the review of income and wealth

Review of Income and Wealth
Series 68, Number 3, September 2022
DOI: 10.1111/roiw.12511

INCREASING INEQUALITY IN LONG-TERM EARNINGS: A TALE OF EDUCATIONAL UPGRADING AND CHANGING EMPLOYMENT PATTERNS

BY MATTHIAS SECKLER*

University of Tübingen

This paper provides a detailed decomposition analysis of rising long-term earnings inequality among West German men born between the years 1955 and 1974 based on high-quality administrative data. Educational upgrading is identified as a leading factor behind increasing inequality in the upper part of the long-term earnings distribution. The study also reveals a substantial shift from full- to part-time employment and shows this to be an important factor in explaining rising inequality in the lower part. This effect seems to be quantitatively more important than the increasing incidence of non-employment for the studied cohorts. Overall, increasing inequality in long-term earnings can primarily be attributed to an increasing inequality in average yearly earnings during times of employment as opposed to changes in the total years of employment. The analysis also reveals similarities with the development in the US by documenting a stagnation in long-term earnings among the cohorts studied.

JEL Codes: C14, D31, D33

Keywords: income inequality, long-term earnings inequality, RIF decomposition

1. INTRODUCTION

Growing wage and earnings inequality around the world has caused an increasing interest in the topic among both policymakers and academics. The latter have so far mainly focused on the increase in cross-sectional inequality over time as documented in a vast literature (see Acemoglu and Autor 2011, for a general overview, and Dustmann *et al*., 2009, for the German case). Surprisingly, relatively little is known about how this increasing cross-sectional earnings inequality has affected the evolution of individual long-term and lifetime earnings across different birth cohorts. From a purely cross-sectional perspective, which usually compares earnings distributions at different points in time, cohort differences are usually non-distinguishable from life cycle trends. For example, when comparing the German

*Note: I would like to thank the two anonymous referees, the editor Conchita D'Ambrosio, as well as Martin Biewen, Bernd Fitzenberger, Uta Schönberg, and participants at the IAAE 2019 Annual Conference, the 32nd Annual Conference of the European Society for Population Economics (ESPE), and the 2018 Summer School of the DFG priority program 1764 for their helpful comments and discussions. The data basis of this paper is the weakly anonymous Sample of Integrated Labour Market Biographies (SIAB) 1975–2014. The data were accessed on-site at the Research Data Centre (FDZ) of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and via remote data access. Financial support through DFG priority program 1764 and DFG project BI767/3-1 is gratefully acknowledged.

*Correspondence to: Matthias Seckler, School of Business and Economics, University of Tübingen, Mohlstr. 36, 72074 Tübingen, Germany (matthias.seckler@uni-tuebingen.de).

earnings distribution of the early 1990s with the one two decades later, it remains unclear to what extent the standard of living of later cohorts differs from that of their predecessors. This is a consequence of the fact that observable differences in cross-sectional earnings are the result of individuals being observed at different points of their career. Moreover, studying long-term earnings from a cohort perspective is likely to be more informative with regard to an individual's or cohort's standard of living, which is ultimately determined by lifetime earnings rather than by earnings at a certain point in time.

Recent studies by Bönke *et al*. (2015a) and Guevenen *et al*. (2017) document a dramatic increase in long-term and lifetime earnings inequality for both Germany and the US among men in later birth cohorts. Though being an ongoing debate, the previous literature has identified different channels underlying the increase in cross-sectional inequality, most prominently skill-biased technological change (*SBTC*), demographical and institutional factors, as well as internationalization and changes in individual employment biographies. A more comprehensive discussion of these channels is provided in Section 2 of this paper. At the same time, it remains unclear to what extent these factors are also responsible for the increasing inequality in long-term and lifetime earnings. This paper intends to shed light on this blind spot by disentangling the increasing inequality in long-term earnings using high-quality administrative employment data for Germany. Methodologically, the paper uses state-of-the-art recentered influence function (RIF) decomposition techniques based on unconditional quantile regressions introduced in the seminal contributions by Firpo *et al*. (2009, 2018).

This paper makes the following contributions to the literature. First, to the best of my knowledge, this is the first study providing a detailed decomposition analysis aimed at explaining the rising inequality in long-term earnings. It reveals that much of the rising inequality at the top of the distribution is associated with educational upgrading, whereas changing employment patterns are associated with rising inequality at the bottom. Second, the results confirm previous findings by Bönke *et al*. (2015a) who documented a sharp rise in long-term and lifetime earnings inequality in Germany based on a different database. Going a step further, this paper also shows that German men born between the years 1955 and 1974 did not only face a higher level of inequality, but also equally suffered from a stagnation in long-term earnings over a major part of their career. This paper also provides first evidence that these trends tend to accelerate for the youngest cohorts.

The rest of this paper is structured as follows: Section 2 summarizes the related literature. Sections 3 and 4 describe the data and the econometric method. Section 5 presents the decomposition results. Section 6 concludes with a discussion of the major findings.

2. Related Literature

This section provides an overview on the most relevant literature for this paper. Most importantly, the study directly adds to the literature on the evolution of individual long-term and lifetime earnings inequality. Using data for the US, an important contribution by Bowlus and Robin (2004) finds that inequality in cross-sectional and lifetime earnings appears to follow a similar pattern over time. Moreover, they show that the level of inequality in lifetime earnings is substantially lower than inequality in cross-sectional earnings because of earnings mobility among young workers. However, changes in earnings mobility are not identified as an important factor in explaining the rising dispersion in lifetime earnings. As the study builds on a relatively short panel, the used measures of lifetime earnings are simulated based on estimates for different parameters (job destruction/re-employment rates, promotion/demotion rates). Kopczuk *et al.* (2010) provide evidence for increasing inequality in male long-term earnings, especially for the US *baby-boomers* born after 1945. This trend is found in all stages of the career, with the level of inequality being generally higher in later episodes of the working life. In a more recent contribution, Guevenen *et al.* (2017) document both a substantial decline in median lifetime earnings of the US men born between the years 1942 and 1958 (after observing gains in earlier cohorts) and a long-run trend of increasing inequality within male cohorts. The authors conclude that the observed changes are mostly because of differences in early career earnings across cohorts. Importantly, they show that later cohorts suffered from earnings losses at young age that were not compensated by a higher future earnings growth. In fact, the study finds that women realized substantial gains in lifetime earnings (starting from a very low level) across the study period which, however, only partly offset the losses suffered by men.

In a seminal contribution for Germany, Bönke *et al.* (2015a) documented a dramatic increase in long-term and lifetime earnings inequality based on an Insurance Account Sample (*Versicherungskontenstichprobe*) containing West German men born between the years 1935 and 1969. The authors resort to the concept of *up-to-age X earnings (UAX)* as a measure for individual long-term earnings, which is defined as the present value of all earnings before reaching a certain age. By imputing earnings for periods of un- and non-employment, they show that parts of the increasing dispersion in lifetime earnings at the bottom can be explained by differential unemployment patterns. Moreover, they establish two other results that are important for the subsequent analysis. First, they show that earnings mobility, which is high at the beginning of the working life, mostly vanishes after age 40. Second, they conclude that the evolution of inequality in lifetime earnings most likely reflects the development in long-term earnings up to age 40. Following this argument, the subsequent analysis focuses on earnings up to age 40, which does not only offer important insights into changes in individual long-term earnings for a major part of the career, but can likely be generalized to inequality in lifetime earnings (see Bönke *et al.*, 2015a, p. 186). Another advantage of this approach is to obtain new evidence on very recent cohorts. In a further contribution, Bönke *et al.* (2015b) provide evidence for an increase in the transitory component for younger workers in the 1970s and a related increase in short-term earnings risk. This paper intends to directly add to these previous findings by trying to pin down the aforementioned increase in lifetime earnings across cohorts to different explanatory factors.

In this aspect, the present study connects to a vast literature trying to explain the well-documented increase in cross-sectional inequality during the past decades as described by various authors (see, for the German case, Dustmann *et al.*, 2009;

Card *et al.*, 2013, among others). These studies are usually concerned about the evolution of cross-sectional inequality and do not explicitly address the question of how these factors affect lifetime earnings inequality across different birth cohorts. Although not having reached a consensus yet, the respective literature identifies several factors that appear to be important for the increase in cross-sectional inequality, which therefore also constitute obvious candidates for the analysis in this paper. Most notably, many studies stress the importance of SBTC for wage polarization and a resulting increase in the US wage inequality (e.g., Autor and Dorn, 2013). However, previous evidence on this link seems to be mixed for Germany (see, e.g., Antonczyk *et al.*, 2009; Rinawi and Backes-Gellner, 2015). Other contributions show that an increasing heterogeneity between firms, combined with a matching of *good workers* and *good firms*, can explain a large part of the recent increase in inequality (Card *et al.*, 2013; Barth *et al.*, 2016; Song *et al.*, 2019). A different strand of the literature (e.g., Dustmann *et al.*, 2009; Baumgarten *et al.*, 2018; Biewen and Seckler, 2019) highlights the importance of institutional changes in the form of deunionization, whereas internationalization seems to be another potential explanation (Baumgarten, 2013). A recent study (Biewen *et al.*, 2018) stresses the importance of an increasing heterogeneity in individual labor market histories. Based on a reweighting method, the authors link a substantial part of the rising earnings inequality to increasing heterogeneity in terms of past employment interruptions and part-time work, especially at the bottom of the distribution.

As the present study identifies changing employment patterns as an important factor, it also relates to a broader literature on the evolution and earnings effects of employment breaks and part-time employment. Previous work by Tisch and Tophoven (2012) compares birth cohorts 1959 and 1965 of the German *baby boomers*. Similar to the results of this paper, they document an increasing incidence of part-time and non-employment episodes in individual employment biographies among individuals born in later years. Taking also more recent cohorts into account, Bachmann *et al.* (2018) find a decline in regular employment together with a simultaneous increase in a-typical employment among West German men born between 1944 and 1986. These trends are found not only in young workers, i.e., as a result of substantially longer time spent in education, but also across all age groups. Although providing new insights, both studies abstain from establishing a direct link to the evolution of earnings inequality over time. Brehmer and Seifert (2008) and Wolf (2010) show that part-time employment is associated with lower hourly wages relative to full-time employment. Finally, a number of studies (Beblo and Wolf, 2002; Görlich and De Grip, 2009; Potrafke, 2012; Fernández-Kranz *et al.*, 2014; Blundell *et al.*, 2016; Paul, 2016) provide direct evidence that both employment interruptions and part-time episodes tend to adversely affect future earnings growth.

3. Data

The analysis in this paper is based on the *Sample of Integrated Employment Biographies (SIAB)*, which constitutes a 2 percent random sample of all employees covered by social security records between the years 1975 and 2014. The data are well suited for studying changes in long-term earnings across cohorts due to the fact that complete employment histories of approximately 1.75 million individuals are provided. For the birth cohorts covered in the present analysis, the SIAB overall includes between approximately 21,000 and 32,000 individuals. The *SIAB* also includes a rich set of covariates related to individual employment biographies, complemented by additional firm-level information of the Establishment History Panel that can potentially explain the increasing dispersion of long-term earnings. In this regard, the data are more suitable for a detailed decomposition analysis than the Federal Pension Register (*Versicherungskontenstichprobe*) that has mostly been used in previous research but includes a very limited number of covariates. On the downside, the *SIAB* does not contain any information before the year 1975. Therefore, the study focuses on individuals born between the years 1955 and 1974 who can at least be observed between the ages of 20 and 40. To facilitate comparability with previous studies, the analysis is restricted to male individuals working in West Germany only. In line with previous studies, the analysis does not consider women.

For the subsequent analysis, a sample comprised of individuals with a sufficient labor market attachment is defined. This is achieved by imposing the following restrictions:[1] First, to ensure that individuals can be observed throughout the relevant part of their career, a *maximum age* for labor market entry depending on educational attainment is imposed, i.e., 30 years (individuals with university degree), 28 (completed high school and vocational training), 25 (without completed high school but with vocational training), and 23 for all others (neither high school degree nor vocational training or missing educational information). Similarly, individuals who have their last observable employment spell more than 3 months before reaching a certain age threshold (e.g., age 40) as well as individuals with a single non-employment spell of more than 5 years are omitted from the sample. Imposing similar restrictions is important to minimize the risk of including individuals who emigrated or became self-employed during their working life. Second, lower bounds on both annual and total long-term earnings are imposed. Regarding annual earnings, individuals are required to have real earnings greater than 5000 euros in at least half of the years they could potentially be working after age 25. For example, to be included in the up-to-age 40 (UA40) earnings sample, individuals need to have real earnings of at least 5000 euros in 8 years or more. In addition, individuals are required to have total long-term earnings that correspond to an average annual earning of at least 5000 euros. Therefore, for total UA40 covering all earnings starting with the year the individual turns 20, a lower bound of 105,000 euros is imposed (130,000 euros for UA45). Finally, individuals with observable employment spells in East Germany are equally omitted. Imposing these restrictions leaves 109,194 (81,271/49,864) individuals for which complete UA40 (UA45/UA50) employment biographies can be constructed. A more detailed overview on the number of observations by cohort is provided in Table SA1 in the Online Supporting Information. The sample defined in this way deliberately does

[1]Imposing similar restrictions is common in the literature on long-term earnings inequality. The restrictions imposed on the sample in this paper follow those in Guevenen *et al*. (2017) and Boll *et al*. (2017).

not include women. This is due to lower labor force participation rates among German women, which result in a significantly smaller number of earnings biographies that fulfill the imposed minimum criteria of labor market attachment. Moreover, changing patterns in terms of selection into employment (and ultimately into the sample) inherently complicate any long-run comparison across cohorts.

