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Increasing inequality in lifetime earnings: a tale of educational upgrading and changing employment patterns

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Increasing inequality in lifetime earnings: a tale of educational upgrading and changing employment patterns[1]

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Abstract. This paper provides a detailed decomposition analysis of rising lifetime earnings inequality in Germany using individual employment biographies constructed from high-quality administrative data. The results show that significant parts of rising lifetime earnings inequality among West German men born between the years 1955 and 1974 can be attributed to a lower labor market participation (as a consequence of longer periods of both part-time and non-employment) as well as the educational expansion among later cohorts. The paper also points towards potentially important changes in the penalty linked to employment interruptions, but only finds a moderate impact of skill-biased technological change beyond educational upgrading. The analysis reveals similarities with the development in the U.S. in the sense that the cohorts studied did not only face an increase in inequality, but also a stagnation in earnings for a major part of their career. This trend is even stronger when looking at changes within education groups.

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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 earnings distribution of the early 1990s with the one two decades later, it remains unclear to what extend the standard of living of later cohorts differs from 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 lifetime earnings from a cohort perspective is likely to be more informative with regards to an individual's or cohort's standard of living, which is 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 lifetime earnings inequality for both Germany and the U.S. 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.[2] It is unclear to what extend these factors are also responsible for the increasing inequality in lifetime earnings. This paper intends to shed light on this blind spot by disentangling the increasing inequality in lifetime earnings using high-quality administrative employment data for Germany. Methodologically, the paper uses state-of-the-art RIF decomposition techniques as introduced by Firpo et al. (2009, 2018).

The paper makes the following contributions to the literature. First, the present study reveals a lower labor market participation (both in terms of longer periods of part-time employment and non-employment) to be the most important factor for the rise in inequality in the lower

[2]For a more comprehensive discussion, see section 2

half of the distribution. Contrary to that, much of the rising inequality at the top is associated with educational upgrading. To the best of my knowledge, this is the first study providing a decomposition analysis aimed at explaining the rising inequality in lifetime earnings. Second, the results confirm previous findings by Bönke et al. (2015a) who documented a sharp rise in lifetime earnings inequality based on a different database. Going a step further, the present paper also shows that German men born between the years 1955 and 1974 did not only face a higher level of inequality, but equally suffered from a stagnation in total earnings for a major part of their career. In fact, this development stems from losses within education groups which are counterbalanced by higher levels of educational attainment. The present 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 empirical 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 the present 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 U.S., an important contribution by Bowlus and Robin (2004) finds that inequality in cross-sectional and lifetime earnings appear 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 due to 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 U.S. *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 U.S. 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 due to differences in early career earnings across cohorts. Importantly, they show that later cohorts suffered from earning losses at young age that were not compensated by a higher future earnings growth.[3]

In a seminal contribution for Germany, Bönke et al. (2015a) documented a dramatic increase in 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.[4] 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 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 most likely be generalized to inequality in lifetime earnings.[5] 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. The present 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 last 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.

[3]In fact, the study finds that women realized substantial gains in lifetime earnings (starting from a very low level) across the study period. However, these gains only partly offset the losses suffered by men.

[4]Despite some methodological differences, the same terminology is also used in the present paper.

[5]Also see Bönke et al. (2015a), p. 186. As already argued above, this finding is also confirmed in Guevenen et al. (2017). Another advantage of this approach is to obtain new evidence on very recent 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 skill-biased technological change (SBTC) for wage polarization and a resulting increase in U.S. 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, Biewen and Seckler, 2017, Baumgarten et al., 2018) highlights the importance of institutional changes in the form of deunionization, whereas internationalization seems to 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 methodology, 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 studies 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 the present 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 not only found in young workers, i.e. as a results of substantially longer time spent in education, but 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 Grip, 2008, Potrafke, 2012, Fernández-Kranz et al., 2015, 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 lifetime earnings across cohorts due to the fact that complete employment histories of approximately 1.75 million individuals are provided. 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 lifetime 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 prior to the year 1975. Hence, the study focuses on individuals born between the years 1955 and 1974 who can at least be observed between age 20 and 40. To facilitate comparability with previous studies, the analysis is restricted to male individuals working in West Germany only.

