess whether income is a sufficient proxy for households' consumption. This is of particular interest as consumption is less volatile than income and therefore reflects long-term living standards better (e.g., Attanasio and Pistaferri, 2016). To construct both parents' and children's marginal income distributions using the EVS, we follow the same procedure as described above for the MZ data with one exception: Since EVS data is not annual but only quinquennial, we compare parents' and children's incomes at a wider age window, namely at ages 30 to 34.

3.3 Results

After combining the marginal income distributions of children and their statistical parents via the copula, we are now able to assess the German trend in absolute income mobility for the first time. We will show that our results are robust across ages, family sizes, data sources, measurement methods and units. Appendix 3.5.2 also shows the robustness of our results regarding the

[41]We set the age limit to 45, assuming that no children are born to parents after age 45. This assumption is not only realistic for mothers. In 2020, only six percent of fathers were 44 or older at the birth of their children (Pötzsch et al., 2020).

copula. Further, we investigate the main drivers of the steep drop in absolute income mobility over time: declining economic growth rates, rising inequality, and demographic changes. Lastly, this is the first study to show results on absolute consumption mobility, evaluating if income as a measurement unit leads to credible results on absolute mobility of living standards.

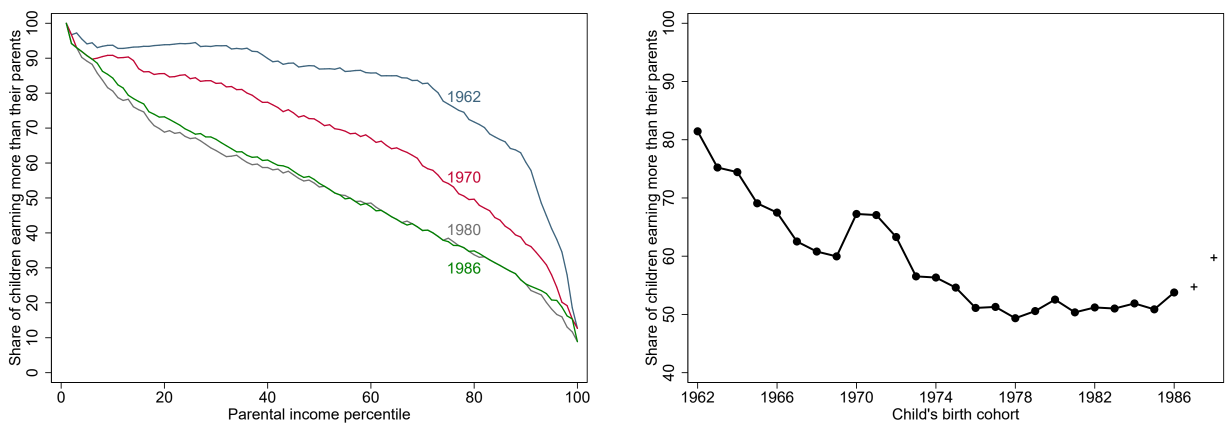
3.3.1 Absolute income mobility

Figure 3.1a shows the fraction of children earning more than their parents at age 30 by parental income percentile for children born in 1962, 1970, 1980 and 1986. In the 1962 cohort, almost all children had more disposable income than their parents did. Rates of absolute mobility naturally declined with higher parental income percentiles since it became harder for children to earn more than their already well off parents.

Afterwards, absolute income mobility rates declined gradually for younger cohorts regardless of their parental income. For example, at the 20th percentile of the parental income distribution, children born in 1962 still had a 94 percent chance to be better off than their parents. For the 1986 cohort, the same likelihood decreased to only 73 percent. At the 80th parental income percentile, the drop for younger cohorts was even more severe with a difference of 37 percentage points between the 1962 and 1986 cohort.

Aggregating absolute mobility rates across all parental incomes then yields the mean rates of absolute mobility for each birth cohort (see Figure 3.1b). Overall, absolute income mobility declined sharply for younger birth cohorts. Children born in 1962 still had a chance of 81 percent to grow up earning more than their parents did. This probability decreased steeply through the 1970s cohorts, with an all-time low of 49 percent for children born in 1978, only 15 years after the oldest cohort of our study was born. Afterwards, mean rates of absolute mobility stabilized around 50 percent for cohorts 1979 through 1985, followed by a slight increase for the younger cohorts. The youngest children born in 1988 experienced a mean rate of absolute income mobility of 59 percent. Overall, absolute income mobility fell by 23 percentage points for children's birth cohorts 1962 through 1988. This result holds also true if we measure parents' and children's incomes at age 35 (see Figure 3.14 in the Appendix).

Figure 3.1. The evolution of absolute income mobility



(a) By parental income

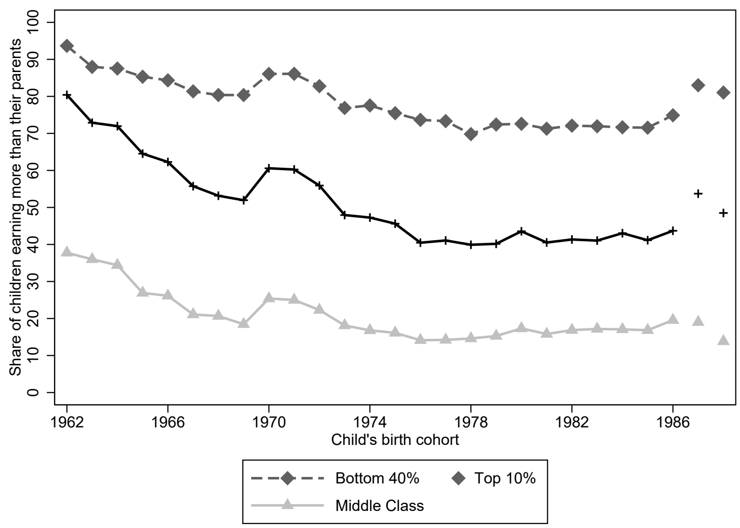
(b) Mean rates

Note: We only have Mikrozensus data until 1986. To show the overall trend in Germany to its fullest extent, we added EVS estimates for children's birth cohorts 1987 and 1988 using plus symbols.
Source: Mikrozensus 1962-2016, EVS 1978-2018, SOEP v38, own calculations.

Noticeably, the short-term bump in absolute mobility rates for children born in the early 1970s stands out from the overall decline. This short-lived uptick has two key drivers: On one hand, parents of the early 1970s cohorts were in the middle of the first oil crisis when we measured their incomes. The first oil crisis caused one of the steepest economic recessions leading to the first rise in mass unemployment in the German postwar era. Hence, average incomes during this period were temporary lower than usual. On the other hand, children's incomes thirty years later in the early 2000s are measured during the last lag of the economic boom after the reunification crisis, leading to higher incomes on average. These two extremes yield the temporary bump in absolute income mobility, showing the importance of economic growth in shaping absolute mobility patterns. However, even with mean rates oscillating through boom and bust periods, the overall decline in absolute income mobility remains steep.

Our results in Figure 3.1a have already hinted at which parts of the income distribution are driving this overall decline in absolute mobility. Figure 3.2 extends this analysis and confirms that children from middle class families were hit hardest.[42] Their absolute mobility declined by 31 percentage points from 80 to 49 percent. This percentage point drop is higher than for children from all other parts of the income distribution. Absolute income mobility in the bottom 40 percent dropped from 94 to 81 percent and in the top 10 percent from 38 to 14.[43]

Figure 3.2. Absolute income mobility of different income groups



Note: We only have Mikrozensus data until 1986. To show the overall trend in Germany to its fullest extent, we added EVS estimates for children's birth cohorts 1987 and 1988 using plus symbols. All subsequent estimations using the Mikrozensus sample will focus on children born from 1962 through 1986 and their parents.
Source: Mikrozensus 1962-2016, EVS 1978-2018, SOEP v38, own calculations.

3.3.2 Sensitivity analysis: Measurement method and data source

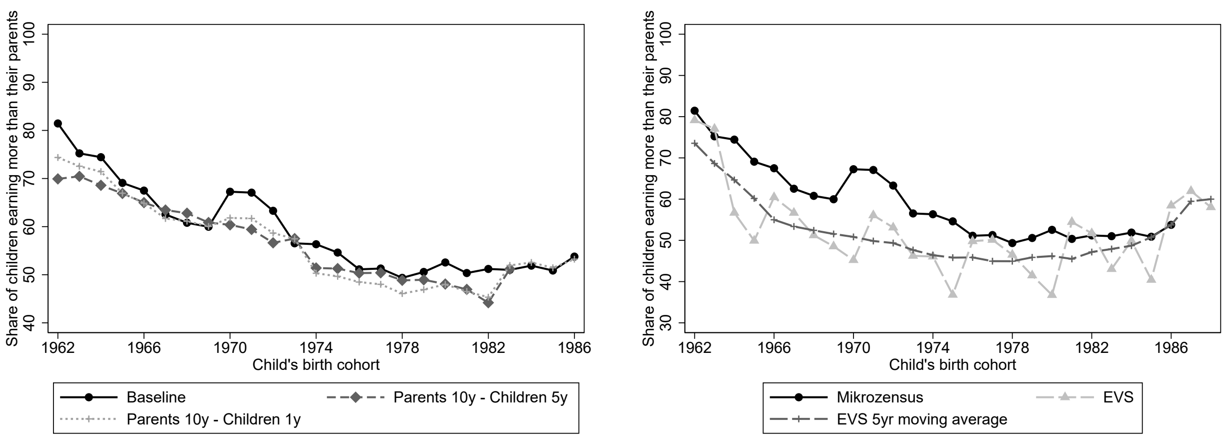
Next, we investigate how sensitive our findings are with regard to the data source, measurement method and measurement unit. For our baseline results, we measure parents and children with MZ data which is collected annually. This is different from other studies on absolute income mobility which only had access to decennial data for parents' incomes (e.g., Chetty et al., 2017). Since our data allows a more precise measurement, it provides us the opportunity to test the influence of the measurement window length on absolute income mobility estimates for the first time. Fig-

[42]We define the middle class as families from the $41^{s}t$ through $90^{t}h$ percentile.
[43]Again, overall mobility rates are smaller for children from higher-income families since it's naturally harder to earn more than their parents did.

ure 3.3a depicts our baseline results, as well as the estimates using decennial data for parents' incomes and quinquennial data or annual data for children. Clearly, all three measurement windows lead to very similar results, illustrating that the drop in absolute income mobility is also robust regarding the measurement method.

Since 3.3a also confirms that decennial data for parents and quinquennial data for children are sufficient to measure absolute income mobility trends reliably, we can use the EVS data with confidence for another robustness check of our baseline results. Figure 3.3b shows the mean rates of absolute income mobility for both data sources, the MZ and the EVS. Despite small deviations, both data sources yield the same conclusion: Absolute income mobility has indeed declined strongly for younger birth cohorts.

Figure 3.3. Sensitivity of absolute income mobility estimates



(a) Different measurement methods

(b) Different data sources

Note: We use the Mikrozensus waves 1962, 1973, 1982, 1992 and 2002 to construct parents' marginal income distributions from decennial data. To obtain children's marginal income distributions from quinquennial data, we use the Mikrozensus waves 1993, 1998, 2003, 2008 and 2013. Hence, the estimates using quinquennial data for children end with the child birth cohort 1983.
Source: Mikrozensus 1962-2016, EVS 1963-2018, SOEP v38, own calculations.

3.3.3 Absolute consumption mobility

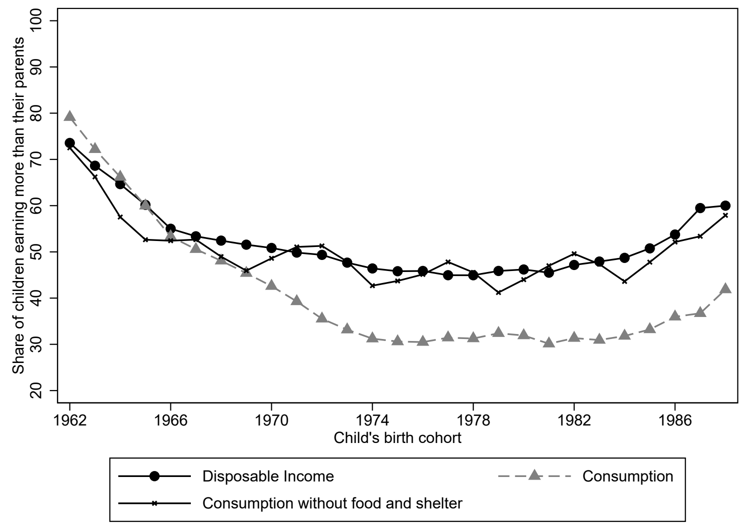
Showing that the MZ and EVS both show the same trend in absolute income mobility does not only serve the purpose of another robustness check for our baseline results. It also confirms that the EVS is a reliable data source to assess absolute mobility trends in general. This is of particular interest since the EVS does not only record households' incomes, but also their expenditures and consumption. Consumption is less volatile than income and reflects long-term living standards better (e.g., Attanasio and Pistaferri, 2016). Since good consumption data is scarce, income is usually the second best proxy to compare the intergenerational mobility of living standards. The EVS provides us with the unique opportunity to compare absolute mobility rates in income and consumption and to assess for the first time whether income really is a reliable proxy for living standards when investigating absolute mobility trends.

Figure 3.4 compares absolute income and consumption mobility trends in Germany using EVS data. Notably, analyzing absolute consumption mobility reveals an even steeper drop in absolute mobility than when using incomes. While both, absolute income and consumption mobility, were still high for the oldest child cohort and dropped steeply for the 1960s and early 1970s child cohorts, starting with children born in 1975 differences in the two absolute mobility trends arise. While absolute income mobility stabilizes around a low level of 45 percent, absolute consumption mobility continues to fall to 30 percent for child cohort 1983. For the youngest cohorts, both measures suggest a small uptick in absolute mobility – however, these increases are not able to offset the previous severe declines in living standards. Though while absolute mobility in income has fallen by 14 percentage points according to the EVS, the decline in consumption mobility is with 38 percentage points more than twice the rate. [44]

However, the steeper decline in absolute consumption mobility is mainly driven by lower absolute mobility rates for shelter and food. If we exclude these two consumption categories, we find that mobility rates of all other consumption categories paint a very similar picture than income. We therefore conclude that disposable income is indeed a reliable proxy for consumption that captures differences in living standards across generations well.