As the earnings information in the SIAB is censored at the limit for the statutory pension fund, earnings above this threshold are imputed following the procedure described in Gartner (2005). A more detailed description of the procedure is provided in the Online Supporting Information to this paper. Depending on the year of observation, up to 15 percent of observations are affected by this right-censoring. Therefore, as it is common practice in studies based on German administrative data, this paper focuses on the development of earnings inequality below the 85th percentile of the different UAX measures. Because of this property, the subsequent analysis might in fact underestimate the true increase in inequality given that parts of the development at the very top of the distribution will not be captured. Starting in 1984, one-time payments were counted toward annual earnings resulting in both an increase in average daily wages and a spurious increase in annual earnings inequality between the years 1983 and 1984. To account for this structural break, the procedure introduced by Bönke *et al.* (2015a) is used, which denotes a modification of the procedure by Fitzenberger (1999) that works on panel data. Similar strategies were used in other studies such as Dustmann *et al.* (2009) and Card *et al.* (2013). The procedure is outlined in the Online Supporting Information.

From a data perspective, another challenge lies in the German reunification and the fall of the Berlin Wall, allowing individuals to move freely between the formerly separated parts of Germany. As the *SIAB* does not include any information on earnings in East Germany before January 1, 1991, individuals with employment spells in the former German Democratic Republic (which remain unobservable), who migrated to West Germany in the aftermath of the fall of the Berlin Wall, potentially end up in the sample. However, an effect on the decomposition results (comparing pooled cohorts 1955–1957 to 1972–1974) can be ruled out due to the following reasons: For the analysis, individuals who can be observed in the SIAB before 1989 are assumed to only consist of West Germans, given the fact that the Berlin Wall did not fall before late 1989 and East–West migration was virtually impossible. Combined with the maximum labor market entry age of 30 (for individuals holding a university degree), individuals born before 1959 are assumed to only consist of West Germans. Similarly, individuals born after 1970 are not affected by relevant unobservable employment spells in East Germany, given the fact that starting in 1991, the SIAB covered both East and West Germany and only earnings starting at age 20 are included in the UAX earnings measures. Therefore, the decomposition results are not diluted by individuals with unobservable employment spells in East Germany.

3.1. *Trends in Long-Term Earnings*

In the analysis of long-term earnings, this paper follows the approach suggested in Bönke et al. (2015a) in calculating *up-to-age X earnings (UAX)* for different ages (though with some methodological differences). The concept of up-to-age X earnings addresses and balances the trade-off between the number of birth cohorts that can be included in the analysis and the time each individual can be observed in the data. In detail, the computation of UAX proceeds as follows. In a first step, daily earnings are aggregated to yearly earnings and inflated/deflated to the level of 2010. In a second step, cumulative earnings are calculated for each individual between the year the person turns 20 up to and including the year the individuals is reaching a certain age threshold (e.g., age 40 for the computation of UA40).

In line with the literature (Bönke *et al*., 2015a; Guevenen *et al*., 2017), two sets of results are provided: First, and as the main specification, nominal earnings are inflated/deflated to real earnings in terms of the year 2010 using the aforementioned German consumer price index. No additional discounting of these real earnings is made in this specification. As argued in the literature (e.g., Guevenen *et al*., 2017), a possible argument in favor of this approach is that there is no clear choice for an appropriate discounting rate of future earnings. Second, as an additional robustness test, the analysis is repeated incorporating an additional discounting of future earnings. For the construction of this measure, individual earnings are discounted to the year a cohort reaches the age of 20. The discount rate chosen is the average yield of German federal bonds, which can be considered as a (mostly) risk-free investment (henceforth: federal discounting). The corresponding time series are obtained from the German Central Bank.[2] These results are presented in the Online Supporting Information.

Both earnings measures only include payments from employment subject to social insurance contributions before tax, i.e., social transfer payments as well as earnings from periods of self-employment are not part of the analysis. Therefore, the earnings measure mirrors the price of labor paid in the market. Contrary to this approach, Bönke *et al*. (2015a) also add employers' social insurance contributions to the earnings measure as certain occupational groups, such as minors and sailors, have differing social security arrangements. As the share of these groups is negligible in the cohorts covered in the present study, a similar adjustment is not made. Earnings from marginal part-time employment (*Minijobs*) are also not included for consistency reasons, as these episodes were unobservable in the data before April 1, 1999.

At this point, it is insightful to descriptively compare the development in long term to cross-sectional inequality among the cohorts covered in the study. Figure 1 illustrates the development of the Gini coefficient in the two UA40 measures with the development in cross-sectional inequality. More precisely, cross-sectional inequality is measured as the mean of annual Gini coefficients (until reaching the age of 40) for each cohort.[3] The lowest line refers to UA40 earnings with an additional discounting of real earnings. Although inequality levels are generally lower

[2]In line with Bönke *et al*. (2015a), the study uses the time series WU0004 available online at the German Central Bank.

[3]A similar representation is provided in Bönke et al. (2015a) for the cohorts 1935–1949 and lifetime earnings. Note that inequality levels tend to be higher in their representation as it refers to lifetime as opposed to UA40 earnings.

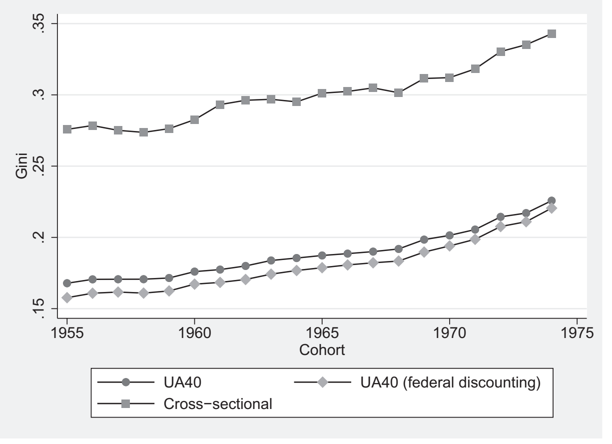


Figure 1. Development of Gini Coefficients

Notes: Development of Gini coefficients in UA40 and cross-sectional earnings (mean of annual Gini coefficients until reaching the age of 40), cohorts 1955–1974. Zero yearly earnings are included in the computation of annual Gini coefficients.

when compared to the specification without this additional discounting, both series follow the same trend and observe a significant increase in the Gini coefficient. The rise is moderately more pronounced for the series with additional discounting of real earnings (approximately +40 percent vs. +35 percent). This is owed to the fact that real interest rates in Germany used to be quite high, but decreased substantially from the late 1990s onwards. This in turn decreased the discounting factor for later cohorts, resulting in higher levels of inequality and, correspondingly, a steeper increase across time. As well known from previous research, the graph shows that inequality levels are generally lower in long-term as opposed to cross-sectional earnings as a result of earnings mobility. More importantly, it also reveals that both measures increased substantially across the cohorts studied with the increase in long-term earnings inequality being moderately more pronounced (approximately +35 percent or +40 percent as opposed to +34 percent).

Based on this insight, the development of long-term inequality is studied more comprehensively. Figure 2 illustrates the indexed (real) growth in UA40 earnings at different percentiles of the unconditional within-cohort distribution for men born between the years 1955 and 1974. The graph reveals three important developments. First, an increasing inequality in UA40 earnings within cohorts which is due to a monotonic development in the sense that, when considering the overall change between cohorts 1955 and 1974, lower percentiles below the median suffered losses whereas the upper half gained. Numerically, the 85th percentile of the UA40 distribution increased by approximately 12 percent, whereas the 15th percentile decreased by as much as 13 percent. Second, over the entire period of study, the graph shows a stagnation in median UA40 earnings with the development resembling an inverse U-shape. More precisely, median earnings increased up to birth cohorts 1965 and gradually deteriorated thereafter. Third, the graphical analysis suggests that the increase in inequality sped up dramatically among cohorts born in the early 1970s, which seems to be driven by severe real earnings losses at the

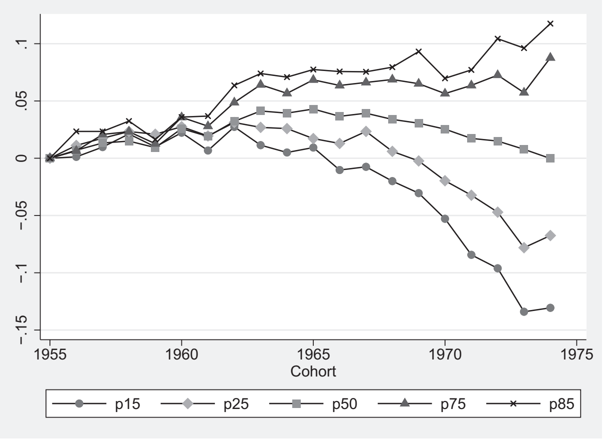


Figure 2. Indexed Real Growth in UA40
Notes: Indexed growth in percentiles of the unconditional UA40 distribution, cohorts 1955–1974

bottom and some moderate gains at the top. Finally, note that these developments are not a direct consequence of a delayed labor market entry, and the overall picture remains when only earnings starting at age 25 are considered (for details, see Figure SA5 in the Online Supporting Information).

The described development matches very well with previous evidence in Corneo (2015a,b) based on the Federal Pension Register. Considering their results on cohorts born in or after 1955 only, this previous study also finds a substantial decline in UA40 earnings at the bottom of the distribution which equally seemed to accelerate sharply for cohorts born in or after the mid-1960s. At the same time, it suggests a similar stagnation in median earnings for the aforementioned period (in contrast to substantial gains for earlier cohorts). Similarly, both studies document significant gains at the top of the intra-cohort distribution which, however, seem to be more pronounced in the present study. Overall, these strong parallels are reassuring that the SIAB data denote a feasible complement to the data of the Federal Pensions Register for studies in need of a larger set of employment-related covariates.

At first glance, the finding of stagnating long-term earnings seems to be at odds with previous work on cross-sectional earnings documenting significant gains in median hourly/daily earnings over the time period covered in the data at hand (e.g., Dustmann *et al.*, 2009). However, looking at the previous findings more closely, the results show that gains in cross-sectional earnings among German men were distributed very unevenly over the overall time period. Dustmann *et al.* (2009) show that real gains were almost exclusively realized before the German unification, whereas median earnings largely stagnated in the post-unification period, i.e., at a time when the later cohorts entered the labor market. Figure SA3 in the Online Supporting Information shows the indexed growth in cross-sectional earnings over the period 1975–2014 among full-time men at different ages. It reveals that cohorts 1955 and 1974 earned largely similar real full-time daily earnings at both age 25 (when most of the cohorts already entered the labor market) and age 40, which can be easily seen by comparing the age-25-earnings in the years 1980 and 1999 as well

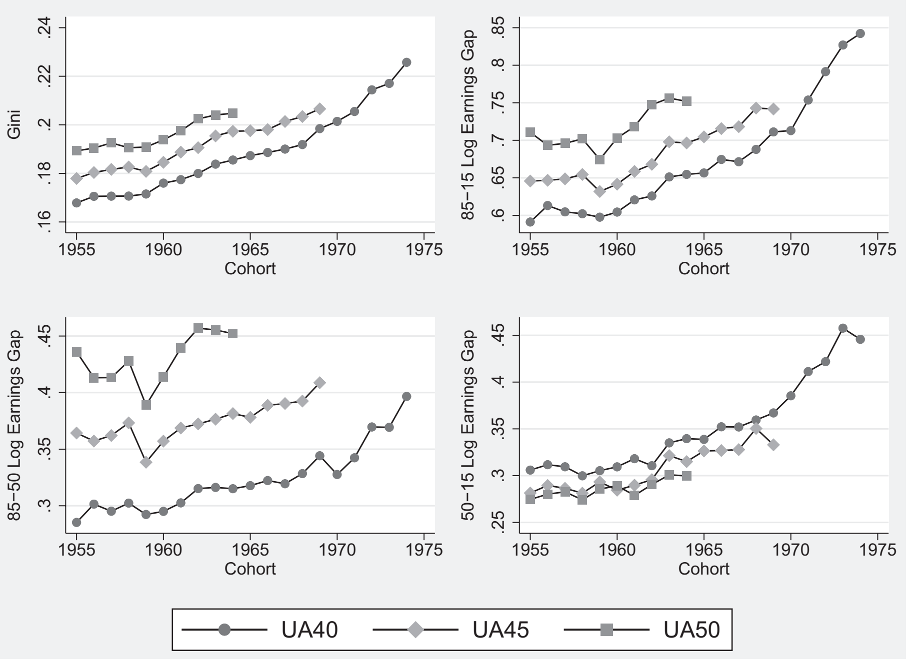


Figure 3. Inequality in *up-to-age-X*
Notes: Development of inequality in long-term earnings (UA40/UA45/UA50), cohorts 1955–1974

as the age-40-earnings in the years 1995 and 2014. Although this finding on cross-sectional earnings does not directly translate into stagnating long-term earnings (mainly because of potential differences in employment patterns), it is well aligned with the finding on stagnating long-term earnings among later cohorts.