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:[6] 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 five 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

[6]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).

the up-to-age 40 (UA40) earnings sample, individuals need to have real earnings of at least 5000 euros in eight years or more. Also, individuals are required to have total long-term earnings that correspond to an average annual earning of at least 5000 euros. Hence, 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) respondents 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 A1 in the appendix.[7]

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).[8] Depending on the year of observation, up to 15 percent of observations are affected by this right-censoring. Hence, 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. Due to 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 towards annual earnings resulting in both an increase in average daily wages as well as 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.[9]

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

[7]This paper does not consider women. This is due to lower labor force participation rates among German women, which in turn results in a significantly smaller number of women whose earnings biographies fulfill the imposed minimum criteria of labor market attachment. Moreover, changing patterns in terms of selection into employment (and ultimately into the sample) inherently complicates any long-run comparison across cohorts.

[8]Please refer to the appendix for more details on the imputation procedure.

[9]Note that similar strategies were also used in other studies such as Dustmann et al. (2009) and Card et al. (2013). The procedure is outlined in the appendix

(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 1955-57 to 1972-74) 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 the UAX earnings measures. Hence, the decomposition results are not diluted by individuals with unobservable employment spells in East Germany.[10]

3.1 Trends in lifetime earnings

In the analysis of lifetime earnings, this paper follows the approach suggested in Bönke et al. (2015) 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 using the German consumer price index (CPI). 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). The 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

[10] Parts of the descriptive analysis also use information from other cohorts, whose results might potentially be affected by east-west migration following the fall of the Berlin Wall. Note, however, that restrictions on maximum ages for labor market entry are imposed to ensure that only individuals whose (mostly) complete earnings biographies are observable are included. Also, descriptive statistics for the first observable employment spell do not detect any significant anomalies. Nevertheless, there might be rare cases of individuals who started working in East Germany and migrated to West Germany before 1991 and prior to reaching the maximum age for labor market entry.

self-employment are not part of the analysis. Hence, the earnings measure mirrors the price of labor paid in the market.[11] 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.

— (Figure 1 here) —

Figure 1 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%, whereas the 15th percentile decreased by as much as 13%. 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. This finding is in contrast to previous studies considering cross-sectional distributions that have documented significant gains in median hourly/daily earnings in the cross-section 1975-2014 (e.g. Dustmann et al., 2009). 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 bottom and some moderate gains at the top. Lastly, note that these developments are not a direct consequence of a delayed labor market entry due to longer times spent in education. As can be seen from figure A1 in the appendix, the overall picture remains when only earnings starting at age 25 are taken into account.

— (Figure 2 here) —

Figure 2 summarizes the impact of this development on different long-term earnings measures (UA40/UA45/UA50). Overall, the graph reveals a strong increase in all parts of the UAX-measures with the aforementioned acceleration among cohorts born in the early 1970s. In terms

[11] 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.

of UA40, this is reflected in a sharp increase in the Gini coefficient from 0.168 to 0.226 (approx.+35%), which affected both the upper part (85-50 log wage gap, approx. +39%) and the lower part (50-15 log wage gap, +45%) 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.[12] Confirming the general trends previously documented 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, only be observed for a limited number of cohorts.

— (Figure 3 here) —

To underpin this hypothesis, figure 3 contains rank correlations between UA40 and UAX at higher ages. Generally, the graph documents high and very persistent rank correlations. For example, the dark grey line documents rank correlations between 0.96 and 0.97 between UA40 and UA45. Similarly, the graph documents rank correlations of about 0.92 (UA50) and 0.88 (UA55) which can be interpreted as evidence that the evolution of lifetime earnings closely follows the development in UA40 (compare also Bönke et al., 2015a).

— (Figure 4 here) —

As the German workforce was subject to some major educational upgrading during the period of study (see proceeding 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* as well as *University* for the pooled cohorts 1972-74 as opposed to pooled cohorts 1955-57. The graph on the left includes the development of inequality in terms of the gini, the graph on the right the change in median earnings. The graph documents that inequality did not only increase among all individuals of later cohorts but also within education groups. This increase was strongest within

[12]One exception is the lower part of the distribution as measured by the 50-15 log wage gap with lower levels of inequality in terms of UA40.

the lowest educational group (approx.+55%), followed by individuals holding a university degree (approx.+29%), and smallest among individuals with a vocational background (approx.+24%). 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. At the same time, the graph reveals a decrease in median earnings within all education subgroups. These losses were strongest for individuals without a degree (approx.-8%), in contrast to rather marginal losses among individuals with vocational training (approx. -1.5%) and individuals holding a university degree (approx. -1.3%). 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 (approx. -0.2%), this results suggests that the losses within educational subgroups were neutralized by a shift towards higher average educational attainment among later birth cohorts.