[44]The shape of the decline in absolute consumption mobility by parental income percentile is very similar to our findings for absolute income mobility (see Figure 3.1).

Figure 3.4. Absolute income and consumption mobility



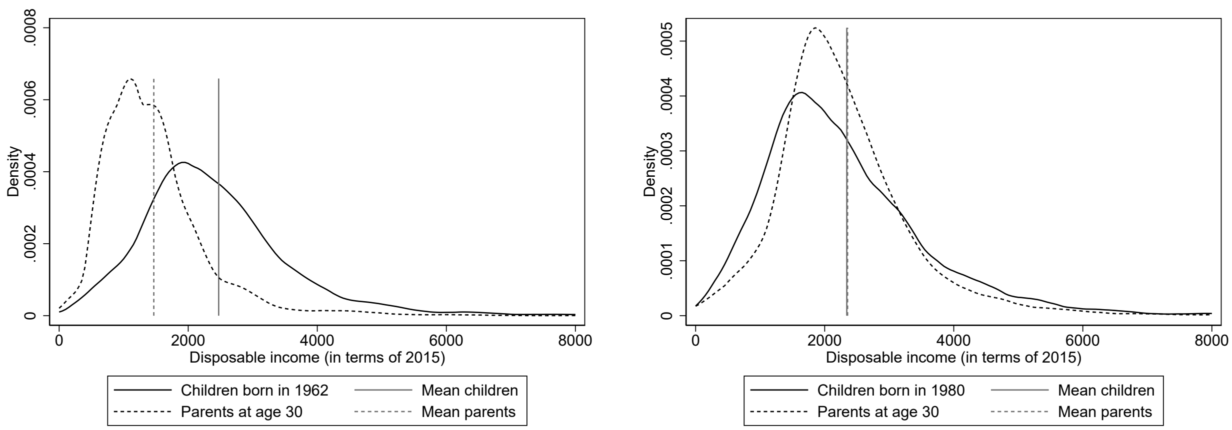
Note: We used five year moving averages to account for the quinquennial EVS data.
Source: EVS 1963-2018, SOEP v38, own calculations.

3.3.4 The roles of growth and inequality

Economic growth plays not only a role in short-term oscillations but is also a possible main driver of the overall downward trend in absolute income mobility. GDP growth declined steeply from the heights of the postwar years until 2018. At the same time, cohort-specific lifetime earnings inequality increased strongly by 85 percent (Bönke et al., 2015). Since we know from other countries that a rise in inequality can also contribute to a drop in absolute income mobility, we will also investigate inequality as a possible source of the decline (Chetty et al., 2017; Berman, 2022b).

Figure 3.5 illustrates why changes in economic growth and inequality likely influence the evolution of absolute mobility over time. It shows the marginal income distributions of (a) children born in 1962, (b) children born in 1980 and their respective parents. For the oldest child cohort, we see that their average real income at age 30 is noticeably higher than that of their parents, hinting at the high income growth this child cohort still experienced. In stark contrast, the mean incomes of the 1980 child cohort and their parents are even hard to tell apart by eye, underlining that the declining GDP growth has made it significantly harder for younger cohorts to earn more than their parents did. However, this is not the only difference between the income distributions. We also observe that both child income distributions are less centralized and reveal a greater spread compared to their respective parents, showing that inequality has increased over time as well.

Figure 3.5. Marginal income distributions of children and their statistical parents



(a) Child birth cohort 1962

(b) Child birth cohort 1980

Source: Mikrozensus 1962-2016, own calculations.

But how would absolute mobility look like for younger cohorts if they still experienced high GDP growth rates? And what would it look like if income inequality had not risen so steeply? To investigate these questions, we follow Chetty et al. (2017) and simulate two counterfactual scenarios: The higher GDP growth scenario and the more inclusive GDP growth scenario.

The first counterfactual scenario analyzes what would have happened if the 1980 child cohort had experienced the same high GDP growth rates as the oldest child cohort 1962 (blue line). To do so, we first estimate the counterfactual 2010 GDP per working-age family

$$G^C_{2010} = G^0_{1980} \text{ x } 1.023^{30}$$

G^C_{2010} is the GDP we would have observed if family incomes had grown 2.3 percent between 1980 and 2010, instead of the truly observed growth rate of 1.7 percent during this time (World Bank national accounts data, and OECD National Accounts data files). This 2.3 percent growth is the same average GDP growth rate the oldest child cohort 1962 experienced between 1962 to 1992, when we measured their incomes at age 30. Next, we calculate the income share $\pi^k_{q,1980}$ for every income percentile q in the marginal income distribution of the 1980 children k. With those two ingredients at hand, we can now estimate the counterfactual income $y^{k,C1}_{q,1980}$ of the 1980 children for each income percentile q as

$$y^{k,C1}_{q,1980} = \pi^k_{q,1980} \text{ x } G^C_{2010}$$

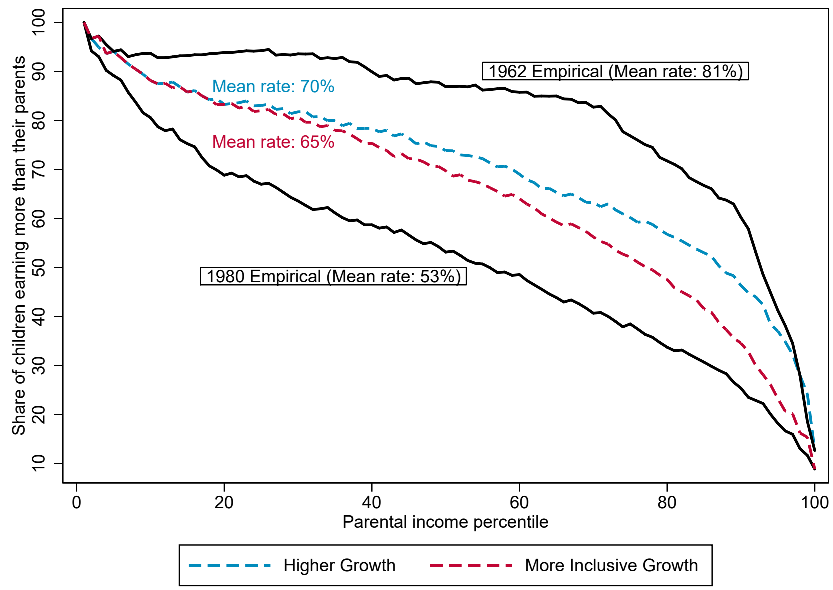
The blue line in Figure 3.6 shows that absolute mobility for the 1980 child cohort would have risen significantly across the entire income distribution if they had experienced the same GDP growth as the 1962 child cohort. The higher GDP growth scenario would have led to a mean rate of absolute mobility of 70 percent, notably higher than the truly observed 53 percent. However, even the higher growth rate would not have been sufficient to avoid the decline in absolute mobility over time. In fact, it would have needed a GDP growth rate of 3.2 percent to offset the entire decline (see Figure 3.15 in the Appendix). This confirms that slower economic growth rates alone do not fully explain the steep downward trend in absolute mobility that we find for younger cohorts.

The second counterfactual analysis investigates how absolute mobility for the 1980 cohort would have evolved if they had still experienced the more inclusive income growth of the 1962 cohort (red line). This time, we do not alter the size of the pie, just how it is distributed. Hence, we redistribute the income shares of the 1980 cohort to match the more equal income distribution of the 1962 cohort without changing the 2010 GDP itself. The more inclusive growth scenario can then be written as

$$y^{k,C2}_{q,1980} = \pi^k_{q,1962} \text{x} G^0_{2010}$$

leading to a counterfactual income distribution for the 1980 child cohort.

Figure 3.6. Counterfactual analysis



Note: Aggregating absolute mobility rates across all parental incomes yields the mean rates of absolute mobility. The empirical mean rates for birth cohorts 1962 and 1980 are also shown in Figure 3.1b.
Source: Mikrozensus 1962-2016, SOEP v38, own calculations.

In the more inclusive GDP growth scenario, we also find that many more children would have earned more than their parents did if incomes were as equally distributed as for the oldest child cohort. Hence, the counterfactual mean rate of absolute mobility amounts to 65 percent. Again, the increase in absolute mobility is visible across the entire income distribution, even though it is - as expected - more pronounced in the bottom 40 percent of the distribution.

Overall, our counterfactual analysis reveals that both lower economic growth rates and higher income inequality had strong negative effects on absolute income mobility in Germany. We also find that the decline in GDP growth had a slightly stronger negative effect. That said, GDP growth rates were extraordinarily high in the 1960s which is why this postwar period is often referred to as the *economic miracle years*. Hence, it will be interesting to repeat this counterfactual analysis with future cohorts to see how the influence of these two main drivers change with more time.

3.3.5 The role of societal changes

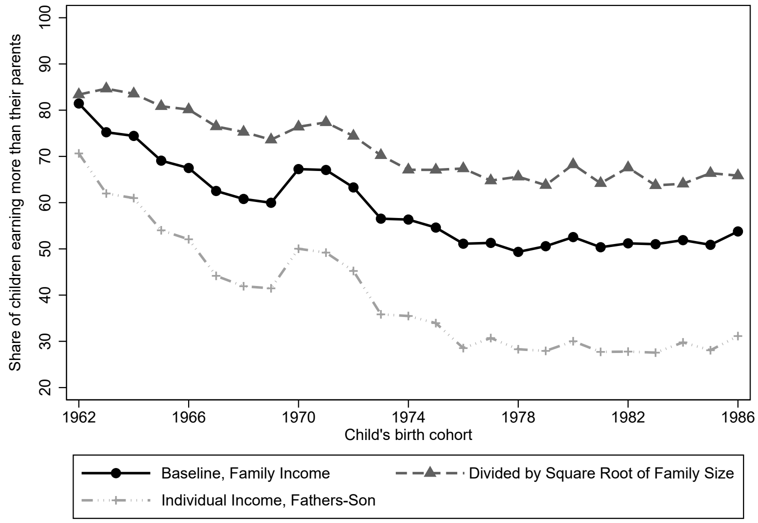
We have identified lower economic growth and rising inequality as main drivers of the decline in absolute income mobility. But the evolution of absolute income mobility in Germany is also rooted in several societal long-term developments: younger cohorts live in smaller households and are more often singles, a general shift away from the male breadwinner model, and changes in family policies regarding parental leave and childcare.

Figure 3.7 depicts the mean rates of absolute mobility when we adjust for family size and the number of earners. The mechanical effect of measuring absolute mobility of family income instead of equivalent income is shown when comparing the black line and the dark grey line, respectively.[45] If family size at age 30 would have been ceteris paribus constant over time, the two lines would coincide. However, since the average family size has shrunk over the past decades, absolute mobility declined less for equivalent income than for unadjusted family income. In addition, younger child cohorts are more likely to (still) be single at age 30 (see Figure 8a). So, while households have less total income nowadays than their parents did, the decline in resources per family member is less severe. Hence, absolute mobility of equivalent income is still at 66 percent for the youngest child cohort 1986, 12 percentage points higher than for family income.

Next, we also want to adjust for the for the number of earners. Over the past decades, we have seen a shift away from the male breadwinner model, with more and more women working and contributing to the family income. When only looking at individual absolute mobility between fathers and sons, we find that the drop in absolute mobility is significantly steeper than for families as the measurement unit. This finding mirrors the general decline in economic opportunities after the economic miracle years in the 1960s and the gradual decline of the industrial sector, which to this day still predominantly employs men.

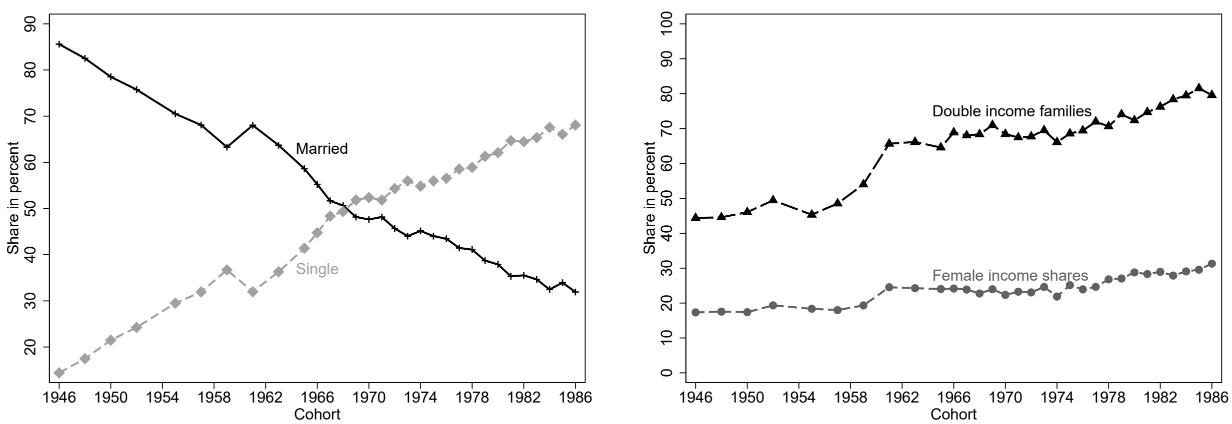
[45]We calculated the equivalent income by dividing the family income by the square root of family members.

Figure 3.7. Mean rates of absolute mobility by income concept



Source: Mikrozensus 1962-2016, SOEP v38, own calculations.

Figure 3.8. Changes in household structures over time



(a) Men's marital status

(b) Double income households

Note: Men's marital status, the share of double income household and the female income shares are all measured at age 30.
Source: Mikrozensus 1962-2016, own calculations.

However, we do not see the severeness of this evolution in the absolute mobility rates of family income. While in the 1960s, the difference between the individual and household perspective is still small, the gap gradually increases with younger cohorts, largely driven by the fact that married women are much more likely to be employed than back in the days (see Figure 3.8b). In the 1962 cohort, 65 percent of married women were active on the labor market, contributing 24 percent to the entire income of both partners. In the 1986 cohort, the share of working wives rose to 80 percent with an average income share of 31 percent, weathering part of the sons' income losses at the household level. This increase in female labor market activity is not only due to changes in social norms, but also due to the decline in paid parental leave duration, the introduction of incentives for both parents to take some time off, while introducing publicly subsidized childcare for children aged one and older in 2013, reducing mother's opportunity costs to return to their jobs. All these policy changes led to the declined importance of the male breadwinner model.[46]

3.4 Conclusion

We provide novel evidence on magnitude, pattern, and evolution of absolute income and consumption mobility in postwar Germany. Our analysis yields three main results for children born between 1962 and 1988 and their parents.