Figure 3 summarizes the impact of the outlined development on inequality in different long-term earnings measures (UA40/UA45/UA50). Overall, the graph reveals a strong inequality increase in all parts of the UAX-measures with the aforementioned acceleration among cohorts born in the early 1970s. In terms of UA40, this is reflected in a sharp increase in the Gini coefficient from 0.168 to 0.226 (approximately +35 percent), which affected both the upper part (85-50 log earnings gap, approximately +39 percent) and the lower part (50-15 log earnings gap, +45 percent) of the distribution. In this regard, the results partly differ from previous findings on Germany (see Bönke *et al.*, 2015a) who assigned most of the increase in inequality to the bottom of the distribution. Interestingly, the increase at the top of the distribution was mostly driven by cohorts born in the early 1970s that were not included in the previous study. In line with existing evidence, inequality as captured by the different measures is increasing over the life cycle. An exception is the lower part of the distribution, which exhibits higher levels of inequality in terms of UA40. Confirming the general trends and argument provided in Bönke *et al.* (2015a), the presented graphical evidence suggests that the development in UA40 earnings appears to be closely linked to the developments in UA45/UA50 which can, however, be observed only for a limited number of cohorts.

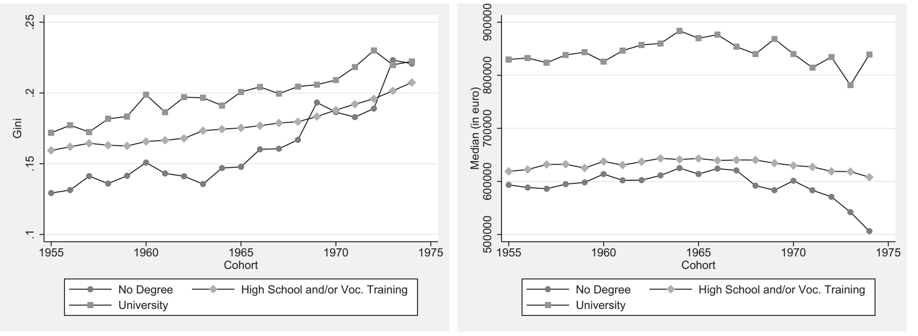


Figure 4. Evolution of UA40 Within Education Groups

Notes: Illustration shows development of Gini coefficient (left) and median (right) within educational subgroups, cohorts 1955–1974

As the German workforce was subject to some major educational upgrading during the period of study (see Section 3.3 for more details), it is important to study the development within the different education groups more carefully. Figure 4 summarizes the development within three broad educational groups, i.e., *No Degree*, *High School and/or Voc. Training*, and *University*. The graph on the left includes the development of inequality in terms of the Gini coefficient, the graph on the right the change in median earnings. The graph documents that inequality increased not only among all individuals of later cohorts but also within education groups. This increase was strongest within the lowest educational group (approximately +70 percent) and roughly similar among individuals holding a university degree or with vocational background (approximately +29 percent). Nevertheless, the impact of the sharp rise of inequality within the lowest educational group on overall inequality should not be overstated given the small relative group size. In addition, the graph shows that inequality levels tend to be highest among individuals with university background. At the same time, the graph reveals a decrease in median earnings among individuals without a university degree. These losses were strongest for individuals without a degree (approximately −17 percent) when compared to rather marginal losses among individuals with vocational training (approximately −1.8 percent). At the same time, university graduates born in 1974 realized marginal gains (approximately +1.1 percent) relative to graduates born in 1955. This mirrors the previous findings of losses in UA40 being mostly located at the bottom of the UA40 distribution. As overall median earnings virtually stagnated (approximately −0.2 percent), this result suggests that the losses among individuals with lower levels of education were neutralized by a shift toward higher average educational attainment among later birth cohorts.

3.2. *Trends in Employment Patterns*

Against the background of the trends outlined in the previous section, it is insightful to take a closer look at factors that can potentially explain this development. Hereby, it is crucial to understand whether the observed changes are caused by changes in individuals' labor market participation during the working

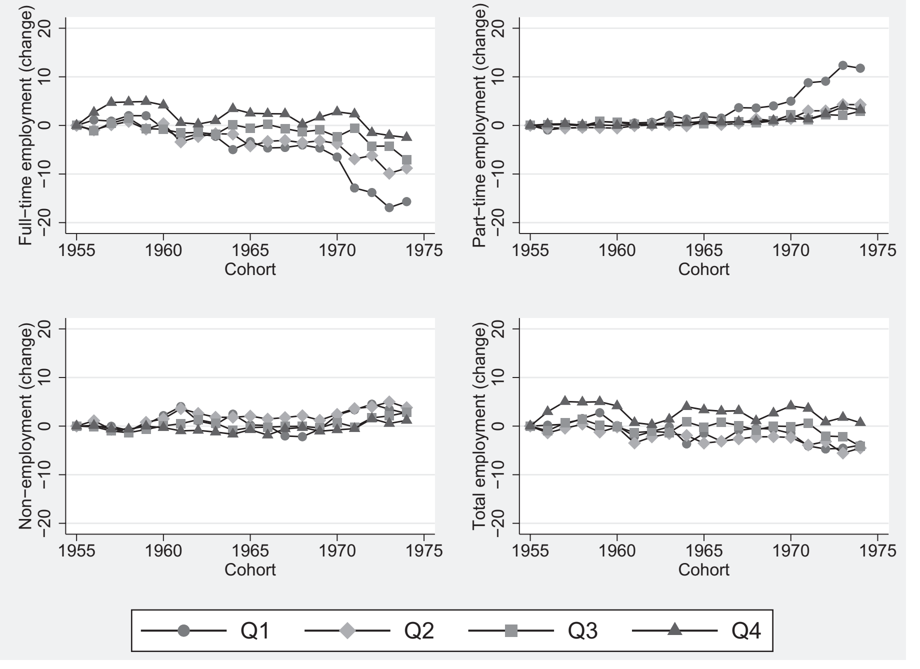


Figure 5. Evolution of Employment Patterns

Notes: Changes in number of months spent in different forms of employment by quartile of the UA40 distribution, cohorts 1955–1974

life, or whether they are because of changes in earnings during the time individuals were actually employed (i.e., changes in long-term hours worked vs. changes in daily/hourly earnings while being employed). Although the *SIAB* does not include precise information on hours worked, the data allow to consistently distinguish between episodes of full-time, part-time, and non-employment in individual employment biographies using the information of the *Employee History (BeH)*. In principle, it would also be possible to distinguish episodes of unemployment from other forms of non-employment by exploiting information on unemployment benefits recorded in the *Benefit Recipient History (LeH)*, the *Unemployment Benefit II Recipient Histories (LHG and XLHG)*, as well as the *Jobseeker-Histories (ASU and XASU)* provided by the Federal Employment Agency. However, the latter data sources are not available in the early years. Furthermore, there were several reforms that affected the entitlement to unemployment benefits, and therefore, a consistent measure across the cohorts used in this study cannot be constructed. As a consequence, the measure used for non-employment is defined as all episodes in individual employment biographies (after labor market entry) where an individual did not follow an employment subject to social insurance contributions. Besides unemployment spells, these include marginal part-time employment (*Minijobs*), self-employment, as well as time spent in further education.

Figure 5 presents the indexed changes in employment patterns across cohorts. It includes changes in the duration of full-time employment, part-time employment, non-employment, and total employment (i.e., either full-time or part-time employment) relative to the baseline cohort 1955. Although remaining the by far most frequent form of employment among German men, the figure reveals a considerable reduction in full-time employment among later cohorts which is found to be strongest for individuals at the bottom of the UA40 distribution. For example, the average time spent in full-time employment among individuals in the bottom quartile of UA40 decreased by approximately 16 months, or 8.7 percent, between cohorts 1955 and 1974. At the same time, there was also some reduction for higher quartiles which is, however, quantitatively less pronounced and decreasing over the distribution. Numerically, the average time spent in full-time employment decreased by on average 8.8 months for quartile 2, 7.1 months for quartile 3, and 2.5 months for the highest quartile.

This development was mirrored by an increase in part-time employment. Starting from a very low level among individuals of birth cohorts 1955–1957, the graph documents an increase in the average duration spent in part-time employment in all parts of the UA40 distribution. The graph also shows that individuals in the bottom quartile of the UA40 distribution were by far most affected by this expansion, with the average time spent in part-time employment increasing by nearly an entire year (11.8 months). This growing importance of part-time employment in recent decades applied, contrary to common perceptions, also to German men (see, e.g., Brenke, 2011; Biewen *et al.*, 2018). Besides ongoing structural changes and a resulting demand for more flexible working arrangements, this development was also enforced by several legal changes, such as the *Teilzeit und Befristungsgesetz (TzBfG)*, which increased the relative attractiveness of part-time employment. The outlined development had a potentially twofold effect on long-term earnings. Besides a simple reduction in long-term labor market participation (in the form of fewer working hours) and the resulting earnings losses, the previous literature (see Section 2 for references) has also documented adverse effects of part-time employment and non-employment on future earnings growth. In addition, the data show that part-time employment does not only occur at the beginning of the life cycle, but also throughout individuals' careers. More precisely, the last observable cohort 1974 exhibited a roughly stable overall part-time employment rate of 3–5 percent until the age of 40 (measured as the share of individuals being employed part-time on June 1 of each year), while the cohort 1955 (the first cohort being part of the analysis) even experienced a moderate growth over the life cycle, though starting from very low levels. Therefore, the finding of higher part-time employment rates up to age 40 among later cohorts can likely be generalized to the overall life cycle.

From a normative perspective, an important question is whether these higher rates of part-time employment are by choice or resulting from a failure to obtain an adequate full-time position. While this question cannot be fully addressed within the scope of this paper, the literature sheds some light on this aspect. On one hand, it shows that the number of involuntary part-time employment has been increasing in the US, explaining most of the rise in part-time employment in recent decades (Tilly, 1996; Canon *et al.*, 2014, Even and Macpherson, 2019). Green and Livanos (2017) argue that involuntary part-time employment has also grown in many European countries, with levels being comparably moderate in Germany. Though being somewhat speculative, the observation of an increasing number of involuntary part-time employment also fits well with the results presented in

Section 5, showing that part-time employment has mainly increased inequality at the bottom of the long-term earnings distribution. On the other hand, it would also be conceivable that, in light of changing gender roles and an increasing relative attractiveness of part-time work, an increasing number of men voluntarily decided to work part-time (e.g., for family reasons).

Simultaneously, this development was accompanied by an increase in the incidence of non-employment which was, however, much more moderate when compared to the increase in part-time employment. Numerically, it amounted to 2.6 months for the lowest and 1.2 months for the highest quartile. A comparison with the results on unemployment in Bönke *et al*. (2015a) reveals some differences that can be resolved on closer examination. Contrary to the findings in this paper, Bönke *et al*. (2015a) provide evidence for a sharp rise in unemployment among individuals in the lowest quartile between cohorts born in the mid-1930s and early 1960s. However, the by far largest part of this increase took place up to the birth cohorts of the late 1950s (mainly as a result of the oil crisis) with growth rates slowing down thereafter. Therefore, while equally documenting the strongest growth in the lowest quartile, observable difference can be traced back to the different cohorts covered. In direct comparison to non-employment, the expansion in part-time employment is found to be substantially stronger (e.g., by approximately the factor 4.5 for the lowest quartile) for the cohorts covered in the present study and more unevenly distributed along the UA40 distribution.

Finally, these findings raise the question of how the total employment duration (i.e., full- or part-time) was affected by these changes. Figure 5 shows a relatively modest decrease of approximately 4 months for the lowest 75 percent of the UA40 distribution and a marginal increase (+0.7 months) for the highest quartile. Overall, the descriptive evidence suggests that much of the reduction in full-time employment among cohorts 1955–1974 was in fact due to a shift toward part-time rather than non-employment.