— (Figure 5 here) —

To get a better understanding of changes over the life-cycle, figure 5 plots the difference in up-to-age X (UAX) for different ages, once more for pooled cohorts 1955-57 and 1972-74. For example, the point 25 on the x-axis represents differences in up-to-age 25 (UA25) earnings between the two groups. The graph shows that some losses in the median of cumulative earnings among individuals born 1972-74 occurred until the age of 25, reflecting a delayed labor market entry as a result of the educational expansion. This was followed by a period of fast catch-up in the late 20s and early 30s which was the likely consequence of a higher share of university graduates entering the labor market and which neutralized the preceding median losses by the age of 30. Importantly, there were no further median gains between the ages 30 and 40, causing the previously described stagnation in UA40 earnings. Though being somewhat speculative, this picture suggest that the stagnation in UA40 earnings is likely to continue for the (still unobservable) remaining part of the cohorts careers. Simultaneously, the graph shows that the gains in cumulative earnings at the top of the within-cohort distribution increased continuously after age 25, whereas losses at the 15th percentile were already strong in terms of UA25 and (after some stabilization) sped up again in the mid 30s.[13]

[13]Note that the percentiles always refer to differences in the within-cohort distributions for cumulative earnings at a certain age, e.g. age 30. Hence, due to high earnings mobility at young ages, individuals at the 15th percentiles of UA25 earnings are likely to be very different from those at the 15th percentile of UA40 earnings.

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 life, or whether they are due to changes in earnings during the time individuals were actually employed (i.e. changes in lifetime hours worked vs. changes in daily/hourly earnings conditional on employment).[14] 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)*, where the latter group will be defined as the reference group in the further analysis. 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 hence, a consistent measure across the cohorts used in this study cannot be constructed.[15] 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 times spent in further education.

— (Figures 6 to 8 here) —

Figure 6 includes the duration spent in full-time employment (up-to-age 40) for the pooled cohorts 1955-57 and 1972-74 for different quartiles of the UA40 earnings distribution. Although full-time employment remained by far the most frequent employment form among German men, there was a considerable reduction which is found to be strongest for individuals at the bottom of the UA40

[14] For example, Biewen and Plötze (2019) show that 10-30% of increasing inequality in monthly earnings among German men between 2001 and 2010 were due to changes in hours worked.

[15] Also see Antoni et al. (2016) for more information.

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 8.9 percent, between pooled cohorts 1955-57 and 1972-74. 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 7.8 months for quartile 2, 4.9 months for quartile 3 and 4.6 months for the highest quartile. Simultaneously, this development was accompanied by an increase in the incidence of non-employment which was strongest for the two lowest quartiles, with the average increases amounting to approximately 3.6 and 4.1 months, respectively. However, these numbers also show that the increase in non-employment episodes was only partly responsible for the observed decline in full-time duration.

Figure 8 illustrates the evolution of part-time employment. Starting from a very low level among individuals of birth cohorts 1955-57, the graph documents a steep 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 on average 11.6 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 lifetime earnings. Besides a simple reduction in lifetime labor market participation (or lifetime working hours) and the resulting earnings losses, the previous literature has also documented adverse effects of part-time employment on future earnings growth (compare section 2).

3.3 Trends in education

— (Figure 9 here) —

The cohorts included in the study also differ substantially in terms of their educational attainment. Figure 9 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% among individuals of birth cohort 1955 to 18.4% 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) as well as 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 will use 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 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

Beyond the the described differences in employment patterns and educational background, further important characteristics related to individual employment biographies are considered as potential sources of increasing lifetime earnings inequality. For example, changing job mobility patterns across cohorts might constitute another source of increasing inequality in lifetime 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 the one hand, and firm changes where both the industry and occupation change (career changes) on the other. 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 extend unclear as it potentially includes a significant share of layoffs or other types of non-voluntary job changes. The descriptive evidence presented in table A2 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 1972-74.