First, we find that the share of children earning more than their parents did steeply declined for cohorts born from 1962 through 1988, dropping from 81 percent to 59 percent. The time trend follows an inverse u-shape: While absolute mobility declined for children's birth cohorts 1962 through the early 1980s, it saw an uptick for the youngest birth cohorts 1986 through 1988. This result is robust across different ages, family sizes, measurement methods, copulas, and data sources. In addition, we show that this trend is very similar to the decline in absolute consumption mobility once we exclude the consumption categories of shelter and food.

Second, when looking at the parental income distribution, we document that children from middle-class families experienced the most significant declines in absolute income mobility, with a drop of 31 percentage points. This decrease is larger than for children from the lower and upper parental income distribution.

Third, our counterfactual analysis revealed that lower economic growth rates and higher in-

[46]We forgo a counterfactual analysis of formation of partnership and families here since the latter is driven by its socioeconomic environment which has changed in many areas over time. Furthermore, those changes have been intertwined in partially unobservable ways. Hence, any reweighting procedures would not be sufficient and introduce more bias than explanation.

come inequality have contributed in similar capacities to the steep decline in absolute income mobility. Hence, the German social market economy was not able to buffer the decline in absolute mobility rates seen in other countries like the United States. In addition to economic factors, societal factors also played a role in shaping absolute mobility. Smaller households, especially among younger generations who are more likely to live alone, intensified the decline in absolute mobility, while the departure from the traditional male breadwinner household model prevented an even more severe decline due to women's higher income contributions for younger birth cohorts.

Even though this study documented a strong decline in absolute income mobility over decades, we do not fully observe the intergenerational mobility of wealth. While incomes from wealth are included in disposable incomes, inheritances and gifts usually transfer much later in life from parents to children than at age 30. However, those intergenerational transfers could offset the steep declines that we see for children from middle- and higher-income families, while children from lower income families might not have access to such resources. Hence, the decline in absolute income mobility along the distribution could have very different real-life impacts on children depending on their parental background. Hence, future research in this field should expand its focus beyond income alone and incorporate a more comprehensive analysis that considers wealth and intergenerational transfers. This approach can offer a more nuanced understanding of the complex nature of intergenerational mobility.

3.5 Appendix

3.5.1 Marginal Income Distributions

The following sections give an overview of all data sources used for each year and provide more information on the generalized Pareto estimation that was used to construct continuous income distributions from tabulated MZ income data.

3.5.1.1 Data sources

Table 3.1. Data sources for this study

Year	Data sources
1962	Income and Expenditure Survey (EVS; SUF), Mikrozensus (MZ; on site, full sample)
1963	Mikrozensus (MZ; on site, full sample)
1964	Mikrozensus (MZ; on site, full sample)
1965	Mikrozensus (MZ; on site, full sample)
1966	Mikrozensus (MZ; on site, full sample)
1967	Mikrozensus (MZ; on site, full sample)
1968	Mikrozensus (MZ; on site, full sample)
1969	Mikrozensus (MZ; on site, full sample)
1970	Census (VZ; SUF)
1973	Mikrozensus (MZ; SUF)
1976	Mikrozensus (MZ; SUF)
1978	Income and Expenditure Survey (EVS; SUF), Mikrozensus (MZ; SUF)
1980	Mikrozensus (MZ; SUF)
1982	Mikrozensus (MZ; SUF)
1983	Income and Expenditure Survey (EVS; SUF)

1985	Mikrozensus (MZ; SUF)
1987	Mikrozensus (MZ; SUF)
1988	Income and Expenditure Survey (EVS; SUF)
1989	Mikrozensus (MZ; SUF)
1991	Mikrozensus (MZ; SUF)
1993	Income and Expenditure Survey (EVS; SUF), Mikrozensus (MZ; SUF)
1995	Mikrozensus (MZ; SUF)
1996	Mikrozensus (MZ; SUF)
1997	Mikrozensus (MZ; SUF)
1998	Income and Expenditure Survey (EVS; SUF), Mikrozensus (MZ; SUF)
1999	Mikrozensus (MZ; SUF)
2000	Mikrozensus (MZ; SUF)
2001	Mikrozensus (MZ; SUF)
2002	Mikrozensus (MZ; SUF)
2003	Income and Expenditure Survey (EVS; SUF), Mikrozensus (MZ; SUF)
2004	Mikrozensus (MZ; SUF)
2005	Mikrozensus (MZ; SUF)
2006	Mikrozensus (MZ; SUF)
2007	Mikrozensus (MZ; SUF)
2008	Income and Expenditure Survey (EVS; SUF), Mikrozensus (MZ; SUF)
2009	Mikrozensus (MZ; SUF)
2010	Mikrozensus (MZ; SUF)
2011	Mikrozensus (MZ; SUF)
2012	Mikrozensus (MZ; SUF)
2013	Income and Expenditure Survey (EVS; SUF), Mikrozensus (MZ; SUF)
2014	Mikrozensus (MZ; SUF)

2015	Mikrozensus (MZ; SUF)
2016	Mikrozensus (MZ; SUF)
2018	Income and Expenditure Survey (EVS; SUF)

3.5.1.2 Generalized Pareto Estimation

Most income distributions share similar statistical characteristics. Following a seminal methodological approach by Blanchet et al. (2022), implemented through their R-package *gpinter* (http://wid.world/gpinter), we take advantage of these similarities and use the generalized Pareto estimation to recover continuous income distributions from tabulated MZ income data. Using this intermediate step, we are able to construct marginal income distributions from MZ data.

Generalized Pareto curves estimate the inverted Pareto coefficients $b(p)$ for each income percentile p included in the tabulated income.[47] Considering a sample of $(X_1, ..., X_n)$ of n independent and identically distributed realizations of X, the empirical estimator of the inverted Pareto coefficient $\widehat{b_n}(p)$ for each income percentile p can be expressed as follows:

$$\widehat{b_n}(p) = \frac{1}{(n - \lfloor np \rfloor) X_{(\lfloor np \rfloor + 1)}} \sum_{k=\lfloor np \rfloor + 1}^{n} X_{(k)} \tag{18}$$

with $\lfloor np \rfloor$ denoting the floor function of x.

After computing $b(p_1), ..., b(p_k)$, the next step consists of the interpolation of the entire generalized Pareto curve $b(p)$. To guarantee that the resulting function will be consistent with the input data, a transformation of the Lorenz curve with its direct relation to the lognormal distribution is used. Afterwards, the methodology by Blanchet et al. (2022) relies on piecewise polynomials of degree five over each income bracket, allowing a flexible interpolation within reasonable boundaries for income distributions. This interpolation method is used for fractiles $p_1, ..., p_k$. To estimate

[47] The MZ provides us with the number of households in each income category. Hence, we can calculate which income percentiles correspond with each income bracket.

the distribution outside of this range, extrapolation for fractiles where $p > pk$ is then applied.

Using extensive tax data, Blanchet et al. (2022) are able to show that these findings offer greater precision than all other estimation methods. In addition, Bönke et al. (2023) are able to match the continuous income distributions provided by the SOEP when they apply this approach to artificially tabulated SOEP data, confirming the high reliability of this methodology.

3.5.2 Copula

3.5.2.1 Copula Estimation

To obtain our copula to connect parents' and their statistical children's marginal income distributions, we proceed in four steps. First, we obtain truly observed parent and child incomes from the SOEP. We follow Chetty et al. (2017) and take the average income for children between ages 30 to 34, and between 30 and 59 for parents. The range of parental income is larger to maximize the number of observations. We are left with 3,465 observations for which we observe both parent and their children's incomes.

Second, we estimate a wide range of maximum-likelihood-based copula models to identify the model best representing the dependency structure of the joint sample. We choose the copula that minimizes both the Akaike information criterion (AIC) and Bayes information criterion (BIC). We find that for income, the survival BB1 copula best resembles the truly observed bivariate distribution (see Table 3.2).[48] A BB1 copula is characterized by the higher dependence at the margins of the distribution and also allows for asymmetric tail dependence (Nikoloulopoulos et al., 2012).

Third, after fitting the shape of the bivariate distribution in step 2, we now estimate the best fit for the underlying marginal distributions – separately for both parents' and children's income. Fourth, applying Sklar's theorem (see Sklar, 1959), we retrieve the fitted bivariate distribution by combining the survival BB1 copula with the chosen marginals. We then simulate ten million parent-child-pairs, which enables us to calculate a stable 100x100 rank-rank-matrix.

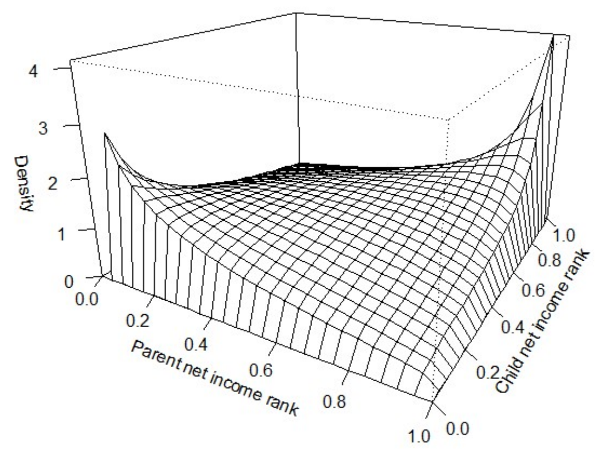
[48]We provide the first ten results in Table 3.2. Other results are available from the authors upon request.

Table 3.2. Comparing copula fits

Rank	Family	Log likelihood	AIC	BIC
1	Rotated BB1 copula (180 degrees; “survival BB1”)	486	-969	-957
2	Rotated BB7 copula (180 degrees; “survival BB7”)	484	-964	-952
3	BB1 copula	483	-963	-951
4	Student t copula (t-copula)	483	-961	-949
5	BB7 copula	481	-959	-946
6	Rotated Gumbel copula (180 degrees; “survival Gumbel”)	460	-918	-912
7	Rotated BB6 copula (180 degrees; “survival BB6”)	460	-916	-903
7	Rotated BB6 copula (180 degrees; “survival BB6”)	460	-916	-903
8	Gaussian copula	446	-891	-885
9	Rotated Tawn type 1 copula (180 degrees)	423	-842	-830
10	Gumbel copula	418	-834	-828

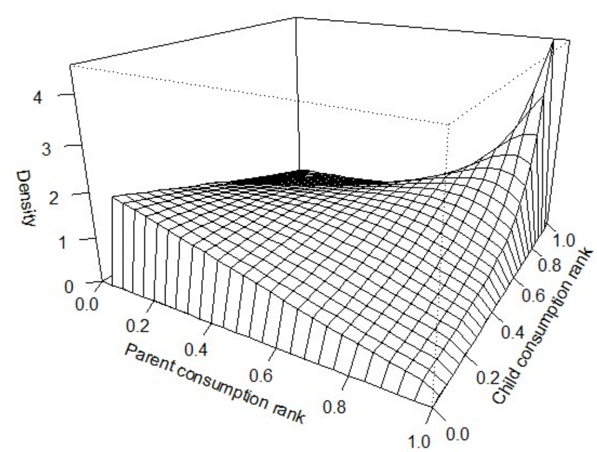
Since we analyze absolute mobility in disposable income and consumption, we cannot assume that we can use the same copula for both concepts. Proceeding as described above, we identify a survival BB8 copula as most likely to resemble the truly observed bivariate distribution for consumption. Compared to a BB1 copula that captures lower and upper tail dependence, a BB8 copula captures upper tail and central dependence (Sriboonchitta et al., 2013). Figure 3.9 and 3.10 show our copulas for income and consumption. When comparing both copulas, the differences between the lower tails of the copulas are most notable, as expected. The intergenerational persistence at the bottom is smaller for consumption than income, the persistence at the top is higher for consumption. Overall, the copulas are quite similar and testing differences using the Hellinger distance underline this finding. These results are in line with Berman (2022b), who shows that marginal distributions are far more important than copulas in shaping absolute intergenerational mobility trends.

Figure 3.9. Income copula



Note: This figure displays a survival BB1 copula with ML parameters $\theta = 0.137$ and $\delta = 1.315$. For BB1 copulas, the ML parameters are restricted to $\theta > 0$ and $\delta \geq 1$.
Source: SOEP v38, own calculations.

Figure 3.10. Consumption copula



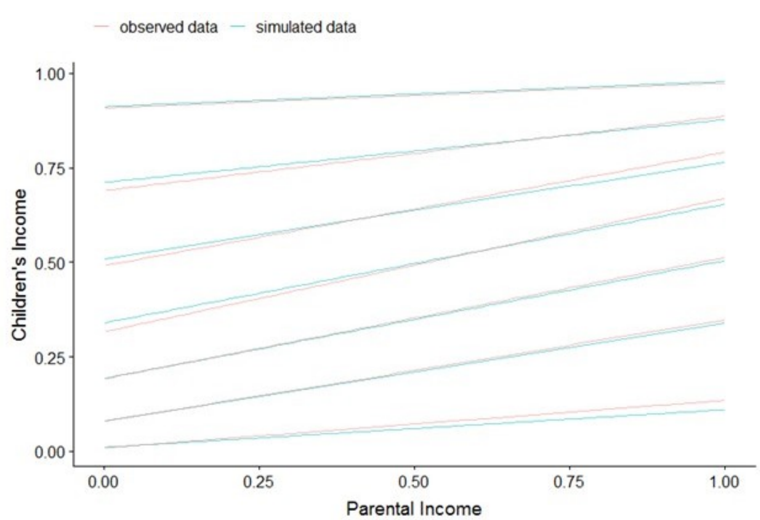
Note: This figure displays a survival BB8 copula with ML parameters $\theta = 2.227$ and $\delta = 0.905$. For BB8 copulas, the ML parameters are restricted to $\theta \geq 1$ and $\delta \in [0, 1]$. Please note that the parameter restrictions are different than for the BB1 copula shown in Figure 3.9, so their values are not directly comparable.
Source: SOEP v38, own calculations.