3.3. *Trends in Education*

The cohorts included in the study also differ substantially in terms of their educational attainment. Figure 6 displays the share of individuals within cohorts in the three broad categories *No Degree*, *High School and/or Vocational Training*, as well as *University*. The graph shows the educational expansion of recent decades as similarly documented in previous research. Most importantly, there was a strong increase in the share of individuals holding a university degree, which increased from 11.5 percent among individuals of birth cohort 1955 to 18.4 percent among those born in 1974. This development was accompanied by corresponding declines in both the share of medium skilled workers (i.e., individuals with a high school degree and/or vocational training) and the share of low skilled workers (i.e., individuals who neither completed vocational training nor hold a high school degree). Note that the later decomposition analysis uses a more fine-grained educational measure distinguishing between six categories: *Lower/middle secondary without vocational training*, *Lower/middle secondary with vocational training*, *Upper secondary (German high school equivalent) without vocational training*, *Upper secondary (German high school equivalent) with vocational training*, *University or*

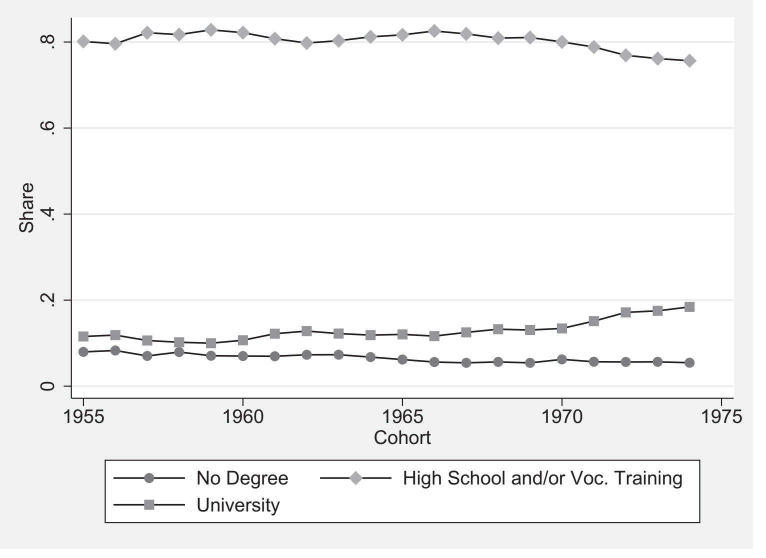


Figure 6. Share of Different Education Groups
Notes: Share of individuals in different educational groups, cohorts 1955–1974

Fachhochschule degree, as well as *Missing information*. To improve on the education variable in the SIAB, which in some cases suffers from both missing and implausible information, the imputation procedure (IP2A) suggested by Fitzenberger *et al.* (2006) is used.

3.4. *Trends in Job Mobility, Migration, and Firm Characteristics*

In addition to changing employment patterns and educational upgrading, the subsequent analysis considers further important characteristics related to individual employment biographies as shown in Table SA1. Some of these have also changed to noteworthy degree and are therefore considered as potential sources of increasing inequality in long-term earnings. A few examples are described below.

For example, changing job mobility patterns across cohorts might constitute another source of increasing inequality in long-term earnings. Against this background, the further analysis distinguishes two different types of job mobility in line with Gius (2014): firm changes within the same industry or occupation (job changes) on one hand, and firm changes where both the industry and occupation change (career changes) on the other hand. Gius (2014) shows this to be an important distinction, given that the first type of job change is associated with a positive earnings effect, whereas the latter one is found to have an adverse effect. The underlying theoretical argument is that individuals with a high number of career changes tend to accumulate fewer industry and occupation-specific human capital and should, on average, have a slower earnings growth over their career. Contrary to that, job changes within a certain occupation or industry (or within both) could potentially be linked to positive earnings effects due to a faster accumulation of human capital. However, the net effect of this second type of job change also remains to a certain extent unclear as it potentially includes a significant share of layoffs or other types of non-voluntary job changes. The descriptive evidence presented in Table SA1 shows that job changes were generally more frequent than career changes and the mean of both type of firm changes moderately increased among individuals born in the years 1972–1974.

To capture the potential impact of migration, a dummy variable indicating whether a person is German by birth is included. According to the definition used in this paper, a person is classified as German by birth if he or she has German citizenship throughout the entire observable working life recorded in the data. During the study period, there was an increase in individuals with migration background with their relative shares increasing from 11 to 22 percent between pooled cohorts 1955–1957 and 1972–1974. Given the previous finding that changing occupational characteristics (as a result of SBTC) potentially explain a significant share of rising cross-sectional wage inequality (see, Ehrl, 2017), a set of 32 occupation dummies are included in the analysis. Differences across industries are captured by the inclusion of sector dummies (44 categories). Both measures refer to the most frequent occupation/sector an individual worked in until the age of 40.

As the previous research on cross-sectional earnings inequality points toward an increasing importance of between-firm differences (see Section 2), the analysis includes a number of firm characteristics that can be constructed from the data. Against the background of the previous literature, the establishment size an individual worked at mostly denotes a potentially important feature for the development of individual long-term earnings. For the subsequent analysis, three firm sizes are distinguished which are small (1–50 employees), medium (51–500 employees), and large (>500 employees) establishments. To capture firm-level technological change, this paper follows a strategy similar to the most recent literature (e.g., Harrigan *et al*., 2016; Barth *et al*., 2017) by exploiting information in the Establishment History Panel on the number of engineers and natural scientists (*Techies*) working in an establishment. As these numbers potentially differ systematically across different industries, an establishment is defined as high tech if its share of engineers and natural scientists lies above the mean of the industry. In an analogues way, regional heterogeneities are accounted for by the inclusion of federal state dummies for the establishment's location (10 categories). Once again, these firm-level measures are aggregated over an individual's biography and therefore refer to the type of firm an individual worked at mostly.

4. Econometric Methods

The subsequent analysis builds on RIF decomposition to disentangle the increasing inequality in UA40 earnings between pooled cohorts 1955–1957 and 1972–1974. The method represents an extension of the well-known Oaxaca–Blinder decomposition that allows to decompose changes in any distributional statistics into a part being because of changes in the distribution of covariates while fixing the corresponding returns (composition effect), and one because of changes in the returns to these covariates leaving the distribution of covariates unchanged (returns effect).[4] Contrary to other decomposition techniques, the major advantage of RIF decomposition lies in the fact that it is the only method that allows for both a path-independent and detailed decomposition of any distributional statistic of interest. Therefore, it allows to link changes in a number of inequality measures (85-15/85-50/50-15 log earnings gaps, Gini, log variance) to the different covariates outlined in Section 3.

The method itself is based on unconditional quantile regression as introduced in the seminal contribution by Firpo *et al.* (2009). The main idea is to run regressions of the RIF of some distributional statistic of interest on explanatory variables. The RIF is a recentered version of the influence function defined as $RIF(y,\nu)=\nu+IF(y;\nu)$, where ν denotes the statistic of interest and $IF(y;\nu)$ the influence function corresponding to an observed outcome (or UA40 earnings) y for a distributional statistic of interest ν. It can easily be shown that the RIF has the same expectation as the original statistic of interest and integrates to ν as $\int RIF(y;\nu)\, dF(y) = \int (\nu + IF(y;\nu))\, dF(y) = \nu\left(F_y\right)$, where F_y is the distribution function of the dependent variable. Assuming that the conditional expectation of the RIF is a linear function of the explanatory variables, the RIF is modeled as $E[RIF(Y;\nu)|X]=X\gamma$, where γ can be estimated by OLS. Given this linear specification, the Oaxaca–Blinder decompositions using the RIF regression coefficients can be used to split up the overall change Δ_O^ν in a distributional statistic of interest ν into a composition Δ_X^ν and a returns effect Δ_S^ν.

$$\Delta_O^\nu = \underbrace{\nu\left(F_{Y_0|c=1}\right) - \nu\left(F_{Y_0|c=0}\right)}_{\Delta_X^\nu} + \underbrace{\nu\left(F_{Y_1|c=1}\right) - \nu\left(F_{Y_0|c=1}\right)}_{\Delta_S^\nu}, \tag{1}$$

where $F_{Y_0|c=s}$ and $F_{Y_1|c=s}$ denote the distributions of UA40 earnings among workers in cohort s receiving the returns to characteristics of cohort 0 and cohort 1, respectively.

Firpo *et al.* (2007) point out that because of their linear specification, the RIFs are only local approximations that potentially lead to biased results in case of large changes in the distribution of characteristics. This shortcoming is addressed by a refined version of the decomposition suggested in Firpo *et al.* (2014, 2018), which additionally incorporates inverse probability weighting (DiNardo *et al.*, 1996). The main idea lies in the creation of an artificial cohort 01, in which the cohort 0 distribution of characteristics X is reweighted to that of the target cohort 1. Using two separate Oaxaca–Blinder decompositions, the overall change Δ_O^ν is split up into four components:

$$\Delta_O^\nu = \underbrace{\left(\overline{X}_{01} - \overline{X}_0\right)\hat{\gamma}_0^\nu}_{\Delta_{X,p}^\nu} + \underbrace{\overline{X}_{01}\left(\hat{\gamma}_{01}^\nu - \hat{\gamma}_0^\nu\right)}_{\Delta_{X,c}^\nu} + \underbrace{\overline{X}_1\left(\hat{\gamma}_1^\nu - \hat{\gamma}_{01}^\nu\right)}_{\Delta_{S,p}^\nu} + \underbrace{\left(\overline{X}_1 - \overline{X}_{01}\right)\hat{\gamma}_{01}^\nu}_{\Delta_{S,c}^\nu}. \tag{2}$$

where $\Delta_{X,p}^\nu$ denotes the estimate for the detailed composition effect, i.e., the effect from changing the distribution of a certain group of covariates while fixing its

[4]The decomposition literature often uses the term wage structure effect. However, as this paper analyzes long-term earnings, as opposed to wages, the suggested terminology is used.

returns (at the level of cohort 0). For instance, the detailed composition effect linked to part-time employment would reflect the change in ν that results from changing the distribution of UA40 part-time spells of cohort 0 to that of cohort 1. The term $\Delta^{\nu}_{X,c}$ denotes the specification error that reflects differences in the estimated RIF coefficients between the cohorts 01 and 0. In other words, it corresponds to the difference between the linear approximation of the composition effect estimated by RIF decomposition and the estimate of the composition effect received from applying DiNardo *et al.* (1996) reweighting (which does not impose any conditions regarding the functional form). Therefore, a small value for the specification error indicates that a linear approximation of the composition effect is appropriate. The term $\Delta^{\nu}_{S,p}$ denotes the detailed returns effects that capture the effect from changes in γ for a certain group of covariates. As γ is estimated from unconditional (as opposed to conditional) quantile regression, it represents changes both between and within subgroups. Finally, $\Delta^{\nu}_{S,c}$ represents the reweighting error that stems from differences in the distribution of covariates between cohort 1 and the reweighted base cohort 01 and should, in case the reweighting procedure was successful, be close to zero.

Fortin *et al.* (2011), among others, point out that the detailed decomposition results of the returns effect for groups of categorical variables depend arbitrarily on the choice of the omitted reference group. To address this concern, RIF regression coefficients are normalized such that they sum up to zero within a group of categorical variables J, i.e., $\sum_{j \in J} \gamma_j = 0$ (see Gardeazabal and Ugidos, 2004), effectively making the results independent of the chosen reference group. As another advantage, this kind of normalization facilitates the interpretation of results as information on the general level of ν is captured by the intercept, whereas the regression coefficients mirror deviations of individual categories from this general level. Accordingly, the intercept also captures changes in the relative importance of different groups of covariates as well as the contribution of unobservable factors (see Biewen and Seckler, 2019, for a more rigorous discussion).

Finally, note that the results from RIF decomposition should not be interpreted as causal effects. This is because of the fact that statistical decomposition techniques (including RIF decomposition) do not account for general equilibrium effects, as they generally assume invariance of the conditional distribution. Similarly, the method does not account for the fact that different explanatory factors might be dynamically related, i.e., changes in one group of covariates (e.g., job mobility) might be the result of changes in another group (e.g., education). Despite these limitations, RIF decomposition represents a highly useful tool to deepen the understanding of what factors are associated with the observed changes in the distribution of individual long-term and lifetime earnings.

5. Decomposition Results

5.1. *Inequality in Average Yearly Earnings vs. Total Years of Employment*

This section provides a descriptive analysis of UA40 earnings inequality along both the extensive and intensive margins, i.e., (i) inequality in total years of employment (=days in full-time or part-time employment/365) and (ii) inequality in

TABLE 1
INEQUALITY UA40/ AVERAGE YEARLY EARNINGS/YEARS EMPLOYED

Pooled Cohort	85-15	85-50	50-15	Gini	Log Variance
UA 40 earnings					
1955–1957	0.605	0.295	0.310	0.170	0.110
1972–1974	0.818	0.381	0.437	0.219	0.183
Change	0.213 (+35.2%)	0.086 (+29.2%)	0.127 (+41.0%)	0.053 (+28.8%)	0.073 (+66.4%)
Average yearly earnings (UA40)					
1955–1957	0.551	0.342	0.209	0.165	0.084
1972–1974	0.721	0.415	0.306	0.213	0.140
Change	0.170 (+30.9%)	0.073 (+21.3%)	0.097 (+46.4%)	0.048 (+29.0%)	0.056 (+66.7%)
Years of employment (UA40)					
1955–1957	0.329	0.075	0.254	0.085	0.037
1972–1974	0.367	0.089	0.278	0.092	0.038
Change	0.038 (+11.6%)	0.014 (+18.7%)	0.024 (+9.5%)	0.007 (+8.2%)	0.001 (+2.7%)

Source: Sample of Integrated Labour Market Biographies (SIAB) 1975–2014 and own calculations.