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 does not have any observable employment spell with foreign nationality throughout the working life. During the observation period, there was an increase of individuals with migration background with their relative shares increasing from 11 to 22 percent between pooled cohorts 1955-57 and 1972-74. 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 is 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 towards 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-run earnings. For the subsequent analysis, three firmsizes 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 hence, refer to the type of firm an individual worked at mostly.

4 Econometric methods

The subsequent analysis builds on Recentered-Influence-Function (RIF) decomposition to disentangle the increasing inequality in UA40 earnings between pooled cohorts 1955-57 and 1972-74.[16] 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 due to changes in the distribution of covariates while fixing the corresponding returns (composition effect), and one due to changes in the returns to these covariates leaving the distribution of covariates unchanged (returns effect).[17] 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.[18] Hence, it allows to link changes in a number of inequality measures (85-15/85-50/50-15 log wage gaps, gini, log variance) to the different covariates outlined in the previous chapter.

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 recentered influence function of some distributional statistic of interest ν on explanatory variables. The RIF is a recented version of the influence function defined as $RIF\left(y,\nu\right) = \nu + IF\left(y;\nu\right)$. It can easily be shown that the RIF has the same expectation as the original statistic of interest ν and integrates to ν as $\int RIF\left(y;\nu\right)dF(y) = \int\left(\nu + IF\left(y;\nu\right)\right)dF(y) = \nu\left(F_y\right)$, 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 $E\left[RIF\left(Y;\nu\right)|X\right] = X\gamma$, where γ can be estimated by OLS.[19] Given this linear specification, an 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

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

[16]The discussion in this chapter in parts follows Firpo et al. (2014, 2018) and Biewen and Seckler (2017).

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

[18]See Fortin et al. (2011) for a comprehensive overview on alternative techniques.

[19]Fig. 1B in Firpo et al. (2009) shows that modeling the RIF as a linear function of covariates yields very similar results compared to more flexible specifications in the case of quantiles. The usage of a linear specification is also recommended in Firpo et al. (2018).

where $F_{Y_0|c=s}$, $F_{Y_1|c=s}$ 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 due to their linear specification, the RIFs are only local approximations which potentially leads to biased results in case of large changes in the distribution of characteristics.[20] 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

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

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 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 $\Delta_{X,c}^\nu$ 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). Hence, a small value for the specification error indicates that a linear approximation of the composition effect is appropriate. The term $\Delta_{S,p}^\nu$ denotes the detailed returns effects which 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. Lastly, $\Delta_{S,c}^\nu$ 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

[20] As outlined in Firpo et al. (2014), this would for example be the case if the underlying true relationship between Y and X was in fact convex (and not linear as assumed by OLS). In such a scenario, an upward-shift of the distribution of X would mechanically increase the estimated coefficients even if the true return structure remained unaltered.

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, Gardezabal 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 are 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, 2017, for a more rigorous discussion).

Finally, note that the results from RIF decomposition should not be interpreted as causal effects. This is due to 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

— (Table 1 here) —

This section presents RIF decomposition results comparing pooled cohorts 1955-57 and 1972-74. For reasons of clarity, the previously presented covariates are summarized in seven groups in line with table 1. For the baseline model, these are *Non-employment*, *Part-time employment*, *Education*, *Occupation*, *Job mobility*, *Nationality* and *Firm*. In the presentation of results, it is insightful to start with a graphical analysis. Results of an alternative specification restricted to German nationals are provided in table A3 in the appendix. As these are very similar, they are not discussed in more detail at this point. In order to highlight the differences due to delayed labor market entry as a consequence of the educational expansion, three sets of results are presented:

one for up to age 40 earnings, one controlling in addition for age at labor market entry and one for earnings received between age 25 and 40.

5.1 Results for UA40

— (Figures 10 to 12) —

Figure 10 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. However, note once more the stagnation in median earnings which is in contrast to significant long-run gains in median daily/hourly earnings (see, e.g. Dustmann et al., 2009). The aggregate composition effect reveals a similarly monotonic pattern, but was negative for most of the distribution and only had a weakly positive effect above the 70th percentile. Also monotonic, the aggregate returns effect is found to be positive above the 40th percentile and negative in the lower part of the distribution.