3.5.2.2 Robustness

Next, we perform several robustness checks to ensure that our identified copula fits our data well. We start with visualizing the rank fit of our copula to the data using conditional quantile regressions. Figure 3.11 reveals virtually no differences between the simulated and observed rank structure.

Next, we analyze subgroup consistency among cohorts. As mentioned in Chetty et al. (2017), the structure of parent-child-ties is not necessarily stable across generations and might be subject to underlying changes. Due to lack of sufficient information on parent-child-links for children born before the 1980s, we assume copula stability over time (e.g., Chetty et al., 2017). This assumes that one copula model holds true for all cohorts born since the 1960s. In various robustness checks, the authors show that this is not a problematic assumption (see Chetty et al., 2014, 2017). Still, ideally, this assumption is challenged empirically.

Figure 3.11. Conditional quantile regression for simulated and observed data



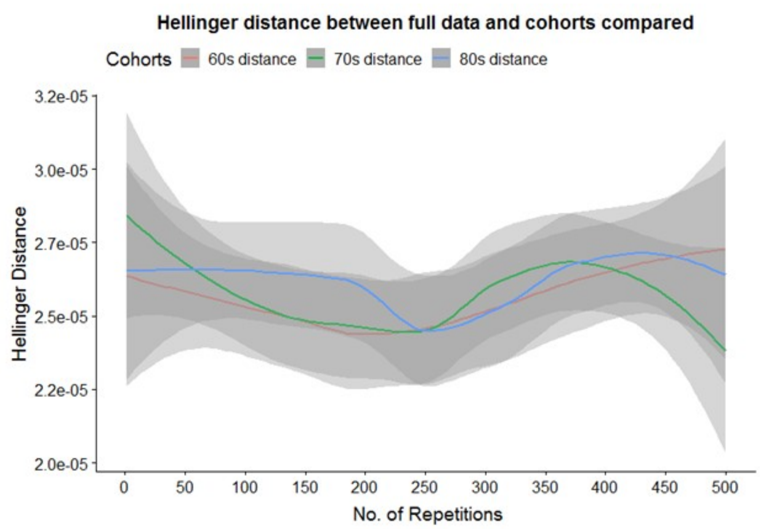
Source: SOEP v38, own calculations.

We compare the simulated copula distributions among cohort groups and the joint sample. To measure the relative distance between probability distributions, we use the Hellinger distance (Hellinger, 1909), which is not affected by data limitations. Its value range lies in the unit interval, where 0 depicts perfect similarity between the distributions and the value 1 total discrepancy.

Although there is no statistically sound threshold, the literature proposes a rule of thumb value of 0.05 or smaller in order for two distributions to be considered equal (e.g., Leulescu and Agafitei, 2013).

Figure 3.12 shows that there is virtually no differences in the dependency structures among the 1960s, 1970s, 1980s cohorts. After repeatedly drawing random samples from the respective copula models, none of the reported differences exhibit any values even close to the proposed threshold of 0.05. These results support the assumption of copula stability over time.

Figure 3.12. Hellinger distance between pooled sample and cohort groups compared

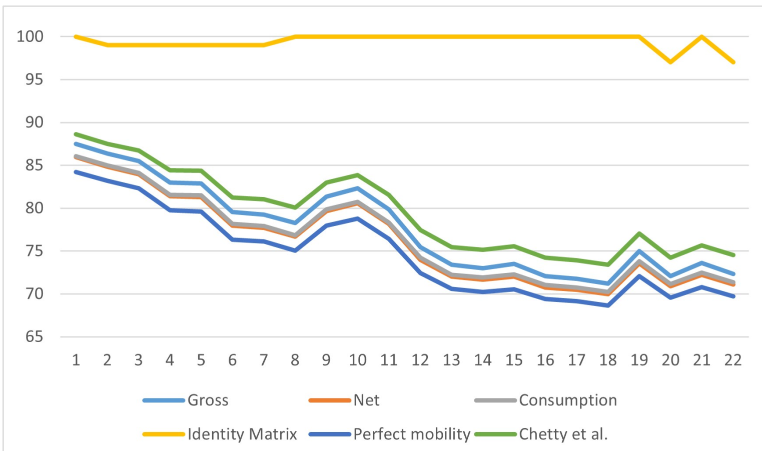


Source: SOEP v38, own calculations.

3.5.2.3 Effects of Different Copulae

We showed that assuming a stable copula over time is rather unproblematic. Still, there are some additional robustness checks we can apply. First, we can see how our results change if we used a different copula. In figure 3.13 we combine our marginal income distributions with different copulae: The copulae we calculated for pre-tax and disposable incomes and consumption from SOEP data, but also the copula from US data provided by Chetty et al. (2017), the identity matrix for an upper bound (no mobility) and last, the matrix of perfect mobility, where each of the 100x100 cells has a value of 0.01. Figure 3.13 shows that all of these different copulae, except for the identity matrix, would have led to similar results for absolute mobility. Between post-tax and disposable incomes, differences are minor and range from 1 to 2 percentage points. Since the identity matrix proposes perfect immobility - which we know describes a theoretical exercise rather than empirical reality - and all other copulae would have led to similar absolute mobility trends, we are safe to assume that even if relative mobility would have been lower than in the US, we would still have observed a similar decline in absolute income mobility.

Figure 3.13. Comparing the effects of using different copulae on mean rates of absolute income mobility



For further confirmation, we also provide a 5x5- transition matrix based on SOEP data of gross incomes. This matrix compares well to the matrices provided by Jäntti et al. (2006) for Nordic countries, the UK and the US. Our matrix can be easily placed between the US and the Nordic countries, with the US being the most immobile society in terms of income. This implies that even with other countries' copulae, we are very likely to yield similar results on the trends of absolute mobility. The level, however, might vary, but the trend would stay the same. This is also in line with Berman (2022b), who proposes that previously documented empirical copulae have rather limited effects on the evolution of absolute mobility.

Table 3.3. Transition matrix for gross income

	Children: P1-P20	Children: P21- P40	Children: P41-P60	Children: P61-80	Children: P81-100
Parents: P1-P20	0.3743	0.1968	0.1954	0.1288	0.1056
Parents: P21-P40	0.2095	0.2243	0.1867	0.1852	0.1939
Parents: P41-P60	0.1662	0.2041	0.2243	0.2069	0.1983
Parents: P61-P80	0.1272	0.2012	0.2098	0.2402	0.2214
Parents: P81-P100	0.1228	0.1737	0.1838	0.2388	0.2808

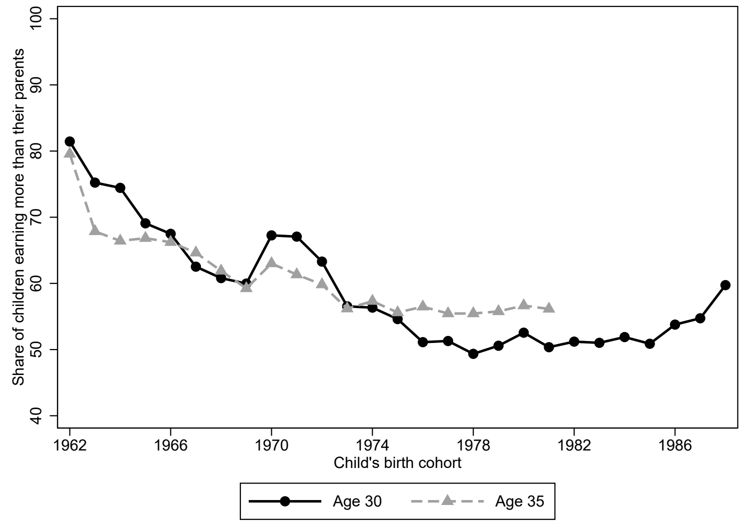
Source: SOEP v38, own calculations.

3.5.3 Absolute income mobility

One can argue that measuring parents' and children's incomes at age 30 is too early in life. Incomes at such young age might not reflect the living standards of families properly since the correlation between annual earnings and lifetime earnings only becomes sufficiently strong starting in the mid-thirties (Bönke et al., 2015). However, Figure 3.14 shows that the steep drop in absolute income mobility holds also true if we measure both parents' and children's income at age 35. This confirms that the decline in absolute mobility is robust across age.

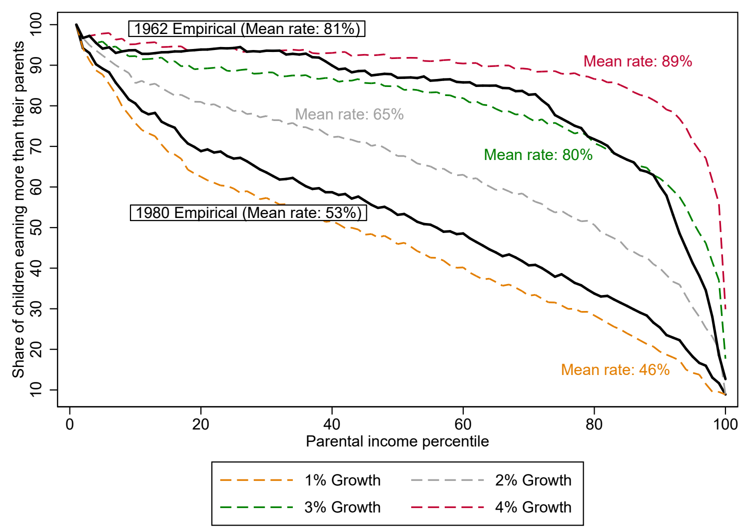
Figure 3.15 shows how absolute income mobility for the 1980 child cohort would have risen if they had experienced GDP growth rates between one and four percent. We find that it would have needed a GDP growth rate of 3.2 percent for the 1980 child cohort to achieve the high absolute income mobility rates that we observe for the 1962 child cohort.

Figure 3.14. Mean rates of absolute income mobility by age



Source: Mikrozensus 1962-2016, EVS 1978-2018, SOEP v38, own calculations.

Figure 3.15. Counterfactual analysis: GDP growth rates



Note: Aggregating absolute mobility rates across all parental incomes yields the mean rates of absolute mobility. The empirical mean rates for birth cohorts 1962 and 1980 stem from our main analysis (see Figure 3.1b).
Source: Mikrozensus 1962-2016, SOEP v38, own calculations.

4 Earnings Growth, Inequality and Absolute Mobility in Germany, 1882-2019

4.1 Introduction

One of the main promises of capitalism is that individuals can work themselves up the economic ladder through hard work, innovation, and entrepreneurship. To assess their economic progress, individuals often compare their earnings to their parents (e.g., Goldthorpe, 1987; Hochschild, 2016). Hence, there is a longstanding interest in understanding the evolution of absolute mobility, defined as the fraction of children earning more than their parents did. Bönke et al. (2024) have already documented a steep drop in absolute mobility rates from 81 to 59 percent for children's birth cohorts 1962 through 1988 in Germany. That said, the very oldest cohorts in that range experienced very high absolute mobility due to the unusually high GDP growth and low unemployment in the years after World War II (WWII). This makes it challenging to contextualize the findings of Bönke et al. (2024); are today's rates of absolute mobility too low, or simply a return to normalcy in the absence of highly unique economic conditions? This study sheds light on this by providing a comprehensive picture of absolute mobility and its two main drivers, growth and inequality, since 1882.

Further, the German case is unique in the global landscape due to its particularly turbulent past: Germany established one of the earliest social welfare systems in the 19th century, experimented with democracy and failed during the Weimar Republic, was at the center of two world wars, rebuilt its economy during the post-war economic miracle years, and faced several major economic recessions starting in the 1970s. This turbulent history provides a unique opportunity to analyze earnings growth, inequality, and absolute mobility in a single country, but under an array of different political regimes and economic conditions. While the German historical context itself is distinctive, the trends we observe under specific regimes do not need to be, and can help inform our understanding and expectations more broadly.

Retrieving continuous earnings data from six different sources, this study provides a comprehensive picture of the evolution of earnings growth, inequality, and absolute mobility in Germany from 1882 to 2019. We document three main findings. First, this study documents for the first time that absolute mobility dropped from 70 percent to 48 percent for children's birth cohorts 1882 through 1989. Covering absolute mobility for over 100 cohorts, we show that only children born between 1932 and 1962 experienced unusually high absolute mobility rates of over 90 percent, meaning that nearly all those children earned more than their parents did. This temporary surge can be attributed to the substantial and inclusive earnings growth during the immediate post-war decades. For all other cohorts, mean rates of absolute mobility ranged between 41 and 72 percent, indicating that today's absolute mobility rates more so reflect a return to normalcy than a significant downward deviation from historical trends. Second, we find that today's earnings inequality is higher than it was in 1882 (between 7 to 33 percent higher, depending on the data source). Gini coefficients remained stable during the industrialization period of the German Reich and WWI (1882-1918), sky-rocketed at the end of the Weimar Republic (1932) due to mass unemployment, decreased to an all-time low during the economic miracle years (1945-1973), and then saw a steep rise until the mid-2000s when it started to plateau at higher levels than in the pre-war era. Third, we find that real monthly labor earnings in 2019 are almost eight times higher than in 1882, but most of this growth was concentrated during the post-war economic miracle years (1945-1973). Other periods saw only low or non-existent earnings growth.

This paper is situated within several strands of literature. First, this study relates to the extensive literature on the evolution of inequality. Most of these studies focus on documenting and explaining the steep rise in wage or earnings inequality in recent decades (e.g., Card et al., 2013; Dustmann et al., 2014; Biewen and Seckler, 2019). For earlier years, the literature becomes naturally scarcer as data becomes harder to get by. Alfani et al. (2022) provide inequality estimates for pre-industrial Germany, documenting a rise in economic inequality between 1450 and 1850, with phases of inequality reduction during the Thirty Years' War (1618–1648) and the 1627–1629 plague. A study by Sweezy (1939) estimates an uptick in average earnings inequality between 1928 and 1936 among employed workers using tabulated tax data, but his method understandably falls short of today's statistical standards. Another study by Bartels (2019) provides a top income share series for Germany between 1871 and 2014, but only documents the evolution of income shares for the bottom 90 percent from 1961 onward. Our study adds to the literature by providing a comprehensive time-series of earnings inequality for the entire German labor force between 1882 and 2019.