TABLE 2
Decomposition of Log(UA40)

Pooled cohort	var(log(UA40))	var(log(av. yearly))	var(log(empl.))	2cov(log(av. yearly), log(empl.))
1955–1957	0.110	0.084	0.037	−0.010
1972–1974	0.183	0.140	0.038	0.005
Pooled cohort	Δvar(log(UA40))	Δvar(log(av. yearly))	Δvar(log(empl.))	Δ2cov(log(av. yearly), log(empl.))
1972/74–1955/57	0.073	0.056	0.001	0.015

Source: Sample of Integrated Labour Market Biographies (SIAB) 1975–2014 and own calculations.
av. yearly = average early earnings; UA40 = up-to-age 40 earnings; empl. = years of employment.

average yearly earnings (=UA40/total years of employment). In doing so, it follows the intuitive logic that long-term (UA40) earnings can be described as UA40 earnings = total years of employment UA40×average yearly earnings UA40. Therefore, it provides a first answer to the question of whether the observed increase in UA40 earnings inequality was due to an increasing inequality in long-term labor market participation (as measured by total years of employment) or due to an increasing inequality in earnings during times of employment (as measured by the average yearly earnings).

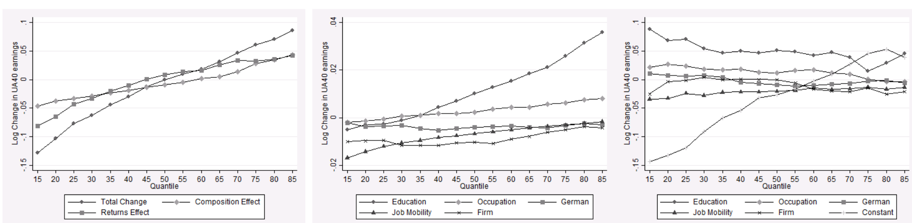
Table 1 summarizes the development in all three quantities. Starting with a description of UA40 earnings, the results show a substantial increase along the entire distribution as shown in Section 3.1. With regard to average yearly earnings, the results reveal a similar pattern. For example, the 85-15 log earnings gap in UA40 increased from 0.605 to 0.818 (i.e., by approximately +35 percent), while the inequality in average yearly earning rose from 0.551 to 0.721 (i.e., approximately +31 percent). Turning to the total years of employment, the analysis shows a moderate increases in all inequality measure, which are, however, quantitatively smaller when compared to the other two quantities. Numerically, overall inequality in terms of the 85-15 log earnings gap rose from 0.329 to 0.367 (approximately +12 percent). Increases in the Gini coefficient and log variance were more modest amounting to 8.2 and 2.7 percent, respectively.

In a further step of analysis, the relative importance of both margins is illustrated in a variance decomposition (see, e.g., Juhn *et al.*, 1993; Blau and Kahn, 2011; Biewen and Plötze, 2019). The total inequality in UA40 is decomposed according to var(logUA40) = var(log(av. yearly earnings UA40)) + var(log(total years of employment UA40) + 2cov(log(av. yearly earnings UA40), log(total years of employment UA40)). The results in Table 2 show that for the cohorts studied, inequality in average earnings explain about three-fourths (approximately 77 percent) of total long-term earnings inequality, with the remaining parts being due to inequality in the total years of employment and the covariance term. Interestingly, the log variance in total employment only increased moderately (+2.7 percent). Therefore, the observable increase (0.073) in UA40 can mostly be attributed to an increasing inequality in average yearly earnings (approximately +77 percent), with the remaining share being due to an increase in the total years of employment (approximately +1 percent) and the covariance term (approximately +12 percent).

How do these results fit to the descriptive evidence on employment patterns presented earlier in the paper? First, it is important to recall that total employment as defined here captures both periods of full-time and part-time employment. Therefore, the substantial shift from full- to part-time employment (see Figure 5) leaves the total years of employment unaltered. Second, as commonly argued in the literature (see, e.g., Biewen and Plötze, 2019), classical variance decompositions are restrictive for several reasons. Most importantly, the analysis is limited to the variance of logs, and therefore, a very specific inequality measure. Therefore, it implicitly assumes that the impact of changes in total years of employment in fact worked through changes in the variance of log total employment. In contrast to the findings on the log variance, the descriptive evidence provided in Table 1 showed substantially stronger increases in the other inequality measures provided. Independent of this discussion, the result persists that the increase in

TABLE 3
Groups of Covariates

Group	Covariates
1. Education	Highest educational degree UA40 (6 categories)
2. Occupation	Most frequent occupation UA40 (32 categories)
3. Nationality	German by birth (binary, no spells with foreign nationality)
4. Job mobility	Number of firm changes UA40 (with change in both occupation/industry)
	Number of firm changes UA40 (without change in both occupation/industry)
5. Firm	Most frequent firm size UA40 (3 categories)
	Mostly in high-tech firm UA40 (binary)
	Most frequent sector UA40 (44 categories)
	Most frequent federal state UA40 (10 categories)



(a) Aggregate decomposition **(b)** Detailed composition effect **(c)** Detailed returns effect

Figure 7. RIF Decomposition, UA40

Notes: Results for pooled cohorts 1955–1957 vs. 1972–1974. Illustration shows changes in unconditional quantiles of the corresponding UA40 distributions. [Colour figure can be viewed at wileyonlinelibrary.com]

UA40 earnings is largely because of an increase in the inequality of average yearly earnings as opposed to the total years of employment.

5.2. *Determinants of Long-Term Earnings Inequality*

The first step of analysis is a decomposition of the observed changes in total long-term (UA40) earnings inequality. For reasons of clarity, the previously presented covariates are summarized in five groups in line with Table 3. For the baseline model, these are *Education*, *Occupation*, *Job mobility*, *Nationality*, and *Firm*. A more comprehensive analysis of the impact of changing employment patterns, which are not included in the baseline model, is provided in a separate analysis in Section 5.5.[5]

[5]As pointed out by a referee, it is generally difficult to include variables related to employment patterns alongside other covariates. This is for two reasons: First because of a mechanically close relationship between long-term earnings and years of employment. Second, because of the fact that factors like educational upgrading likely impacted both employment patterns (such as increasing part-time employment) and long-term earnings simultaneously. Therefore, it is difficult to assess the importance of both channels relative to each other. Nevertheless, there are also examples in the literature using a similar estimation strategy (e.g., Boll *et al.*, 2017).

TABLE 4
RIF Decomposition Results

	UA40					Average Yearly					Years of Employment				
Inequality measure	85-15	85-50	50-15	Gini	Log Var	85-15	85-50	50-15	Gini	Log Var	85-15	85-50	50-15	Gini	Log Var
Total change	21.35***	8.58***	12.77***	4.91***	7.25***	17.00***	7.31***	9.69***	4.71***	5.53***	3.81***	1.35***	2.46***	0.69***	0.11
	(1.12)	(0.68)	(0.88)	(0.20)	(0.36)	(0.99)	(0.86)	(0.51)	(0.19)	(0.23)	(0.64)	(0.26)	(0.73)	(0.12)	(0.10)
Total composition	7.11***	4.38***	2.73***	1.68***	2.06***	10.09***	8.02***	2.07***	2.61***	2.38***	4.73***	3.46***	1.28***	1.68***	1.03***
	(0.57)	(0.36)	(0.39)	(0.13)	(0.21)	(0.49)	(0.39)	(0.27)	(0.14)	(0.12)	(0.37)	(0.23)	(0.29)	(0.11)	(0.09)
Education	4.10***	2.59***	1.52***	0.87***	0.90***	8.22***	6.50***	1.72***	2.14***	1.92***	2.61***	1.84***	0.76***	0.98***	0.50***
	(0.35)	(0.23)	(0.21)	(0.07)	(0.11)	(0.40)	(0.32)	(0.16)	(0.11)	(0.09)	(0.28)	(0.14)	(0.20)	(0.07)	(0.05)
Occupation	1.01***	0.58***	0.42***	0.20***	0.27***	1.38***	0.81***	0.57***	0.33***	0.31***	0.48***	0.12*	0.36***	0.12***	0.12***
	(0.23)	(0.16)	(0.18)	(0.05)	(0.07)	(0.22)	(0.17)	(0.12)	(0.06)	(0.05)	(0.13)	(0.07)	(0.12)	(0.03)	(0.03)
Nationality	−0.08	0.10	−0.18	0.06	0.12	−0.64***	−0.12	−0.52***	−0.09**	−0.09**	0.56***	0.78***	−0.22	0.17***	0.13***
	(0.22)	(0.16)	(0.19)	(0.05)	(0.09)	(0.16)	(0.15)	(0.14)	(0.04)	(0.04)	(0.13)	(0.09)	(0.14)	(0.03)	(0.04)
Job mobility	1.52***	0.51***	1.01***	0.39***	0.60**	0.47***	0.27***	0.20***	0.08***	0.06**	0.67***	0.51***	0.16***	0.28***	0.20***
	(0.26)	(0.09)	(0.17)	(0.07)	(0.11)	(0.09)	(0.06)	(0.05)	(0.02)	(0.02)	(0.12)	(0.08)	(0.06)	(0.05)	(0.04)
Firm	0.56**	0.60***	−0.04	0.16**	0.17	0.67***	0.57***	0.10	0.15***	0.18***	0.40**	0.19**	0.21	0.13***	0.09**
	(0.24)	(0.21)	(0.22)	(0.06)	(0.11)	(0.21)	(0.20)	(0.14)	(0.05)	(0.05)	(0.16)	(0.09)	(0.15)	(0.04)	(0.04)
Total effect returns	12.34***	3.43***	8.91***	3.29***	5.17***	4.19***	−3.27***	7.48***	2.56***	3.45***	−3.34***	−0.83***	−2.52***	−0.89***	−0.86***
	(1.25)	(0.70)	(0.98)	(0.22)	(0.44)	(1.11)	(0.97)	(0.54)	(0.19)	(0.23)	(0.76)	(0.34)	(0.76)	(0.13)	(0.15)
Education	−4.24	−0.56	−3.68	−2.07**	−6.94***	−3.72	−2.36	−1.37	−1.80**	−4.86***	−0.62	−1.60	0.98	−0.69	−0.45
	(5.24)	(2.94)	(4.38)	(0.93)	(2.52)	(3.76)	(2.77)	(2.77)	(0.78)	(1.77)	(3.06)	(1.68)	(2.78)	(0.49)	(0.45)
Occupation	−2.50	−1.56	−0.94	−0.42	−0.62	−4.91***	−5.03***	0.12	−0.73***	−0.99**	1.22	0.05	1.17	0.10	0.23
	(1.86)	(1.05)	(1.71)	(0.31)	(0.71)	(1.33)	(1.10)	(0.94)	(0.26)	(0.39)	(1.09)	(0.47)	(1.06)	(0.20)	(0.23)
Nationality	−1.60	0.35	−1.95	−0.17	−0.16	−0.12	0.56	−0.68	−0.31*	−0.20	−0.91	−0.73*	−0.18	−0.03	0.08
	(1.27)	(0.86)	(1.12)	(0.22)	(0.49)	(0.88)	(0.87)	(0.65)	(0.18)	(0.21)	(0.88)	(0.44)	(0.90)	(0.16)	(0.22)
Job mobility	2.04	0.67	1.37	0.04	1.03	2.41*	0.21	2.19***	0.28	0.52*	−1.37	−0.77	−0.60	−0.14	−0.08
	(2.81)	(0.95)	(2.14)	(0.53)	(1.04)	(1.35)	(0.99)	(0.76)	(0.25)	(0.30)	(1.08)	(0.55)	(0.89)	(0.28)	(0.26)
Firm	0.40	−2.04	2.44	−0.09	−0.60	0.49	1.50	−1.02	0.17	−0.26	0.47	−0.19	0.66	0.21	0.21
	(2.14)	(1.37)	(1.75)	(0.38)	(0.62)	(1.78)	(1.54)	(0.99)	(0.34)	(0.40)	(1.11)	(0.66)	(1.00)	(0.21)	(0.22)
Constant	18.25***	6.57**	11.67**	6.00***	12.46***	10.06**	1.83	8.22**	4.96***	9.24***	−2.14	2.40	−4.55	−0.34	−0.86
	(5.74)	(3.26)	(5.08)	(1.07)	(2.77)	(4.61)	(3.35)	(3.33)	(0.93)	(1.96)	(3.50)	(2.01)	(3.15)	(0.57)	(0.56)

TABLE 4 (CONTINUED)

	UA40					Average Yearly					Years of Employment					
Specification error	1.81***	0.80**	1.01*	−0.06	0.02	2.66***	2.59***	0.07	−0.34 ***	−0.14***	2.40***	−1.26***	3.66***	−0.11 ***	−0.07*	
	(0.61)	(0.37)	(0.52)	(0.05)	(0.09)	(0.61)	(0.59)	(0.20)	(0.05)	(0.04)	(0.61)	(0.21)	(0.60)	(0.03)	(0.04)	
Reweighting error	0.09	−0.03	0.12	0.00	0.01	0.05	−0.03	0.08	−0.02	−0.03	0.02	−0.02	0.04	0.01	0.01	
	(0.19)	(0.11)	(0.13)	(0.04)	(0.07)	(0.25)	(0.19)	(0.09)	(0.05)	(0.05)	(0.14)	(0.08)	(0.09)	(0.03)	(0.03)	

Source: Sample of Integrated Labour Market Biographies (SIAB) 1975–2014 and own calculations. Log differentials×100. Bootstrapped standard errors (100 replications) in parentheses. ***/**/* statistically significant at 1 percent/5 percent/10 percent-level.