Second, this paper contributes to the literature on intergenerational mobility. It has been well documented that for Germany, the US, and many other countries, relative intergenerational mobility is low and that children's outcomes are closely tied to their parental background (e.g., Schnitzlein, 2009; Chetty et al., 2017; Bratberg et al., 2017). But despite the clear importance of understanding the evolution of absolute income mobility, such studies have remained rare due to high data requirements. The first seminal work in this field has been produced by Chetty et al. (2017), which documented that absolute income mobility dropped from 90 percent to 50 percent for children born between 1940 and 1980 in the US. For Germany, Bönke et al. (2024) find a similar drop in absolute income mobility from 81 to 59 percent for children's birth cohorts 1962 through 1988. So far, only one study by Berman (2022a) has provided absolute mobility time series that span into the early 20th century for the US, France, and Sweden. He documents an initial rise in absolute income mobility during the first half of the 20th century in the United States and France, followed by a decline in the second half of the 20th century. Our study makes two key distributions to this relatively novel strand of literature: First, we extend the German absolute mobility time series extensively by adding data for 80 cohorts. Due to Germany's unique turbulent history, this allows to investigate absolute mobility under various political and economic settings. Second, this is the first study worldwide to provide absolute mobility estimates reaching back into the 19th century, covering the height of the industrialization period and improving understanding of absolute mobility levels in the pre-war era.

The remainder of our paper is organized as follows. Section 4.2 gives an overview of the methodologies and data sources used to estimate the evolution of earnings growth, inequality, and absolute mobility. Section 4.3 presents our results. Section 4.4 concludes.

4.2 Data and Methodology

This paper investigates the long-term evolution of earnings growth, inequality and absolute mobility since 1882. All three outcomes are measured in pre-tax labor earnings since our older data sources do not include any data on pre- or post-tax income.[49] In addition, the German tax structure and welfare system has experienced major changes over the past 137 years which would have made it impossible to distinguish whether trend changes in growth, inequality and absolute mobility were actually rooted in changing labor market forces or changes in re-distributional policies. The following sections present the methodologies and data sources used to measure each concept.

4.2.1 Earnings Growth and Inequality

We document earnings growth by presenting the evolution of average monthly labor earnings in 2018 prices. Earnings inequality is measured using the Gini coefficient. The Gini coefficient takes values between 0 and 1, with higher values reflecting more unequal earnings distributions. The data sources used to measure the evolution of earnings growth and inequality over time are the same that we use to construct marginal earnings distributions to measure absolute mobility. Hence, we present all six data sources together in section 4.2.2.2.

4.2.2 Absolute Mobility

Absolute earnings mobility is measured as the share of children in a given birth cohort who earn the same or more than their parents. It is defined as the sum of the dichotomous comparison

[49] In Germany, labor earnings are still the predominant income source for the bottom 99 percent of the income distribution (Bartels and Jenderny, 2015). Half of all German households do not even have any savings, contributing to the fact that only less ten percent of German households participate in the capital market in the first place (Bönke et al., 2017).

between parent and child earnings, divided by the number of children N_c in each birth cohort:

$$A_c = \frac{1}{N_c} \sum_i 1\{y_{ic}^k \geq y_{ic}^p\} \tag{1}$$

with y_{ic}^k being the income of child i in birth cohort c and y_{ic}^p being the income of its parents.

In a perfect world, a comprehensive analysis of intergenerational mobility would use true family connections and earnings data for parents and their own children at similar ages. Measuring absolute mobility would then be straightforward. In reality, such data is infrequently available and exists only for a few select German birth cohorts which would not allow us to investigate long-term trends in absolute mobility. We use Sklar's theorem (1959) as a workaround for this limitation. It demonstrates that any multivariate cumulative distribution can be derived from the corresponding copula and its marginals. This allows us to estimate absolute mobility without having access to data with true family connections and complete income histories.

We implement Sklar's theorem by connecting parents' and children's marginal earnings distributions with a copula (e.g., Chetty et al., 2017; Berman, 2022a; Bönke et al., 2024). Absolute mobility for a given cohort c, A_c, is then estimated as the product of the marginal distributions and the copula of child and parent ranks, denoted as $C_c(r^k, r^p)$. $Q_c^k(r^k)$ and $Q_c^p(r^p)$ represent the r^{th} quantile of the child and parental distributions, respectively. Equation (2) then describes the dichotomous comparison of child and parent earnings quantiles, weighed by the likelihood of the respective intergenerational quantile combination:

$$A_c = \int 1\left\{Q_c^k(r^k) \geq Q_c^p(r^p)\right\} C_c(r^k, r^p) dr^k dr^p \tag{2}$$

The first part of equation (2) becomes 1 if a child of rank r^k earns weakly more than their parent of rank r^p. The copula, a 100 x 100 transition matrix that captures the likelihood of each parent-child rank combination, then weighs the likelihood of each pair's occurrence. This yields our absolute earnings mobility estimate between 0 (all children earn less than their parents) and 1 (all children earn weakly more than their parents) for children's birth cohort c. Sections 4.2.2.1

and 4.2.2.2 describe the two ingredients needed to measure absolute mobility: the copula and marginal earnings distributions.

4.2.2.1 Copula

We use the German Socio-Economic Panel (SOEP) to construct our copula. The SOEP constitutes a highly representative German panel dataset that follows individuals and their children since 1984 (Goebel et al., 2019). It is the only data source for Germany that allows to observe both parents' and their own children's earnings.

To estimate our copula, we follow the methodology by Bönke et al. (2024), but use pre-tax earnings instead of disposable incomes which is measured after taxes and transfers. Following Chetty et al. (2017), we use parental earnings between the ages 30 and 60 to obtain their relative earnings ranks, and earnings between the ages 30 and 34 for their children to do the same. Afterwards, we have 3,456 parent-child pairs that we use to determine the most likely copula fit. Bönke et al. (2024) offer a detailed description of this methodological approach and show in extensive checks that it leads to a robust copula. Since we can only observe true family ties for a few select birth cohorts in the SOEP, we further need to assume copula stability over time to estimate absolute mobility for several generations. This is an unproblematic assumption; Berman (2022a) shows that the marginal distributions rather than the shape of the copula determine absolute mobility rates.

4.2.2.2 Marginal earnings distributions

Our study utilizes six different data sources to measure earnings growth and inequality and construct the marginal earnings distributions to estimate absolute mobility from 1882 until 2019. To construct marginal income distributions to measure absolute mobility, we need to restrict our sample to individuals aged 30 to 44 for two main reasons: First, it is crucial to compare parents and children in the same age range when analyzing intergenerational mobility to avoid any measurement errors (Chetty et al., 2014). Second, annual earnings between 30 and 44 are already highly correlated with lifetime earnings and provide a good proxy for parents' and children's long-term resources (e.g., Björklund, 1993; Haider and Solon, 2006; Bönke et al., 2015). For comparability, we therefore also base our estimates for earnings growth and inequality on the same sample.[50]

The first 90 years of our time series are based on three historical data sources: (1) The Workplace and Occupation Census (*Berufszählung*, BZ), (2) the Wage and Salary Structure Survey (*Gehalts- und Lohnstrukturerhebung*, GLS), and (3) the Income Tax Statistics (*Einkommensteuerstatistik*, StvA). For the last 50 years of our time series, we use more recent and commonly used earnings data sources: (4) The Income and Expenditure Survey (*Einkommens- und Verbraucherstichprobe*, EVS), (5) the German Socio-Economic Panel (*Sozio-oekonomisches Panel*, SOEP) and (6) German Pension register data (*Versicherungskontenstichprobe*, VSKT).[51]

While later earnings distributions were easy to retrieve from modern micro data sources, obtaining the distributional earnings information from the historical data sources came with challenges. Not only is historical data harder to access, but it also only provides tabulated earnings data. Using different statistical approaches specific to each data source, we were able to derive continuous earnings distributions from the tabulated data needed to estimate earnings growth, inequality and absolute mobility. In a next step, we combined these historical data with more recent data sources. This approach required some additional harmonization work, but provides two main advantages: First, our combined and harmonized database includes a few years in which we have both historical data and modern micro data sources available. For those years, we were able to confirm that there are only minor differences in the results across the different data sources, indicating that our statistical approaches in reconstructing earnings distributions from tabulated historical data yields reliable results. Second, we are able to provide a complete picture of the evolution of inequality and absolute mobility of earnings in Germany in the last 137 years, and therefore distinguish between short-term oscillations and long-term trends.

[50] Using the full sample yields similar results. For example, differences in the Gini coefficients only ranged between one and two percentage points between the full sample and the sample restricted to individuals aged 30 through 44.

[51] Note that as this paper focuses on pre-tax earnings distributions, we do not use the Mikrozensus as it only collects information on disposable incomes.

The following sections provide a short overview of each data source and, if applicable, the methodologies used to derive continuous earnings distributions. In addition, Appendix 4.5.1.1 provides an overview of all data sources used by year.

(1) Workplace and Occupation Census (BZ). The BZ was collected between 1875 and 1970 and captures the number of individuals by gender, age, marital status, and occupation for the entire German population (Kleber and Willms, 1982). Our study focuses on the occupation census that started in 1882.[52] The BZ does not collect earnings information directly, but Hohls (1991) provides both the mean and variance of annual pre-tax labor earnings by occupational group for this time period. Linking those to the occupation censuses yields the exact number of German employees and workers in each occupation group, linked to their annual mean pre-tax earnings and the variance of earnings in each subgroup. Using this information, we define a mapping from the empirical cumulative distribution function to the target distribution functions which satisfies both the existence and uniqueness conditions. Therefore, we can also map the densities, resulting in reliable continuous earnings distributions.

(2) Wage and Salary Structure Survey (GLS). These data were collected by the Federal Statistical Office and include information on wages, earnings, and working hours categorized by industry, gender, and company size between 1951 and 1972. The survey represents approximately 15 percent of all employees and is considered representative (Hohls, 1991).[53] Since the GLS does not provide data on unemployment, we use the exact unemployment counts from the BZ for the years in which both data sources overlap. To further retrieve continuous earnings distributions from the binned earnings data in the GLS, we follow Blanchet et al. (2022) and use generalized Pareto estimations. Appendix 4.5.1.2 provides a summary of this methodological approach.

(3) Payroll tax on wages (StvA). The StvA was first introduced in 1920 and was part of a major

[52] Data from the workplace censuses were excluded for two main reasons: First, only the occupation censuses break numbers down by age. This is important since we have to compare parents' and children's earnings at the same age to avoid biased estimates due to measurement errors. Second, the workplace censuses excluded the agriculture sector which still constituted an important income source for a large share of the population at the end of the 19^{th} and beginning of the 20^{th} century. Please see Stockmann (1984) for more details on the differences between the workplace and occupation censuses.

[53] See Federal Statistical Office (1954, 1960, 1965) for more details on data from the Wage and Salary Structure Survey.

income tax reform introducing a uniform tax nationally (Metzger and Weingarten, 1989). It contains information on the number of individuals the tax was collected from, their pre-tax earnings, and the total paid tax. In most years, it was also broken down by socioeconomic characteristics such as gender, age, and occupation.[54] Earnings data from the StvA are also only available as tabulated data. Hence, we again use the generalized Pareto method (see Blanchet et al., 2022) to obtain continuous earnings distributions (see Appendix A.2).

(4) Income and Expenditure Survey (EVS). This survey is administered every five years since 1962/63 by the German Federal Statistical Office.[55] It covers a representative household sample of 0.1% of the German population and collects data on sociodemographic characteristics, earnings, and expenditures. Bönke et al. (2013) provide additional details on this data source and how the different waves were harmonized.

(5) German Socio-economic Panel (SOEP). In addition to using the SOEP to estimate the copula, we can also use these data to measure earnings growth and inequality as well as to construct marginal earnings distributions. The SOEP, initiated in 1984, conducts a comprehensive annual panel survey that involves questioning around 30,000 individuals from 15,000 households and is considered representative. It collects detailed information about the socioeconomic backgrounds and labor market statuses of households and their individuals, including continuous information on labor earnings.

(6) German Pension Register Data (VSKT). In Germany, the majority of employees are required to enroll in the national pension insurance, resulting in pension data that covers over 90 percent of the population (Rehfeld and Mika, 2006). Our study uses the VSKT provided by the German Federal Pension Register. These administrative data provide earnings biographies for individuals on a monthly basis starting at age 14. Himmelreicher and Stegmann (2008) provide a detailed overview of the VSKT data.

[54] See Reichsamt (1940) for a more detailed overview of this income data source.
[55] With the exception of waves 1968 and 1973, for which there is no EVS data.

4.3 Earnings Growth and Inequality

This chapter investigates the evolution of both economic growth and inequality, which are also the two key determinants of absolute mobility (e.g., Chetty et al., 2017; Bönke et al., 2024). To do so, we analyze data from a time period of 137 years, covering five different political phases in Germany (see Table 4.1).

Table 4.1. Germany's political phases between 1882 and 2019

1882-1918	German Reich and WWI
1918-1933	Weimar Republic
1933-1945	The Nazi Regime and WWII
1945-1990	Postwar Germany
1990-2019	Reunited Germany

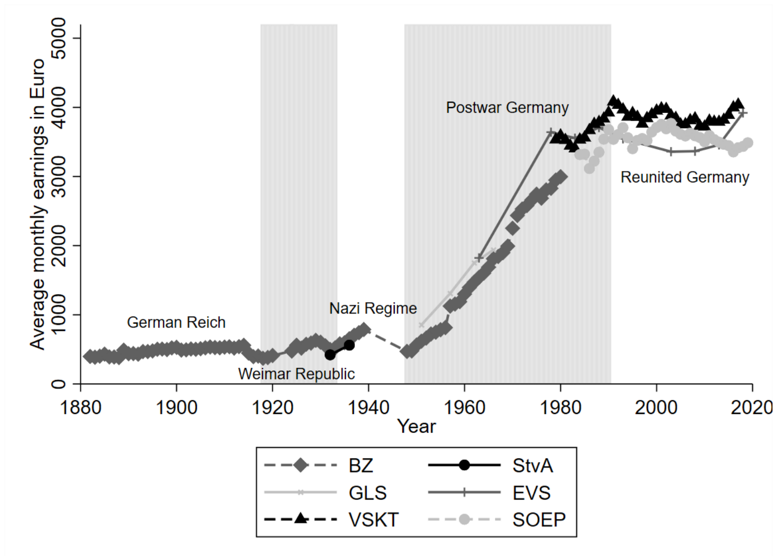
4.3.1 Earnings Growth

This section presents the evolution of earnings growth. Figure 4.1 shows the average monthly labor earnings in 2018 prices between 1882 and 2019 for the German labor force using all six of our data sources.[56]

Average labor earnings remained relatively stable during the industrialization period of the German Reich, the Weimar Republic and the Nazi Regime, never exceeding an average of 1,000 Euro per month. This picture changed drastically in the post-war era after 1945. The extensive destruction in Germany during WWII led to a substantial demand for labor and goods during the subsequent reconstruction of housing, infrastructure, and businesses (e.g., Buenstorf and Guenther, 2011; Bartels, 2014). Therefore, the 1950s through early 1970s were characterized by exceptionally low levels of unemployment and high levels of GDP growth (e.g., Bönke et al., 2019). Accordingly, they are often referred to as economic miracle years. With this flourishing economy came a steep increase of average earnings, more than tripling the average monthly earnings by the time the first oil crisis hit in 1973.