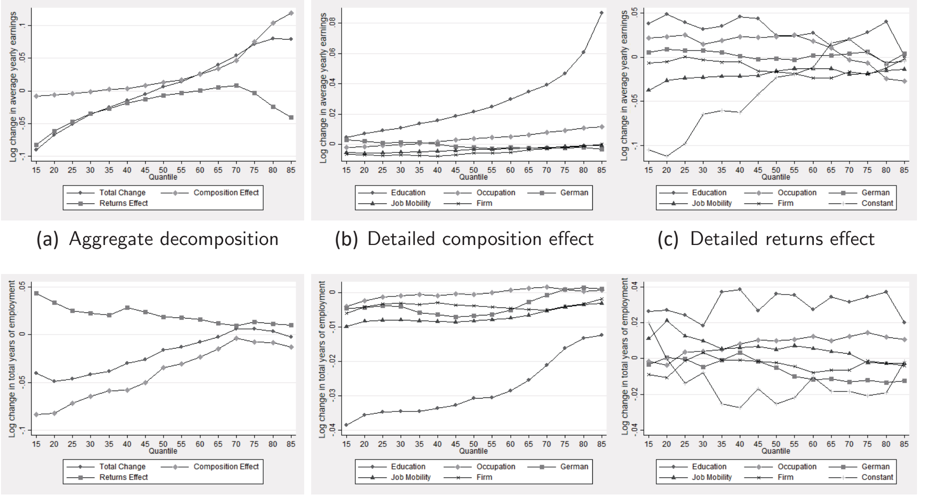
In the presentation of results, it is insightful to start with a graphical analysis. Figure 7a includes the total change in unconditional quantiles together with the aggregate composition and returns effect. The total change in unconditional quantiles was characterized by a monotonic development in the sense that unconditional quantiles below the median suffered losses in terms of UA40, whereas the upper half gained. In this regard, the development somewhat resembles previous findings on inequality in daily/hourly earnings. The aggregate composition effect reveals a similar monotonic pattern, but was negative for most of the distribution and only had a weakly positive effect above the 60th percentile. Also monotonic, the aggregate returns effect is found to be weakly positive in the upper and negative in the lower part of the distribution.

Figure 7b further disentangles the overall composition effect by displaying the detailed composition effects linked to the groups of covariates. Being the most important individual composition effect, compositional changes in education led to an upward shift of the UA40 distribution across all quantiles. Beyond education, the analysis reveals only moderate composition effects, e.g., because of changes in occupation or job mobility. Figure 7c provides detailed results for the returns effect. The analysis reveals an important contribution of a general returns effect as captured by the constant, which had a very negative impact on the bottom of the distribution and was favorable for the top. As argued in Section 4, the constant captures that part of the returns effect that cannot be attributed to the characteristics included in the decomposition (e.g., unobserved ability or idiosyncratic shocks), but might as well reflect changes in the relative importance of different groups of covariates.

Table 4 presents the corresponding numerical results for the decomposition of UA40 earnings, which underpin the findings of the preceding graphical analysis. Numerically, the total composition effect (7.11) explains only about one-third of the overall 21.35 log percentage points increase in the 85-15 log wage differential, with the specification and reweighting error (together) amounting to 1.90 points. Note that this result is partly due to the fact that the decomposition does not contain explicit controls for differences in employment patterns. By far the strongest composition effect was due to changes in educational attainment (4.10 points). Further, there seemed to be moderate composition effects linked to changes in the job mobility (1.52 points) as well as the occupational structure (1.01 points). The bottom half of the table, displaying detailed results for the returns effect, shows that the estimated effects are less precise and mostly turn out insignificant.

5.3. *Determinants of Inequality in Average Yearly Earnings*

It is again informative to start the study of changes in average yearly earnings with a graphical representation. Figure 8a reveals that overall changes in average yearly earnings were also monotonic over the unconditional distribution (of average yearly earnings). More precisely, individuals below the median suffered losses whereas the upper half gained substantially. The overall composition effect is negligible in the lower half of the distribution and monotonically increasing in the upper half. The aggregate returns effect resembles an inverse U-shape and is found to have a particularly negative effect in the lower tail of the average yearly earnings



(a) Aggregate decomposition (b) Detailed composition effect (c) Detailed returns effect

(d) Aggregate decomposition (e) Detailed composition effect (f) Detailed returns effect

Figure 8. RIF Decomposition, Average Yearly Earnings (Top Row), and Total Employment (Bottom Row)

Notes: Results for pooled cohorts 1955–1957 vs. 1972–1974. Illustration shows changes in unconditional quantiles of the corresponding average yearly earnings (top row) and total years of employment (bottom row) distributions. [Colour figure can be viewed at wileyonlinelibrary.com]

distribution. Figure 8b further disentangles the overall composition effect. It exhibits the outstanding role of educational upgrading, which once more increases over the distribution and sharply rises in the upper tail. Further, it indicates that changes in the occupational composition of cohorts seemed to have moderately favored the upper half of the distribution. Similar to the results on UA40, Figure 8c stresses an important contribution of the constant term that puts downward pressure on the lower tail of the distribution.

The corresponding numerical results in Table 4 confirm the outstanding importance of compositional changes in education. More precisely, the factor alone explains nearly half (48 percent) of the increase in overall inequality in terms of the 85-15 log earnings gap and nearly the entire increase in average earnings inequality at the top (6.50 of 7.31 in terms of the 85-50 log earnings gap). At the same time, its effect was only moderate at the bottom of the distribution. In comparison to the decomposition in UA40, composition effects were generally more important, explaining close to 60 percent (10.09 of 17.00 points) of the increase in overall inequality. Once again, the table finds evidence for moderate composition effects linked to occupation (1.38 points) and job mobility (0.47 points). Apart from the constant, the results provide some evidence in favor of a relatively large negative returns effect linked to occupation that seems to have compressed wages at the top of the distribution. At the same time, the numbers suggest that the returns effect linked to job mobility increased inequality at the bottom of the distribution. However, both effects should not be overemphasized given that the effect turns out to be insignificant in the decomposition over overall UA40.

5.4. *Determinants of Inequality in Total Years of Employment*

The graphs in the bottom row of Figure 8 provide results of a graphical analysis for the total years of employment. Overall, Figure 8d shows a monotonic change in the sense that total employment decreased below the 70th percentile of the unconditional distribution (of total employment) and remained mostly unchanged above. A very similar image emerges for the overall composition effect that tends to even moderately exceed the total change. At the same time, the overall returns effect seems to have moderately compressed the distribution of total years of employment, especially in the lower half of the unconditional distribution. A detailed analysis of the related composition effect is provided in Figure 8e. Again, the findings show a leading role of compositional shifts in education in the sense that it decreased total employment throughout the entire distribution (but more in lower quantiles). This appears plausible because of the higher share of individuals with university background among later cohorts. Because of the additional time spent in education, these high-skilled individuals ended up at the bottom of the distribution of total years of employment thereby shifting the lower tail downwards. The returns effects in Figure 8f seem to be relatively homogenous along the unconditional distribution, suggesting a somewhat- limited impact on inequality in total years of employment. As shown in Table 4, education emerges once more as the decisive factor explaining close to 70 percent of the overall increase in inequality (2.61 of 3.81 in terms of the 85-50 log earnings gap) and even seems to overexplain changes in the Gini coefficient or the log variance. The same holds true for the aggregate composition effect. Simultaneously, the table also shows moderate inequality-increasing effects linked to the other factors. As stated earlier, the total returns effect turns out negative, especially at the bottom of the distribution. However, the individual effects are estimated less precisely and are generally insignificant.

5.5. *A More Cautious Look on the Role of Employment Patterns*

The decomposition results presented so far did not differentiate between part-time and full-time employment. At the same time, the presented descriptive evidence in Section 3.2 showed a substantial shift from full-time to part-time employment among the cohorts covered in the present study. It is therefore insightful to study the impact of increasing part-time employment within a separate analysis and to determine its importance relative to other channels, most notably employment interruptions in the form of non-employment. In doing so, two sets of results are provided: first, decomposition results including employment patterns (years of part-time employment/years of non-employment) only, and second, the two variables mentioned alongside the covariates used in the preceding analyses.

The results on the isolated effect of changing employment patterns (i.e., without conditioning on other covariates) in Table 5 show a strong composition effect linked to part-time employment, explaining up to 12.06 of the 21.35 points increase in the 85-15 log earnings gap. Confirming descriptive evidence, this effect was particularly pronounced at the bottom of the distribution (8.68 of 12.77 increase in the 50-15 log earnings gap). At the same time, the results show that the effect of increasing part-time work was much stronger than that of non-employment,

TABLE 5
Detailed Decomposition Results for Employment Patterns, UA40

Inequality measure	85-15	85-50	50-15	Gini	Log Variance
Total change	21.35***	8.58***	12.77***	4.91***	7.25***
	(1.23)	(0.77)	(0.99)	(0.20)	(0.34)
	Composition effects (without additional covariates)				
Part-time	12.06***	3.37*	8.68***	3.19***	5.58***
	(1.84)	(0.59)	(1.50)	(0.46)	(1.07)
Non-employment	1.51***	0.51***	1.00***	0.41***	0.68***
	(0.59)	(0.20)	(0.39)	(0.16)	(0.27)
	Composition effects (with additional covariates)				
Part-time	2.51***	0.34**	2.18***	0.69***	1.33***
	(0.34)	(0.16)	(0.26)	(0.09)	(0.23)
Non-employment	2.03***	0.55***	1.48***	0.55***	0.95***
	(0.31)	(0.09)	(0.23)	(0.09)	(0.15)
	Returns effects (without additional covariates)				
Part-time	−1.63*	0.06	−1.70**	0.00	0.55
	(0.91)	(0.28)	(0.82)	(0.13)	(0.33)
Non-employment	0.50 ***	−0.59***	1.09***	0.80**	3.64***
	(3.15)	(0.75)	(3.27)	(0.29)	(0.96)
	Returns effects (with additional covariates)				
Part-time	−1.51**	−0.19	−1.32**	−0.24**	−0.09
	(0.69)	(0.25)	(0.59)	(0.12)	(0.29)
Non-employment	4.22*	0.69	3.53*	0.57**	3.13***
	(2.24)	(0.81)	(1.90)	(0.29)	(0.74)

Notes: Log differentials×100. Bootstrapped standard errors (100 replications) in parentheses ***/**/* statistically significant at 1 percent/5 percent/10 percent-level. Additional covariates as outlined in Table 3.

Source: Sample of Integrated Labour Market Biographies (SIAB) 1975–2014 and own calculations.

explaining only 1.51 of the 21.35 points increase in the 85-15 log earnings gap. Note that this sort of decomposition analysis using variables on employment patterns only likely overestimates their effect, as it tends to spuriously pick up the effect of the left-out variables. For example, individuals with a high incidence of part-time employment might also have less favorable characteristics in terms of other covariates such as education or other occupational characteristics. Therefore, to obtain a more conservative estimate of its overall effect and to rule out spurious findings, the table equally shows results of a specification including years of part-time and non-employment along the other covariates used in the previous analysis. In this alternative specification, the composition effect linked to part-time employment shrinks considerably, whereas the one attached to non-employment remains largely unchanged. Nevertheless, the results still suggest that approximately 12 percent (2.51 of 21.35 points in terms of the 85-15 log earnings gap) of overall inequality and 17 percent (2.18 of 12.77 points in terms of the 50-15 log earnings gap) of increasing inequality at the lower tail can be explained by the expansion of part-time employment.

Tables SA6 and SA7 in the Online Supporting Information contain decomposition results for the two subcomponents average yearly earnings and total years of employment. While both are important, the former is in the1 focus of the further discussion. Table SA6 shows that increasing part-time employment explains up to 62 percent (10.53 of the 17.00 points) of the increase in average yearly earnings when studying the isolated effect of changing employment patterns. Once again,

TABLE 6
RIF Decomposition Results, Predetermined Factors

	UA40					Average yearly					Years of employment				
Inequality measure	85-15	85-50	50-15	Gini	Log Var	85-15	85-50	50-15	Gini	Log Var	85-15	85-50	50-15	Gini	Log Var
Total change	21.35***	8.58***	12.77***	4.78***	6.95***	17.00***	7.31***	9.69***	4.71***	5.53***	3.81***	1.35***	2.46***	0.61***	0.06
	(1.22)	(0.61)	(1.10)	(0.19)	(0.36)	(1.22)	(1.07)	(0.58)	(0.22)	(0.27)	(0.64)	(0.26)	(0.59)	(0.12)	(0.10)
Total composition	6.42***	4.08***	2.34***	1.60***	1.99***	8.79***	7.09***	1.70***	2.40***	2.19***	4.26***	3.38***	0.88***	1.65***	1.00***
	(0.55)	(0.38)	(0.38)	(0.12)	(0.20)	(0.46)	(0.39)	(0.22)	(0.13)	(0.11)	(0.35)	(0.22)	(0.27)	(0.11)	(0.09)
Education	4.39***	2.74***	1.65***	0.90***	0.93***	8.45***	6.41***	2.04***	2.08***	1.85***	2.54***	1.86***	0.69***	0.99***	0.52***
	(0.37)	(0.25)	(0.23)	(0.08)	(0.12)	(0.39)	(0.30)	(0.16)	(0.11)	(0.09)	(0.26)	(0.14)	(0.19)	(0.07)	(0.05)
Occupation	0.40***	0.35**	0.06	0.11**	0.16**	0.37**	0.39**	−0.01	0.17***	0.17***	0.30***	0.08	0.22**	0.05**	0.03
	(0.19)	(0.14)	(0.14)	(0.04)	(0.08)	(0.16)	(0.15)	(0.10)	(0.04)	(0.04)	(0.10)	(0.07)	(0.09)	(0.02)	(0.03)
Nationality	0.05	−0.01	0.06	0.09*	0.20*	−0.54***	−0.15	−0.39***	−0.05	−0.03	0.60***	0.73***	−0.12	0.18***	0.14***
	(0.24)	(0.17)	(0.20)	(0.05)	(0.10)	(0.15)	(0.15)	(0.13)	(0.04)	(0.04)	(0.14)	(0.09)	(0.14)	(0.04)	(0.04)
Job mobility	1.75***	0.66***	1.09***	0.46***	0.72***	0.54***	0.38***	0.16***	0.11***	0.10***	0.73***	0.56***	0.17**	0.32***	0.22***
	(0.27)	(0.10)	(0.18)	(0.07)	(0.12)	(0.09)	(0.07)	(0.04)	(0.02)	(0.02)	(0.13)	(0.08)	(0.07)	(0.05)	(0.04)
Firm	−0.17	0.34*	−0.52**	0.03	−0.01	−0.03	0.07	−0.10	0.09*	0.10**	0.09	0.16	−0.07	0.10***	0.09**
	(0.22)	(0.19)	(0.20)	(0.05)	(0.09)	(0.19)	(0.18)	(0.13)	(0.05)	(0.04)	(0.15)	(0.10)	(0.12)	(0.03)	(0.04)
Total effect returns	12.08***	3.57***	8.51***	3.18***	4.84***	4.81***	−3.02***	7.83***	2.58***	3.44***	−3.02***	−0.86***	−2.16***	−0.87***	−0.85***
	(1.14)	(0.70)	(0.94)	(0.22)	(0.43)	(1.14)	(0.98)	(0.57)	(0.18)	(0.22)	(0.76)	(0.30)	(0.75)	(0.13)	(0.14)
Education	−4.87	−1.93	−2.94	−2.56**	−8.25***	−9.20***	−6.02**	−3.18	−2.48***	−5.89***	0.71	−1.85	2.56	−0.54	−0.37
	(5.44)	(2.78)	(4.61)	(1.03)	(2.84)	(3.50)	(2.43)	(3.22)	(0.89)	(2.13)	(3.33)	(1.61)	(2.97)	(0.58)	(0.50)
Occupation	−4.89**	−2.64**	−2.25	−0.93***	−1.13*	−3.57**	−3.11**	−0.46	−0.76**	−0.73*	−3.36***	−0.24	−3.12***	−0.44*	−0.21
	(1.84)	(1.22)	(1.43)	(0.30)	(0.67)	(1.54)	(1.50)	(0.85)	(0.33)	(0.40)	(1.25)	(0.58)	(1.10)	(0.23)	(0.24)
Nationality	0.18	0.79	−0.61	0.26	0.65	1.79*	2.62***	−0.84	0.08	0.29	−0.46	−0.39	−0.07	0.11	0.19
	(1.52)	(0.92)	(1.21)	(0.25)	(0.53)	(1.05)	(0.92)	(0.68)	(0.21)	(0.25)	(0.93)	(0.46)	(0.86)	(0.18)	(0.22)
Job mobility	3.72	1.08	2.64	0.34	1.46	3.60**	0.34	3.26***	0.46	0.70	−1.39	−0.66	−0.73	−0.13	−0.17
	(3.45)	(1.22)	(2.49)	(0.69)	(1.32)	(1.75)	(1.24)	(0.85)	(0.36)	(0.44)	(1.18)	(0.64)	(0.92)	(0.33)	(0.28)
Firm	−1.08	−0.73	−0.35	−0.51	−1.80**	−0.47	1.56	−2.04*	−0.08	−0.68	−0.95	0.04	−1.00	−0.08	−0.08
	(2.38)	(1.81)	(1.87)	(0.41)	(0.74)	(2.09)	(1.83)	(1.11)	(0.41)	(0.47)	(1.52)	(0.68)	(1.40)	(0.25)	(0.24)
Constant	19.02***	7.00*	12.02**	6.57***	13.91***	12.67***	1.59	11.08***	5.36***	9.75***	2.44	2.24	0.20	0.21	−0.19
	(6.67)	(3.66)	(4.87)	(1.31)	(3.25)	(4.86)	(3.75)	(3.59)	(1.21)	(2.42)	(3.73)	(1.98)	(3.29)	(0.66)	(0.58)

TABLE 6 (CONTINUED)

	UA40					Average yearly					Years of employment				
Inequality measure	85-15	85-50	50-15	Gini	Log Var	85-15	85-50	50-15	Gini	Log Var	85-15	85-50	50-15	Gini	Log Var
Specification error	2.24***	1.03***	1.21***	0.05	0.20**	3.32***	3.18***	0.13	−0.23**	−0.05	2.47***	−1.20***	3.67***	−0.10 ***	−0.06
	(0.48)	(0.35)	(0.40)	(0.04)	(0.08)	(0.63)	(0.64)	(0.18)	(0.05)	(0.04)	(0.55)	(0.18)	(0.56)	(0.03)	(0.04)
Reweighting error	−0.13	−0.09	−0.04	−0.05	−0.08	−0.22	−0.18	−0.04	−0.04	−0.05	−0.14	−0.16**	0.02	−0.06**	−0.04**
	(0.20)	(0.11)	(0.13)	(0.04)	(0.06)	(0.23)	(0.17)	(0.08)	(0.04)	(0.04)	(0.13)	(0.08)	(0.09)	(0.03)	(0.02)

Notes: Log differentials×100. Bootstrapped standard errors (100 replications) in parentheses. ***/**/* statistically significant at 1 percent/5 percent/10 percent-level.
Source: Sample of Integrated Labour Market Biographies (SIAB) 1975–2014 and own calculations.

the effect of non-employment seems to be substantially less pronounced (0.44 of 17.00 points). At the same time, the effect linked to part-time employment turns out more moderate when conditioning on the full set of other covariates (0.89 of 17.00 points). In this regard, the result confirms the difficulty to determine the importance of changing employment patterns relative to other covariates discussed at the beginning of Section 5.2. In substantive term, a possible interpretation of this finding is that while both changes in the intensive margin (via part-time employment) and the hourly wage rate seem to be important, their relative contributions cannot be completely disentangled.

Besides the outlined composition effects, Table 5 indicates potentially important contribution from changes in the returns to non-employment and part-time work. Note that these findings should generally be interpreted with some caution because of the relatively large standard errors. Nevertheless, the findings on non-employment indicate a returns effect at the bottom of the distribution, suggesting that later birth cohorts faced greater losses in terms of long-term earnings following an episode of non-employment. Simultaneously, the results indicate a reverse effect for part-time work, i.e., a shrinking of the long-term earnings penalty linked to part-time work.

5.6. *The Role of Predetermined Factors*

Another aspect worth studying is the role of predetermined factors. It addresses the question of how much of increasing long-term earnings inequality is because of factors that are predetermined at the beginning of an individual's career, such as education or nationality, as opposed to other transmission channels (e.g., job mobility or changing employment patterns). To shed light on this blind spot, a separate set of decomposition results is provided. Hereby, the previously used modal categories (i.e., most frequent occupation and firm characteristics) are replaced by the respective realizations at the beginning of an individual's career (i.e., the information contained in the first observable spell in the data).

Overall, the analysis shows that beyond education, the other predetermined factors only had a moderate impact on the recent increase in long-term inequality. For example, Table 6 shows that the impact of the initial occupation (as opposed to the respective modal category) only explains about 0.40 of the 21.35 points increase in the 85-15 log earnings gap. Similarly, the effect related to characteristics of the first firm the individual worked seems inconclusive. At the same time, the composition effect related to education is found to be once more very robust in this specification with effect sizes marginally increasing. Compared to the specifications including the respective modal categories (see Table 4), the unexplained part tends to increase both in the decomposition of total long-term earnings and for the two margins. Overall, mostly due to the strong impact attributed to education, compositional changes in predetermined factors (i.e., education, nationality, first occupation, and characteristics of first firm) account for approximately 22 percent (4.67 of 21.35 points) of the increase in the 85-15 log earnings gap of UA40. For average yearly earnings and total employment, the corresponding shares amount to approximately 49 percent (8.25 of 17 points) and up to 93 percent (3.53 of 3.81 points).

It is important to highlight that because of the administrative nature of the data, important predetermined factors such as ability or socioeconomic background remain unobservable. As an example, it would be conceivable that, against the background of educational upgrading, later cohorts experienced an increasing heterogeneity in the remuneration of unobservable ability. Similarly, family background or other early child characteristics might have gained in importance. In this regard, the inability to observe these factors in administrative data potentially adds to explain the remaining unexplained part found in all decompositions. Nevertheless, the result persists that pre-determined factors in the form of education seem to be a leading factor in explaining long-term earnings inequality.

6. Summary and Discussion

This study has investigated potential determinants of increasing long-term earnings inequality using detailed employment biographies of West German men born between the years 1955 and 1974. Adopting a perspective based on cohorts, the paper contributes to a comparatively small but growing literature documenting an increasing inequality in individual long-term and lifetime earnings (Bönke *et al*., 2015a; Corneo, 2015a,b; Guevenen *et al*., 2017). The paper goes beyond previous contributions by formally disentangling these changes by means of a detailed decomposition analysis based on RIF regression.

The analysis explicitly addresses changes in long-term inequality along both the extensive (total years of employment) and intensive (average yearly earnings while being employed) margin. The descriptive analysis provides evidence for an increasing dispersion in both quantities. However, most of the increasing inequality in long-term earnings can in fact be attributed to an increasing disparity in average yearly earnings. Simultaneously, the analysis shows a substantial shift from full- to part-time employment which was considerably stronger than the increase in non-employment. Therefore, while leaving the total years of employment unaltered, the latter development corresponded to a reduction in overall long-term working hours.

The results suggest a leading role of composition effects linked to education, both in terms of total long-term earnings inequality and along the intensive and extensive margin. This educational expansion predominantly explains changes in the upper part of the long-term earnings distribution. In this way, about 20 percent of increasing inequality in total long-term earnings can be attributed to a shift in educational patterns. At the same time, the study documents that the higher educational attainment is able to explain about half of the increasing inequality in average yearly earnings and more than two-thirds of increasing inequality in the total years of employment. The analysis also shows that long-term earnings tend to be more compressed among individuals with high school degree and/or vocational training as compared to individuals holding a university degree. It also provides evidence for a substantial and persistent long-term university earnings premium. Therefore, it seems more than plausible that the sharp increase in the share of individuals with tertiary background substantially increased long-term earnings inequality, both by shrinking the education group where long-term earnings were more compressed and by simultaneously increasing the still comparably small share of the population receiving a university earnings premium.

These findings on education are also striking from a policy perspective, as they show that higher average levels of education do not necessarily reduce long-term inequalities. In fact, it is very likely that its inequality increasing effect will be even larger in terms of lifetime earnings. This is because of university graduates suffering earnings losses in their early career caused by the delayed entry into the labor market, which, however, decreases in importance when looking at lifetime earnings. Finally, the provided evidence also fits the hypothesis of SBTC increasing the demand for high-skilled labor. At the same time, the analysis finds only limited evidence for an effect beyond educational upgrading. As such, only a moderate impact from changes in the composition of occupations is found.

A detailed analysis of employment patterns shows a robust effect of part-time employment in explaining increasing inequality in long-term earnings. Contrary to the findings on education, its effect was mostly limited to the lower half of the distribution. This result seems very plausible given the strong expansion of part-time work among individuals in the lowest quartile of later cohorts. The findings from this study also complement Biewen *et al.* (2018) by showing that the increasing incidence of part-time employment among German men does not only explain increasing inequality in cross-sectional earnings, but is also reflected in a substantial increase in long-term inequality. At the same time, only a relatively small fraction of the overall inequality increase is attributed to changes in total years of employment, which is in line with the finding of an only moderate increase in the incidence of non-employment. These results are nevertheless not at odds with the findings of Bönke *et al.* (2015a) because of the different cohorts covered. Instead, the study adds to the literature by showing that the increasing inequality among cohorts born in the years 1955–1974 was, in addition to a moderate effect linked to non-employment, driven by the educational expansion and longer episodes of part-time employment. At the same time, the analysis shows that changing employment patterns can only partly explain losses suffered by individuals at the bottom of the long-term distribution. This points toward some similarities with the development in the US where losses in lifetime earnings of later cohorts were mostly due to a decline in the levels of earnings while being employed (Guevenen *et al.*, 2017).