[56]The labor force is defined as the sum of both employed and registered unemployed individuals. Figure 4.6 in the Appendix shows the average earnings growth when we restrict our sample to only employed individuals.

Figure 4.1. Evolution of average real monthly earnings, 1882 - 2019



Note: All earnings are in 2018 prices.
Source: BZ, StvA, GLS, VSKT, EVS, SOEP, own calculations.

With the first and second oil crises (1973-1975 and 1980-1982, respectively) average earnings growth started to level off. While the precise year of the conversion from steep earnings growth to stagnation differs by data source, the trend is clear: the accelerated growth of the economic miracle years was over by the mid-1970s. Until the mid-2000s, two additional major economic crises hit the German economy (aftermath of the German unification in 1990 and the high tech crisis in 2001) and left it with low GDP growth rates, high unemployment, and high national debt. As a result, at that time Germany was even referred to as "the sick man of Europe" (Economist, 2004).[57]

After 2005, the EVS and VSKT both show a slight uptick in average earnings, while the SOEP data shows a slight decrease in average earnings. This trend is particularly interesting in light of the major policy changes occurring at that time. In response to the economic difficulties of the pre-

[57]Even though average earnings plateaued during these decades, earnings growth patterns varied greatly across the earnings distribution. While almost all male, prime-age workers experienced real earnings losses during recessions, only the top 40 percent of the pre-recession earnings distribution recovered from those losses, while the bottom 60 percent experienced a permanent negative earnings shock (Harnack-Eber, mimeo).

vious decades, former Chancellor Gerhard Schröder introduced a comprehensive policy reform package known as *Agenda 2010* in 2003. This initiative included various labor market policies further deregulating the German labor market and aiming to re-establish Germany's economic competitiveness in the face of an increasingly globalized market. However, existing research indicates that the *Agenda 2010* package was not the main driver of Germany's economic recovery, but instead precursor policy changes. In the mid-1990s, measures were already introduced to deregulate the labor market and decentralize wage bargaining, but due to the aftermath of the unification in 1990, the effects of these policies were delayed (Dustmann et al., 2014).[58] While all these measures played an important part in resurrecting Germany's economy, the increasing labor market deregulation may have come at the cost of stagnating average earnings levels.

In addition, Figure 4.5 in the Appendix shows the evolution of the national income per capita since 1900 using data from from the World Inequality Database (WID). Since income includes both labor and capital income, the comparison between the evolution of average labor earnings and the evolution of national income per capita can provide additional insights on capital income growth over time. Except some temporary differences during the Nazi regime, growth trends for both concepts looked very similar until the 1980s, indicating that most of the growth stemmed from labor earnings during these earlier decades. But while labor earnings growth started to stagnate in the 1980s, national income per capita continued to rise due to the growing importance in capital income in recent decades (Bengtsson and Waldenström, 2018).[59]

4.3.2 Earnings Inequality

Next we investigate the long-term evolution of earnings inequality, the second key ingredient for absolute earnings mobility. Figure 4.2 shows the Gini coefficients between 1882 and 2019 for the German labor force.[60]

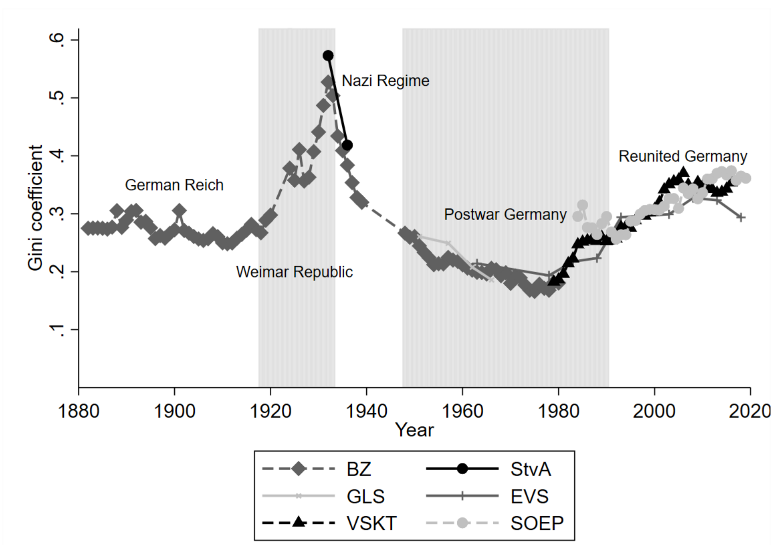
[58] Please find a detailed overview of labor market policy changes in Germany from 1950 to 2019 in Bönke et al. (2019).

[59] However, only a small fraction of the German population has benefited directly from the increase in capital income. Half of all German households do not own any wealth hindering them from participating in this trend, and less than 10 percent participate in the capital market (Bönke et al., 2017).

[60] Figure 4.7 in the Appendix shows the evolution of earnings inequality when we restrict the sample to employed individuals.

During the industrialization period of the German Reich and WWI (1882-1918), Gini coefficients remained stable between 0.25 and 0.31 due to low average earnings (see Figure 4.1) and a homogeneous wage structure across the entire labor force. The inequality levels changed drastically during the Weimar Republic (1918-1933). The German labor force experienced a steep, unprecedented rise in earnings inequality, with Gini coefficients doubling to over 0.5 in the last year of the Weimar Republic. Figure 4.7 in the Appendix shows that Gini coefficients only rose from 0.26 to 0.31 (BZ) or 0.38 (StvA) over the same time period when restricting our sample to employed individuals. This shows that the steep rise in inequality observed in the full sample is driven primarily by the extensive labor margin; rising unemployment was a greater factor than an unequal distribution among those employed.

Figure 4.2. Evolution of earnings inequality, 1882 - 2019



Source: BZ, StvA, GLS, VSKT, EVS, SOEP, own calculations.

Given we observe evidence that unemployment is the primary driver of the steep rise in earnings inequality, we explore the historical underpinning of unemployment changes during this time period. In the early years of the Weimar Republic, the number of unemployed workers rose from roughly one million in 1922 to more than four million in 1923. Germany had fallen behind on its reparations payments and France and Belgium chose to occupy the Ruhr region, one of Germany's economic powerhouses at that time. The government of the Weimar Republic called on its citizens for passive resistance, leading to general strikes that paralyzed the economy, worsened supply shortages and ended in hyperinflation (Bundesarchiv, n.d.). Due to international pressure, France agreed to sign the Dawes Plan which lowered Germany's reparation payments significantly. France and Belgium ended the Ruhr occupation in early 1925, and by the end of that year, the number of unemployed workers had already dropped back to one million. But soon the young Weimarer Republic faced the next big challenge: Black Friday, the stock market crash of October 25, 1929, marked the onset of a global economic recession. Paired with the withdrawal of short-term American loans, this economic downturn hit particularly hard in Germany, leading to company bankruptcies and mass layoffs. By 1932, unemployment had reached its all-time high with 5.6 million individuals (or 30% of the labor force) unemployed (Reichsamt, 1940), and with it, an all-time high in earnings inequality.

Following Hitler's seizure of power in January of 1933 and the beginning of the Nazi Regime, the Gini coefficient dropped sharply. The primary factor contributing to this decline in earnings inequality among the German labor force was the establishment of employment opportunities in the arms industry and highway construction, reducing the number of unemployed individuals in the Third Reich. By 1937, full employment was achieved and the labor force participation rate stabilized at around 50 percent, comparable to rates observed prior to WWI (Boldorf, 2015).[61] By the end of WWII, earnings inequality had reached similar levels to the pre-war times.

When we restrict our sample to employed individuals (see Figure 4.7 in the Appendix), we see a much smaller (StVA) or non-existent (BZ) drop in earnings inequality after the Nazis gained power in 1933. These findings are contrary to those of Sweezy (1939) for 1928 through 1936 (see Figure 4.8 in the Appendix). Applying the graphic Pareto method to available income and wage tax data from that time, Sweezy (1939) estimated that average inequality for employed individuals decreased between 1928 and 1932, and increased between 1932 and 1936, even surpassing the 1928 level. We believe that our new estimates provide a more accurate picture of the evolution of earnings

[61]It should be noted that the official number of unemployed also declined due to the exclusion of certain beneficiaries (Debus, 2015).

inequality during this time for two main reasons: First, the Generalized Pareto estimation that we use is far more precise than the graphic Pareto method (Blanchet et al., 2022). Even though the latter method was helpful at the time, the underlying distributional assumption ignores key components of earnings distributions. Second, the available data at that time was inadequate. It excluded roughly a quarter of German workers, most of them stemming from the bottom quarter of the earnings distribution. Their omission, therefore, misses a crucial part of the full picture of earnings inequality.

Following WWII, the Federal Republic of Germany were established and the postwar economic miracle years (1945-1973) began. The steep drop in the Gini coefficient of 35 percent from 0.26 to 0.17 illustrates that earnings growth during this period were not only unusually large (see Figure 4.1), but also that it was inclusive of the entire German labor force. Earnings inequality reached an all-time low in the mid-1970s with a Gini coefficient of 0.17.

This picture began to change when the first and second oil crises hit (1973-75 and 1980-82, respectively). In this new economic phase, earnings inequality began its steep rise that continued throughout the reunification of Germany until the mid-2000s, resulting in Gini coefficients ranging as high as 0.31 (SOEP) and 0.37 (VSKT). This result is in line with other studies that documented the steep increase in earnings and wage inequality in recent decades (e.g., Dustmann et al., 2009; Card et al., 2013; Biewen and Seckler, 2019). While major global economic recessions with low GDP growth and high unemployment rates yielded steep increases in earnings inequality in many industrialized countries (e.g., see Autor, 2014 for the US), one other potential key driver of the rising inequality that has been widely discussed in the German context were changes in unionization during this time. While some evidence supports the decline in unionization as a key driver for the rise in inequality (e.g., Dustmann et al., 2009; Biewen and Seckler, 2019), other studies instead pointed to increasing heterogeneity in wage setting at the firm level (e.g., Antonczyk et al., 2010; Card et al., 2013).[62]

During the last 15 years of the reunified Germany, the different data sources tell slightly distinct

[62] Please also see Antonczyk et al. (2018) for a detailed overview of the rise in wage inequality in Germany and the US since the 1970s.

stories about the evolution of earnings inequality. While the Gini coefficients estimated with the SOEP and VSKT show a relative stable pattern of earnings inequality between 2005 and 2019, the EVS indicates a moderate drop in earnings inequality. In 2018, the Gini coefficients estimated with these three data sources range between 0.29 (EVS) and 0.36 (SOEP). But despite the differences by data source, one message remains quite clear: Nowadays, earnings inequality is consistently higher than in pre-war times.

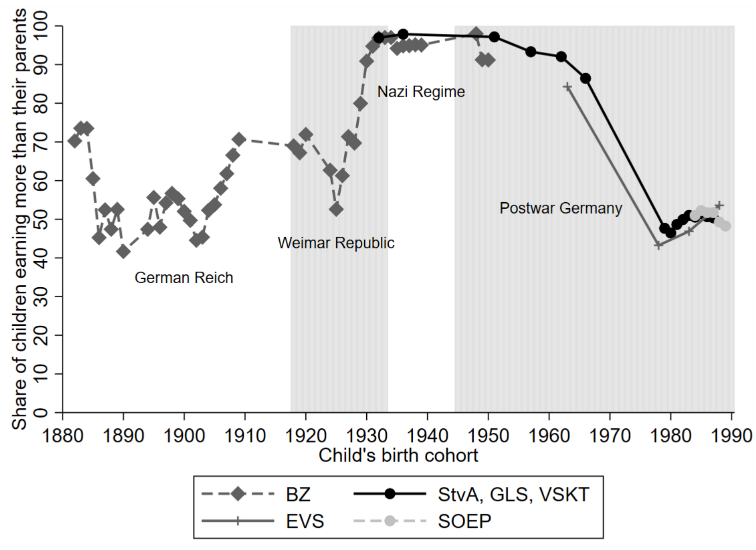
4.3.3 Absolute Earnings Mobility

Absolute earnings mobility is mainly shaped by earnings growth and earnings inequality. We have seen that both average earnings and inequality experienced steep rises, falls and stagnation since 1882. We now combine these two key ingredients when assessing the evolution of absolute mobility between generations. Figure 4.3 shows the fraction of children that earned more than their parents did for children's birth cohorts 1882 through 1989.[63]

The mean rate of absolute earnings mobility was 70 percent for the oldest child birth cohort. This means that children born in 1882 had an overall likelihood of 70 percent to earn more than their parents did. Mean rates of absolute mobility then dropped significantly for the first time for children born between 1886 and 1903. While these children were still born in the industrialization phase of the German Reich, the majority of them were ages 30 and 44 during the Weimar Republic (1918-1932) when earnings growth was slow and unemployment surging, driving this drop in absolute mobility estimates. Accordingly, only between 41 and 57 percent of children born during these years earned more than their parents did. Afterwards, absolute mobility estimates bounced back to around 70 percent for children born between 1903 and 1921. These cohorts were in their prime-age working years during WWII and the beginning of the post-war period; times characterized by job growth and full employment (1937), and economic growth through national recovery, respectively. These beneficial economic conditions enabled children to again out-earn their parents with greater frequency.

[63]Absolute mobility estimates include zero earnings on both parents' and children's sides by definition. Hence, no time series restricted to employed individuals is provided for absolute earnings mobility.