The present study also shows a stagnation in long-term earnings until the age of 40, i.e., during a major part of the career. In this regard, the development in Germany resembled the one in the US, though somewhat delayed and less pronounced. For the latter, Guevenen *et al.* (2017) document significant losses in lifetime earnings among men starting with cohorts born in 1942. Similarly, the results of the present study show moderate earnings losses among individuals without tertiary education, which were counterbalanced by the educational expansion.

References

Acemoglu, D. and D. Autor, "Skills, tasks and technologies: Implications for employment and earnings," in: Ashenfelter, O. and D. Card (eds), *Handbook of Labor Economics*, Amsterdam: North Holland Press, Elsevier, Vol. 4b, 1044–166, 2011.

Antonczyk, D., B. Fitzenberger, and U. Leuschner, "Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?" *Journal of Economics and Statistics*, 229, 214–38, 2009.
Autor, D. H., and D. Dorn, "The Growth of Low-Skilled Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, 103, 1553–97, 2013.
Bachmann, R., R. Felder and M. Tamm, "Labour Market Participation and Atypical Employment over the Life Cycle: A Cohort Analysis for Germany," IZA Discussion Paper No. 12010, IZA Institute of Labor Economics, Bonn, 2018.
Barth, E., A. Bryson, J. C. Davis, and R. Freeman, "It's Where You Work: Increases in Dispersion of Earnings across Establishments and Individuals in the United States," *Journal of Labor Economics*, 34, 67–97, 2016.
Barth, E., J.C. Davis, R.B. Freeman and A.J. Wang, "The Effects of Scientists and Engineers on Productivity and Earnings at the Establishment Where They Work," NBER Working Paper No. 23484, National Bureau of Economic Research, Cambridge, Massachusetts, 2017.
Baumgarten, D., "Exporters and the rise in wage inequality: Evidence from German linked employer-employee data," *Journal of International Economics*, 90, 201–17, 2013.
Baumgarten, D., G. Felbermayr, and S. Lehwald, "Dissecting between-plant and within-plant wage dispersion - Evidence from Germany," Discussion Paper, No. 125, Ludwig-Maximilians-Universität München und Humboldt-Universität zu Berlin, Collaborative Research Center Transregio 190 - Rationality and Competition, München, Berlin, 2018.
Beblo, M., and E. Wolf, "How much does a year off cost? Estimating the wage effect of employment breaks and part-time periods," *Brussels Economic Review*, 45, 191–217, 2002.
Biewen, M., B. Fitzenberger, and J. de Lazzer, "The role of employment interruptions and part-time work for the rise in wage inequality," *IZA Journal of Labor Economics*, 7(10), 2018.
Biewen, M., and D. Plötze, "The Role of Hours Changes for the Increase in German Earnings Inequality," *Journal of Economics and Statistics*, 239, 277–304, 2019.
Biewen, M., and M. Seckler, "Unions, Internationalization, Tasks, Firms, and Worker Characteristics: A Detailed Decomposition Analysis of Rising Wage Inequality in Germany," *The Journal of Economic Inequality*, 17, 461–98, 2019.
Bönke, T., G. Corneo, and H. Lüthen, "Lifetime Earnings Inequality in Germany," *Journal of Labor Economics*, 33, 171–208, RWI - Leibniz Institute for Economic Research, Essen, 2015a.
Bönke, T., M. Giesecke, and H. Lüthen, "The Dynamics of Earnings in Germany: Evidence from Social Security Records," Ruhr Economic Papers No 582, 2015b.
Blau, D.F. and L.M. Kahn, "Inequality and Earnings Distribution," in: Nolan, B., Salverda, W. and T.M. Smeeding (eds), *The Oxford Handbook of Economic Inequality*, Oxford University Press, Oxford, 177–203, 2011.
Bowlus, A., and J. M. Robin, "Twenty Years of Rising Inequality in U.S. Lifetime Labour Income Values," *Review of Economic Studies*, 71, 709–42, 2004.
Boll, C., M. Jahn, and A. Lagemann, "The Gender Lifetime Earnings Gap: Exploring Gendered Pay from the Life Course Perspective," *Journal of Income Distribution*, 1, 1–53, 2017.
Blundell, R., M. C. Dias, C. Meghir, and J. Shaw, "Female Labor Supply, Human Capital and Welfare Reform," *Econometrica*, 128, 1705–753, 2016.
Brenke, K., "Anhaltender Strukturwandel zur Teilzeitbeschäftigung," *DIW Wochenbericht, German Institute for Economic Research (DIW)*, 42, 3–12, 2011.
Brehmer, W., and H. Seifert, "Sind atypische Beschäftigungsverhältnisse prekär? Eine empirische Analyse sozialer Risiken," *Journal for Labour Market Research*, 41, 501–31, 2008.
Canon, M. E., M. Kudlyak, G. Luo, and M. Reed, "Flows To and From "Working Part-Time for Economic Reasons" and the Labor Market Aggregates During and After the 2007-09 Recession," *FRB Richmond Economic Quarterly*, 100, 87–111, 2014.
Card, D., J. Heining, and P. Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *The Quarterly Journal of Economics*, 128, 967–1015, 2013.
Corneo, G., "Income Inequality from a Lifetime Perspective," *Empirica*, 42, 225–39, 2015a.
______, "Earnings Inequality in Germany and Its Implications," *Economic and Political Studies*, 3, 60–84, 2015b.
DiNardo, J., N. M. Fortin, and T. Lemieux, "Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach," *Econometrica*, 64, 1001–44, 1996.
Dustmann, C., J. Ludsteck, and U. Schönberg, "Revisting the German Wage Structure," *The Quarterly Journal of Economics*, 124, 843–81, 2009.
Ehrl, P., "A Breakdown of Residual Wage Inequality in Germany: Wage Decompositions Using Worker-, Plant-, Region-, and Sector-Specific Determinants," *Oxford Economic Papers*, 69, 75–96, 2017.
Even, W. E., and D. A. Macpherson, "The Affordable Care Act and the Growth of Involuntary Part-Time Employment," *ILR Review*, 72, 955–80, 2019.

Fernández-Kranz, D., M. Paul, and N. Rodríguez-Planas, “Part-Time Work, Fixed-Term Contracts, and the Returns to Experience,” *Oxford Bulletin of Economics and Statistics*, 77, 512–41, 2014.
Firpo, S., N.M. Fortin, and T. Lemieux, "Decomposing Wage Distributions using Recentered Influence Functions Regressions," Working Paper, University of British Columbia, 2007.
Firpo, S., N. M. Fortin, and T. Lemieux, “Unconditional Quantile Regression,” *Econometrica*, 77, 953–73, 2009.
Firpo, S., N.M. Fortin, and T. Lemieux, “Occupational Tasks and Changes in the Wage Structure," Working Paper, University of British Columbia, 2014.
Firpo, S., N. M. Fortin, and T. Lemieux, “Decomposing Wage Distributions Using Recentered Influence Function Regressions,” *Econometrics*, 6, 28, 2018.
Fitzenberger, B., “Wages and Employment Across Skill Groups: An Analysis for West Germany,” *ZEW Economic Studies*, Centre for European Economic Research (ZEW), Mannheim, 6, 1999.
Fitzenberger, B., A. Osikominu, and R. Völter, “Imputation Rules to Improve the Education Variable in the IAB Employment Subsample,” *Journal of Applied Social Science Studies*, 126, 405–36, 2006.
Fortin, N., T. Lemieux, and S. Firpo, “Decomposition Methods in Economics,” in: Ashenfelter, O. and D. Card (eds), *Handbook of Labor Economics*, Amsterdam: North Holland Press, Elsevier, 4, 1–102, 2011.
Gardeazabal, J., and A. Ugidos, “More on Identification in Detailed Wage Decompositions,” *Review of Economics and Statistics*, 86, 1034–36, 2004.
Gartner, H., “The Imputation of wages above the contribution limit with the German IAB employment sample,” FDZ Methodenreport, No. 2, Research Data Centre (FDZ) of the Federal Employment Agency (BA), Nuremberg, 2005.
Gius, M., “The Impact of Job Mobility on Earnings: Using Occupational and Industrial Classifications to Identify Job Changes,” *International Review of Applied Economics*, 28, 181–90, 2014.
Görlich, D., and A. De Grip, “Human Capital Depreciation During Hometime,” *Oxford Economic Papers*, 61, 98–121, 2009.
Green, A., and I. Livanos, “Involuntary non-standard employment in Europe,” *European Urban and Regional Studies*, 24, 175–92, 2017.
Guevenen, F., G. Kaplan, J. Song and J. Weidner, “Lifetime Incomes in the United States Over Six Decades," NBER Working Paper No. 23371, National Bureau of Economic Research, Cambridge, Massachusetts, 2017.
Harrigan, J., A. Reshef and F. Toubal, “The March of the Techies: Technology, Trade, and Job Polarization in France, 1994–2007," NBER Working Paper No. 22110, National Bureau of Economic Research, Cambridge, Massachusetts, 2016.
Juhn, C., K. M. Murphy, and B. Pierce, “Wage Inequality and the Rise in Returns to Skill,” *Journal of Political Economy*, 101, 410–42, 1993.
Kopczuk, W., E. Saez and J. Song, “Earnings Inequality and Mobility in the United States: Evidence from Social Security Data," *The Quarterly Journal of Economics*, 125, 91–128 2010.
Paul, M., “Is There a Causal Effect of Working Part-Time on Current and Future Wages?” *Scandinavian Journal of Economics*, 118, 494–523, 2016.
Potrafke, N., “Unemployment, Human Capital Depreciation and Pension Benefits: An Empirical Evaluation of German Data," *Journal of Pension Economics and Finance*, 11, 223–41, 2012.
Rinawi, M. and U. Backes-Gellner, “Skill Prices, Skill Composition, and the Structure of Wages," Discussion Paper No. 0112, University of Zurich, Institute for Strategy and Business Economics (ISU), 2015.
Song, J., D. J. Price, F. Guevenen, N. Bloom, and T. Von Wachter, “Firming up Inequality,” *The Quarterly Journal of Economics*, 134, 1–50, 2019.
Tilly, C., *Half a Job: Bad and Good Part-time Jobs in a Changing Labor Market*. Temple University Press,Philadelphia, 1996.
Tisch, A., and S. Tophoven, “Employment Biographies of the German Baby Boomer Generation,” *Schmollers Jahrbuch*, 132, 205–32, 2012.
Wolf, E., “Lohndifferenziale zwischen Vollzeit- und Teilzeitbeschäftigten in Ost- und Westdeutschland,” WSI Discussion Paper No. 174, The Institute of Economic and Social Research (WSI), Hans Böckler Foundation, 2010.

Supporting Information

Additional supporting information may be found in the online version of this article at the publisher’s web site:

Figure SA1 Changes in UAX *Notes*: Differences in UAX earnings for different ages between pooled cohorts 1955–57 and 1972–74

Figure SA2 Inequality in up-to-age-X, federal discounting *Notes*: Development of inequality in long-term earnings (UA40/UA45/UA50), cohorts 1955–1974

Figure SA3 Indexed growth in daily earnings, years 1975–2014 *Notes*: Numbers in the illustration are based on all West Germany men in full-time employment on June 1 of each year (whereas the present study generally covers only individuals with a sufficient labor market attachment). This is due to the fact that the conditions for a sufficient labor market attachment can only be derived for cohorts 1955–1974

Figure SA4 Evolution of UA40 within education groups, federal discounting *Notes*: Illustration shows development of Gini coefficient within educational subgroups, cohorts 1955–1974

Figure SA5 Indexed real growth in earnings age 25–40 *Notes*: Indexed growth in percentiles of the unconditional distribution, cohorts 1955–1974

Figure SA6 Inequality in earnings age 25–40 *Notes*: Development of inequality in long-term earnings (UA40/UA45/UA50), cohorts 1955–1974

Figure SA7 Inequality in earnings age 25-40, federal discounting *Notes*: Development of inequality in long-term earnings (UA40/UA45/UA50), cohorts 1955-1974

Table SA1 Observations per cohort

Table SA2 UA40/Inequality average yearly earnings/years employed, federal discounting

Table SA3 Decomposition of log(UA40), federal discounting

Table SA4 RIF decomposition results, federal discounting

Table SA5 Detailed decomposition results for employment patterns, UA40, federal discounting

Table SA6 Detailed decomposition results for employment patterns, average yearly earnings (UA40)

Table SA7 Detailed decomposition results for employment patterns, total years of employment (UA40)

Table SA8 RIF decomposition results, initial endowments, federal discounting

Table SA9 RIF decomposition results, UA40

Table SA10 RIF decomposition results, UA40, federal discounting