Figure 4.3. Evolution of absolute earnings mobility, 1882 - 2019



Note: To produce the maximum number of absolute mobility estimates, we combine marginal earnings distribution of the StvA, GLS, and VSKT.
Source: BZ, StvA, GLS, VSKT, EVS, SOEP, own calculations.

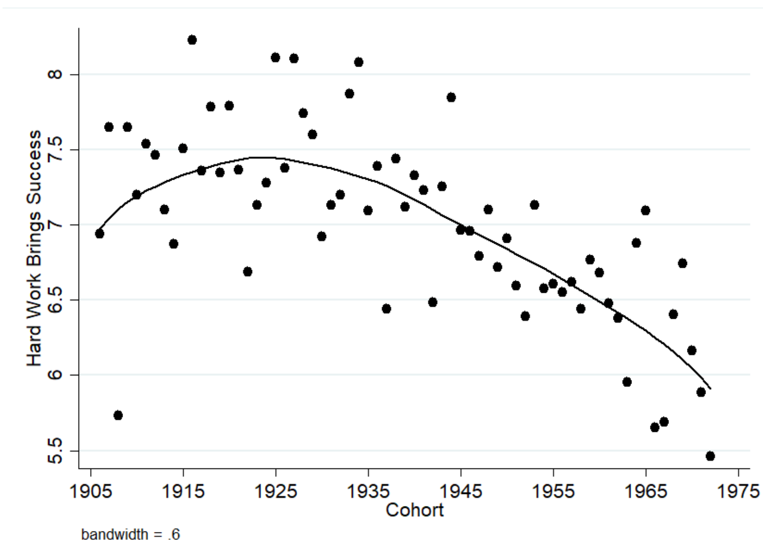
Aside from some trend-deviations by select individual cohorts, rates of absolute mobility sharply increased for the next grouping of birth cohorts (1920 to 1932). Depending on the data source, between 97 and 99 percent of children born in 1932 earned more than their parents did - a more than 25 percentage points higher share than children born only twelve years earlier. Main drivers of this jump were both the steep earnings growth in the economic miracle years after WWII and the low levels of earnings inequality that these cohorts experienced between ages 30 and 44. Afterwards, we observe rates of absolute mobility consistently over 90 percent for children born through 1962, comprising an entire generation in which almost all children were doing better than their parents did.

For children born in the mid 1960s, absolute mobility rates started to fall below 90 percent and subsequent cohorts saw sharp decreases. For children born in 1979, absolute mobility had already dropped to 48 percent - an unprecedented decline of more than 44 percentage points from children's birth cohorts 1962 through 1979. Depending on the data source, absolute mobility rates for child cohorts born in the 1980s then remained relatively stable or saw a slight uptick.

Using the SOEP, we estimate absolute mobility at 48 percent for the youngest birth cohort 1989, 22 percentage points lower than for the oldest child cohort 1882.

Bönke et al. (2024) document a decline in absolute mobility of disposable income from 81 to 59 percent for children's birth cohorts 1962 through 1988. Disposable income is thereby defined as as household income after taxes and benefits. Our study finds a decline from 92 percent to between 49 percent (SOEP) or 54 percent (EVS) in absolute mobility of labor earnings for the same child birth cohorts. This indicates that the German welfare state had only a very limited effect on buffering the decline in intergenerational mobility, also hinting at the limited positive effect of the economic recovery phase since 2005 and more structural problems in our society and labor market.

Figure 4.4. Perception of whether hard work can bring economic success by birth cohort



Note: We use the 1990 European Values Survey as this is the only survey wave that asks the pertinent question concerning beliefs about whether hard work brings success. Cohorts with less than 10 observations were dropped to avoid capturing noise; this removes 14 cohorts. We also reversed the directionality of the original coding to make interpretation more intuitive with high values (up to 10) representing agreement with the statement and low values (down to 1) representing disagreement. The figure then presents the resulting values by cohort and a smoothed line of best fit.

Source: European Values Survey 1990, own calculations.

Nowadays, less than half of all children earn more than their parents did. Subsequently, younger cohorts also believe less and less that hard work can bring economic success (e.g., see Figure 4.4). This lack of belief in the possibility of upward mobility is rooted in reality and can have significant negative implications for individuals and society. Some potential risks include decreased motivation and apathy, economic stagnation, or even social unrest.

4.4 Conclusion

Constructing continuous earnings distributions from historical tabulated data and harmonizing six different data sources, our study presents new findings on the trends in earnings growth, inequality and absolute mobility for Germany between 1882 and 2019. We document three key findings.

First, this study finds that real monthly labor earnings in 2019 are nearly eight times higher than those in 1882. This growth can primarily be attributed to one economic phase: the postwar economic miracle years until the mid-1970s. During all other periods, earnings growth was small or nonexistent.

Second, we document that the inequality of earnings in 2018/2019 surpasses that of 1882. Depending on the data source, today's Gini coefficients are between 7 and 33 percent higher. That said, the evolution of earnings inequality over time was highly volatile. Earnings inequality was relatively stable during the industrialization period of the German Reich and WWI (1882-1918), with Gini coefficients oscillating between 0.25 and 0.31. A surge in earnings inequality followed during the Weimar Republic, leading to peaking Gini coefficients of over 0.5 in 1932 due to mass unemployment. During the postwar economic miracle years, earning inequality dropped to an all-time low of 0.17 in the mid-1970s. We then show a steep rise in earnings inequality until the mid 2000s when Gini coefficients began to stabilize at a high level.

Third, mean rates of absolute earnings mobility, measured as the share of children earning more than their parents did, declined from 70 percent for children born in 1882 to 48 percent for children born in 1989. Extremely high rates of absolute mobility of over 90 percent were only observed for children's birth cohorts 1932 and 1962, driven by the unusually high and inclusive earnings growth during the post-war economic miracle years. For all other birth cohorts, absolute mobility estimates ranged from 41 to 72 percent. These findings suggest that current absolute mobility levels are more likely a return to relative normalcy, even though estimates are on the lower end of the spectrum.

Combining all our findings yields the following picture: Today's average earnings are high, but not inclusive. Earnings inequality is higher and absolute mobility is lower than it was in 1882. This provides empirical evidence to support the already prevalent notion that younger cohorts' increasingly disbelieve in their ability to work themselves up the economic ladder. To date, no study has investigated the causal impact of policy changes and programs on absolute mobility. Future research in this field should expand its focus from observational documenting the evolution of absolute mobility trends to researching effective policies.

4.5 Appendix

4.5.1 Data and Methodology

The following sections provide an overview of all data sources used and more details on the methodology applied to construct continuous income distributions from binned earnings data.

4.5.1.1 Data sources

We use six different data sources in this study: (1) The Workplace and Occupation Census (*Berufszählung*, BZ), (2) the Wage and Salary Structure Survey (*Gehalts- und Lohnstrukturerhebung*, GLS), (3) the Income Tax Statistics (*Einkommensteuerstatistik*, StvA), (4) the Income and Expenditure Survey (*Einkommens- und Verbraucherstichprobe*, EVS), (5) the German Socio-Economic Panel (*Sozio-oekonomisches Panel*, SOEP) and (6) German Pension register data (*Versicherungskontenstichprobe*, VSKT). Table 4.2 summarizes which data sources have been used for each survey year.

Please also note that the German Pension Register Data waves contain monthly earnings biographies. Hence, each data wave allows us to measure outcomes for a range of years. For earnings growth and earnings inequality, we draw estimates from 1979 through 2017 from the VSKT. For absolute mobility, we use the 2002 wave for birth cohorts 1935 and 1936, the 2004 wave for birth cohort 1937, the 2005 wave for birth cohort 1938, the 2006 wave for birth cohort 1939, the 2007 wave for birth cohort 1940, the 2008 wave for birth cohort 1941, the 2009 wave for birth cohort 1942, the 2010 wave for birth cohort 1943, the 2011 wave for birth cohort 1944, the 2012 wave for birth cohort 1945, the 2013 wave for birth cohort 1946, the 2014 wave for birth cohort 1948, the 2015 wave for birth cohort 1949, and the 2017 wave for birth cohorts 1950 through 1987.

If no other data was available, we also used the data points above to construct earnings distributions between the original data points, accounting for inflation and growth rates and assuming no changes in the composition of the labor force.

Table 4.2. Data sources for this study

Year	Data sources	Year	Data sources	Year	Data sources
1882	BZ	1985	SOEP	2003	EVS, SOEP, VSKT
1895	BZ	1986	SOEP	2004	SOEP, VSKT
1907	BZ	1987	SOEP	2005	SOEP, VSKT
1925	BZ	1988	EVS, SOEP	2006	SOEP, VSKT
1932	StvA	1989	SOEP	2007	SOEP, VSKT
1933	BZ	1990	SOEP	2008	EVS, SOEP, VSKT
1936	StvA	1991	SOEP	2009	SOEP, VSKT
1939	BZ	1992	SOEP	2010	SOEP, VSKT
1950	BZ	1993	EVS, SOEP	2011	SOEP, VSKT
1951	StvA	1994	SOEP	2012	SOEP, VSKT
1957	StvA	1995	SOEP	2013	EVS, SOEP, VSKT
1961	BZ	1996	SOEP	2014	SOEP, VSKT
1962	EVS, GLS	1997	SOEP	2015	SOEP, VSKT
1966	GLS	1998	EVS, SOEP	2016	SOEP
1970	BZ	1999	SOEP	2017	SOEP, VSKT
1978	EVS	2000	SOEP	2018	EVS, SOEP
1983	EVS	2001	SOEP	2019	SOEP
1984	SOEP	2022	SOEP, VSKT		

4.5.1.2 Generalized Pareto estimation

Many income distributions exhibit similar statistical features. In a statistical approach introduced by Blanchet et al. (2022) and implemented through their R-package gpinter (http://wid.world/gpinter), we capitalize on these commonalities. Our method utilizes generalized Pareto curves to construct continuous income distributions from tabulated income data provided in the GLS and the StVA data. This allows us to retrieve continous earnings distributions and measure earnings growth and inequality as well as absolute earnings mobility.

Generalized Pareto curves estimate inverted Pareto coefficients, denoted as $b(p)$, for each income percentile (p). Considering a sample of $(X_1, ..., X_n)$ of n independent and identically distributed realizations of X, the empirical estimator of the inverted Pareto coefficient $\widehat{b_n}(p)$ for each income percentile p can be expressed as follows:

$$\widehat{b_n}(p) = \frac{1}{(n - \lfloor np \rfloor) X_{(\lfloor np \rfloor + 1)}} \sum_{k=\lfloor np \rfloor + 1}^{n} X_{(k)} \tag{19}$$

with $\lfloor np \rfloor$ denoting the floor function of x.

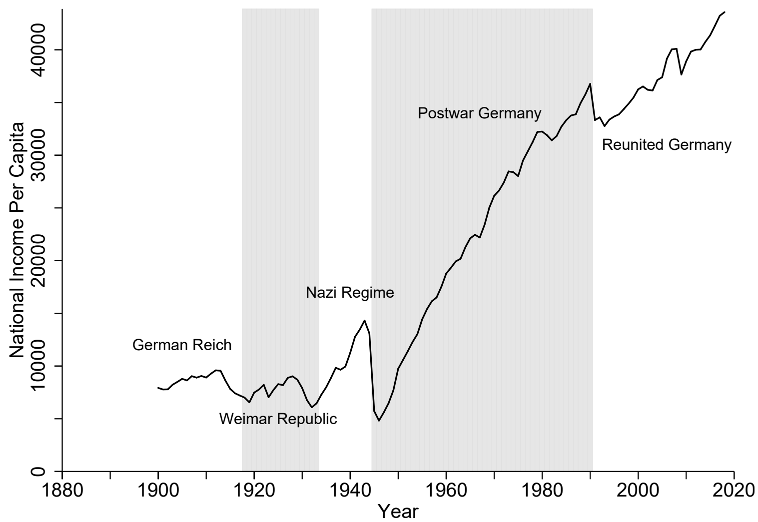
The process of estimating a continuous income distribution from tabulated data initiates with a transformation of the Lorenz curve, establishing a direct link to the lognormal distribution. For percentiles where $p \leq pk$, interpolation is used, while extrapolation is used for percentiles where $p > pk$.

Leveraging administrative data, Blanchet et al. (2022) show that their approach provides greater precision compared to commonly used interpolation methods. Other successful applications of this methodological approach using German data are demonstrated in Bönke et al. (2023) for the Socioeconomic Panel (SOEP) and in Bönke et al. (2024) for the Mikrozensus, confirming that this methodology yields reliable continous earnings and income distributions.

4.5.1.3 National Income per Capital

The results in Figure 4.1 focus on individual labor market earnings. In addition, Figure 4.5 shows the evolution of the national income per capita using data from the World Inequality Database (WID). The latter includes both labor and capital income.

Figure 4.5. Evolution of the national income per capita, 1900 - 2022



Note: This figure shows national income per adult; children are not included in the denominator. Prices are shown in Euro (2022 PPP).
Source: World Inequality Database, own calculations.

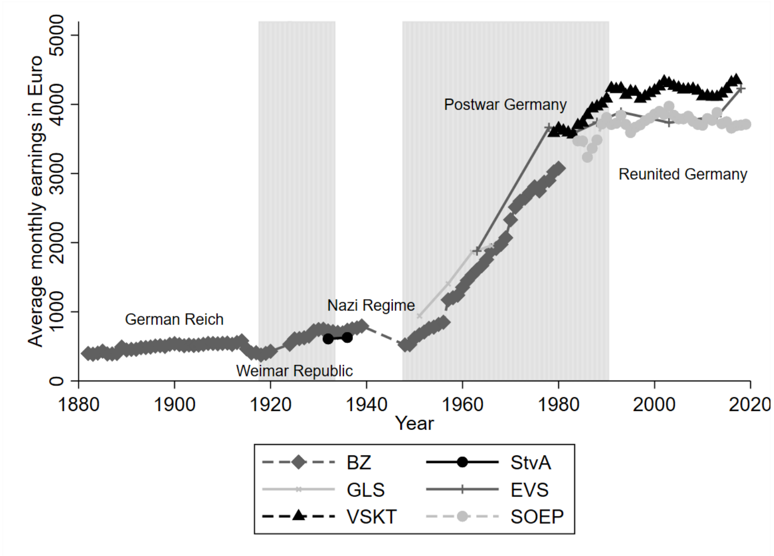
We see that average labor earnings and the national income per capita have both remained relatively stable through the German Reich and Weimar Republic. Differences between the two concepts occur for the first time during the Nazi Regime where national income saw a short-lived surge due to a temporary increase in capital income, while labor earnings hardly changed. After WWII, we see the same steep increase in the national income per capita that we observed in the individual average labor earnings. But while labor earnings growth started to stagnate again since the 1980s, national income per capita has continued its rise ever since. This is mainly driven by the growing importance of capital income in recent decades. Bengtsson and Waldenström (2018) show that the share of capital income of the German national income has increased from 20 percent to 30 percent, while labor income only accounts for 70 percent nowadays. However, only a small fraction of the German population has benefited directly from the increase in capital income. Half of all German households do not own any wealth and less than 10 percent participate in the capital market (Bönke et al., 2017).

4.5.2 Role of Employment in Results

The following sections show our main results when restricting our sample to employed individuals.

4.5.2.1 Earnings growth

Figure 4.6. Evolution of average real monthly earnings for employed individuals, 1882 - 2019

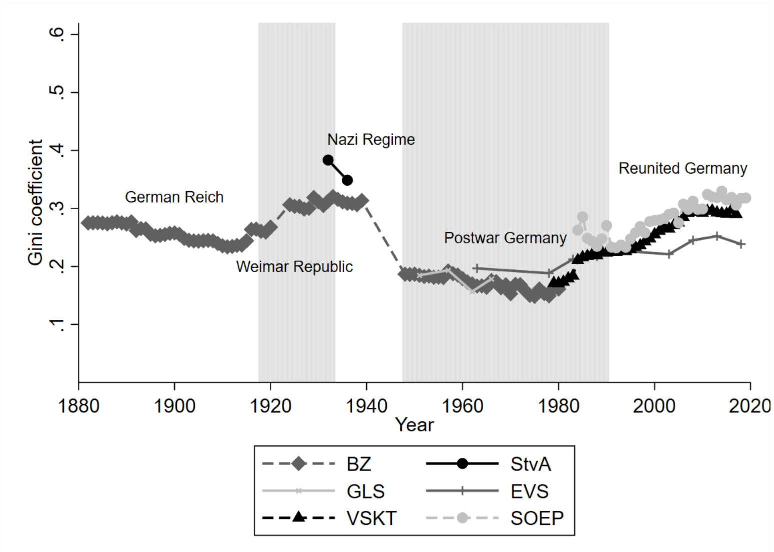


Note: These results only include employed individuals. All earnings are in 2018 prices.
Source: BZ, StvA, GLS, VSKT, EVS, SOEP, own calculations.

4.5.2.2 Inequality

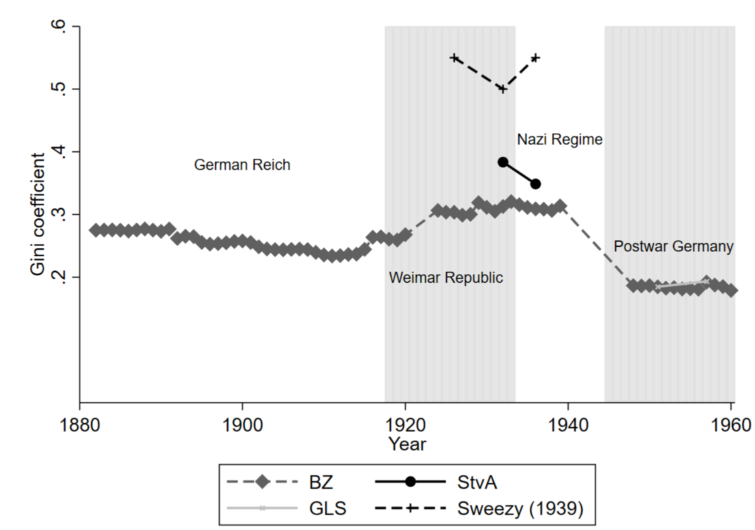
Figure 4.7 displays the evolution of earnings inequality when restricting our sample to employed individuals. Figure 4.8 then compares our estimates to the few data points available for Germany before 1960 provided by Sweezy (1939).

Figure 4.7. Evolution of earnings inequality for employed individuals, 1882 - 2019



Note: These results only include employed individuals.
Source: BZ, StvA, GLS, VSKT, EVS, SOEP, own calculations.

Figure 4.8. Evolution of earnings inequality for employed individuals compared to Sweezy (1939), 1880 - 1945



Note: These results only include employed individuals.
Source: BZ, StvA, GLS, Sweezy (1939), own calculations.

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English Summary (Abstracts)

Chapter 1: Many Lose, Few Win: Patterns of Earnings Growth Across Business Cycles

This paper examines the impact of business cycles on the earnings of prime-age workers and labor market entrants in Germany using pension register data on birth cohorts 1935 through 1982. I document three main results: First, during recessions, prime-age workers at the lower end of the prerecession earnings distribution experienced the highest average earnings losses. These losses gradually decrease in magnitude with higher prerecession earnings. Second, the majority of the German population were unable to recover from their average earnings losses in subsequent economic expansions, with the exception of those in the top 30 percent of the prerecession earnings distribution. Third, lower educated men entering the labor market during poor economic conditions face a significant earnings reduction. A one-point increase in the initial unemployment rate leads to, on average, a six percent decrease in annual earnings in the first year after graduation. This negative effect attenuates after five years.

Keywords: Business cycles, recessions, earnings growth, inequality, labor market entrants
JEL Classification: D31, E32, J21, J31

Chapter 2: The Gender Gap in Lifetime Earnings: The Role of Parenthood

To obtain a more complete understanding of the persisting gender earnings gap in Germany, this paper investigates both the cross-sectional and biographical dimension of gender inequalities. Using an Oaxaca Blinder decomposition, we show that the gender gap in annual earnings is largely driven by women's lower work experience and intensive margin of labor supply. Based on a dynamic microsimulation model, we then estimate how gender differences accumulate over work

lives to account for the biographical dimension of the gender gap. We observe an average gender lifetime earnings gap of 51.5% for birth cohorts 1964-1972. We show that this unadjusted gender lifetime earnings gap increases strongly with the number of children, ranging from 17.3% for childless women to 68.0% for women with three or more children. However, using a counterfactual analysis we find that the adjusted gender lifetime earnings gap of 10% differs only slightly by women's family background.

Keywords: Gender Gap, Lifetime Inequality, Female Employment, Earnings Distribution.
JEL-Classification: D31, H0, J62

Chapter 3: The Broken Elevator: Declining Absolute Mobility of Living Standards in Germany

This study provides the first absolute income mobility estimates for postwar Germany. Using various micro data sources, we uncover a steep decline in absolute mobility rates from 81 percent to 59 percent for children's birth cohorts 1962 through 1988. This trend is robust across different ages, family sizes, measurement methods, copulas, and data sources. Across the parental income distribution, we find that children from middle class families experienced the largest percentage point drop in absolute income mobility (-31pp). Our counterfactual analysis shows that lower economic growth rates and higher income inequality contributed similarly to these trends.

Keywords: Absolute mobility, Intergenerational mobility, Income distributions, Consumption, Inequality.
JEL Classification: D31, H0, J62

Chapter 4: Earnings Growth, Inequality and Absolute Mobility in Germany, 1882-2019

Utilizing six different data sources, this study provides a comprehensive picture of absolute mobility and its two key ingredients, earnings growth and inequality, for Germany between 1882 and 2019. We document that today's earnings inequality is higher than it was in 1882. This comes after significant variation in inequality over time including Gini coefficients of over 0.5 at the end of the Weimar Republic and estimates below 0.2 during the mid-1970s. We also find that mean rates of absolute earnings mobility declined from 70 percent to 48 percent for children's birth cohorts 1882 through 1989. While children born between 1932 and 1962 experienced unusually high absolute mobility rates of over 90 percent due to the postwar economic miracle years, estimates for all other birth cohorts ranged between 41 and 72 percent.

Keywords: Inequality, intergenerational mobility, absolute mobility, economic growth, Germany

JEL: D31, J62, N33, N34

Deutsche Zusammenfassung

Die Dissertation besteht aus vier empirischen Forschungsartikeln, welche die Entwicklung der Einkommensungleichheit und Einkommensmobilität innerhalb und zwischen Generationen untersuchen.

Das erste Kapitel untersucht die Auswirkungen von Konjunkturzyklen auf die Einkommen von Berufseinsteigern und etablierten Arbeitskräften in Deutschland für die Geburtsjahrgänge 1935 bis 1982. Basierend auf Rentenversicherungsdaten dokumentiere ich drei Hauptergebnisse: (1) Geringer qualifizierte Berufseinsteiger, die während schlechter wirtschaftlicher Bedingungen in den Arbeitsmarkt eintraten, mussten erhebliche Einkommensverluste in Kauf nehmen. Ein einprozentiger Anstieg der anfänglichen Arbeitslosenquote führte im Durchschnitt zu einem Rückgang der jährlichen Einkommen um sechs Prozent im ersten Jahr nach dem Abschluss. Dieser negative Effekt verschwand erst nach fünf Jahren. (2) Etablierte Arbeitskräfte mit den niedrigsten Einkommen vor Eintritt der Rezession verzeichneten durchschnittlich die höchsten Einkommensverluste. Die Verluste nahmen graduell mit höheren Einkommen vor Rezessionseintritt ab. (3) Die Mehrheit der deutschen etablierten Arbeitskräfte konnte ihre Einkommensverluste während der Rezessionen in den darauf folgenden wirtschaftlichen Aufschwüngen nicht ausgleichen. Nur die oberen 30 Prozent der Einkommensverteilung vor Eintritt der Rezession konnten Einkommensgewinne seit der zweiten Ölkrise (1980-82) erzielen.

Das zweite Kapitel untersucht den Gender Gap in Löhnen, jährlichen Einkommen und Lebenseinkommen. Mithilfe einer Oaxaca-Blinder-Zerlegung zeigen wir, dass die Einkommensunterschiede zwischen Männern und Frauen in den jährlichen Einkommen größtenteils auf die durchschnittlich geringere Berufserfahrung und Arbeitsstunden von Frauen zurückgeführt werden kann. Basierend auf einem dynamischen Mikrosimulationsmodell schätzen wir dann, wie sich geschlechtsspezifische Unterschiede im Laufe des gesamten Arbeitslebens ansammeln, um die biografische Dimension des Gender Gaps zu analysieren. Wir finden, dass Frauen der Geburtskohorten 1964 bis 1972 über ihr gesamtes Erwerbsleben durchschnittlich 52 Prozent weniger verdienen als gleichaltrige Männer. Diese Einkommenslücke ist für kinderlose Frauen am geringsten (17 Prozent) und steigt mit der Anzahl der Kinder (68 Prozent für Mütter mit drei oder mehr Kindern). Unsere kontrafaktische Analyse zeigt jedoch, dass der bereingte Gender Gap in den Lebenseinkommen nur geringfügig von der Kinderanzahl der Frau abhängt und für alle Frauen etwa 10 Prozent beträgt.

Das dritte Kapitel zeigt die ersten ersten Schätzungen zur absoluten Einkommensmobilität für Deutschland basierend auf der Einkommens- und Verbraucherstichprobe, dem Mikrozensus, und dem Sozio-oekonomischen Panel. Absolute Einkommensmobilität wird als Anteil der Kinder einer Geburtskohorte definiert, der das gleiche oder ein höheres Einkommen als ihre Eltern im Alter von 30 Jahren erzielt hat. Unsere Berechnungen zeigen einen starken Rückgang der absoluten Einkommensmobilität von 81 Prozent auf 59 Prozent für die Geburtsjahrgänge der Kinder von 1962 bis 1988. Wir beobachten diesen Trends auch, wenn wir Kinder und Eltern im späteren Alter betrachten, verschiedene Familienkonzepte verwenden oder unterschiedliche Messmethoden, Copulas oder Datenquellen benutzen. Weithin stellen wir fest, dass Kinder aus Mittelschichtfamilien mit 31 Prozentpunkten den größten Rückgang der absoluten Einkommensmobilität erfuhren. Unsere kontrafaktische Analyse zeigt, dass die Abnahme des Wirtschaftswachstums und die Zunahme der Einkommensungleichheit über die letzten Jahrzehnte in ähnlichem Maße zur starken Abnahme der absoluten Einkommensmobilität beigetragen haben.

Das vierte Kapitel zeichnet unter Verwendung von sechs verschiedenen Datenquellen (Berufszählung, Gehalts- und Lohnstrukturerhebung, Einkommensteuerstatistik, Einkommens- und Verbraucherstichprobe, Sozio-oekonomisches Panel, Versicherungskontenstichprobe) ein umfassendes Bild von der Entwicklung der preisbereinigten Einkommen, Einkommensungleichheit und absoluter Einkommensmobilität in Deutschland zwischen zwischen 1882 und 2019. Wir zeigen, dass die heutige Einkommensungleichheit höher ist als im Jahr 1882. Dabei hat die Einkommensungleichheit über die letzten 137 Jahre stark geschwankt: Am Ende der Weimarer Republik betrugen die Gini-Koeffizienten mehr als 0.5, während sie Mitte der 1970er Jahre sogar unter 0.2 fielen. Weiterhin dokumentieren wir, dass die absolute Einkommensmobilität für die Geburtsjahrgänge der Kinder von 1882 bis 1989 von 70 Prozent auf 48 Prozent gesunken ist. Während Kinder, die zwischen 1932 und 1962 geboren wurden, aufgrund der Wirtschaftswunderjahre der Nachkriegszeit noch ungewöhnlich hohe absolute Mobilitätsraten von über 90 Prozent erlebten, lagen die Schätzungen für alle anderen Geburtskohorten zwischen 41 und 72 Prozent.

Rechtliche Erklärung

Erklärung gem. §4 Abs. 2 (Promotionsordnung)

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe, und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

Erklärung gem. §10 Abs. 3 (Promotionsordnung)

Hiermit erkläre ich, dass ich für die Dissertation folgende Hilfsmittel und Hilfen verwendet habe: LaTeX, Stata, R, Literatur siehe Literaturverzeichnis. Auf dieser Grundlage habe ich die Arbeit selbstständig verfasst.

(Astrid Harnack-Eber)

Washington D.C., Juli 2024