Figure 11 further disentangles the overall composition effect by displaying the detailed composition effects linked to the groups of covariates. The graph shows strong composition effects linked to changing employment patterns (via both non-employment and part-time) as well as education. The increasing incidence of both part-time and non-employment spells played an important role at the bottom of the UA40 distribution. Interestingly and in line with the descriptive evidence, the effect linked to the expansion of part-time employment was even slightly stronger than the effect associated with the increasing incidence of non-employment. Note also that both effects, despite being strongest at the bottom, had a negative effect on most parts of the distribution. Being the most important individual composition effect (but smaller than the joint effect from changing employment patterns), compositional changes in education led to an upward shift of the UA40 distribution across all quantiles. It is found to be the most important single factor for inequality at the top. In this regard, both the results on changing employment patterns and educational upgrading are in line with the general trends described in the preceding chapters. The analysis also reveals a moderate composition effect linked to changes in the occupational background as well as a minor effect of job mobility, with the other factors being rather negligible.

Figure 12 provides detailed results for the returns effect, which seems to be similarly important when compared to the overall composition effect. Besides the constant term, the graph indicates an important contribution from changes in the returns to non-employment that led to a downward shift of the lower half of the distribution. In other words, besides being more likely to be affected by non-employment episodes, later birth cohorts equally faced greater losses in terms of long-term earnings following an episode of non-employment. A possible interpretation would be that these cohorts found it increasingly difficult to re-integrate into the labor market after an episode of non-employment, which might potentially reflect the difficult labor market conditions in the late 1990s (which the individuals in the cohort 1972-74 had to face at an early stage of their career), but might as well reflect factors such as a faster human capital depreciation or a lower job match quality upon re-entry. Note that this finding should be interpreted with some caution due to the relatively large standard errors shown in table 2. The picture also suggests a positive return effect linked to education, which shifted up the entire within-cohort distribution. As its effect is very homogenous, no significant effect on the different inequality measures is found (see, table 2).

The analysis also 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 very 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, but might as well reflect changes in the relative importance of different groups of covariates. For example, the constant might represent factors such as systematic differences in earnings dynamics within firms as well as differing idiosyncratic shocks that remain unobservable in administrative data.

— (Table 2 here) —

Table 2 presents the corresponding numerical results for the decomposition of UA40 earnings, which underpin the findings of the preceding graphical analysis. Numerically, both the total composition (9.05) and the total returns effect (9.09) contributed equally to the overall 21.35 log percentage points increase in the 85-15 log wage differential, with the specification and reweighting error amounting to 3.22 points. The strongest composition effects were due to changes in educational attainment (3.17 points) as well as changes in part-time (2.51 points) and non-employment (2.03 points) patterns. Further, there seemed to be moderate composition effects linked to changes in the occupational structure (0.92 points) as well as job mobility (0.38

points). The bottom half of the table, displaying detailed results for the returns effect, shows that the estimated effects are generally less precise. Besides the previously described returns effect linked to non-employment, it equally reveals a moderate inequality-reducing effect from changing returns to part-time employment at the bottom of the distribution.

5.2 Results for UA40 controlling for age at labor market entry

— (Table 3 here) —

Regarding the question of whether the increasing inequality in lifetime earnings was driven by changes in labor market participation as opposed to changes in earnings received during times of employment, the evidence presented in the previous section suggests that some 21 percent of the overall increase was linked to a lower labor market participation among individuals of later cohorts. However, this baseline decomposition did not control for changes in the age at labor market entry due to its presumable very close relationship with educational upgrading. Hence, the estimate of the effect linked to a lower lifetime labor market participation did not capture the delayed labor market entry of later cohorts as a result of educational upgrading. An alternative model specification that equally controls for the age at labor market entry is provided in table 3. The results of this alternative specification suggest that up to 31 percent of the increase in 85-15 might in fact be due to the overall lower lifetime labor market participation (i.e. due to the joint effect from changes in non-employment/part-time/age at labor market entry). However, the composition effect linked to education equally shrinks significantly in this specification, confirming the a-priori expectation of both effects being closely related.

5.3 Results for earnings between ages 25 and 40

— (Table 4 here) —

Looking more closely at earnings between ages 25 and 40, i.e. only considering earnings from an age where most individuals already entered the labor market, reveals further valuable insights. The corresponding decomposition results are presented in table 4. This earnings measure is better comparable with the literature which typically considered earnings starting at age 25 (e.g. Guevenen et al., 2017). Overall, the results point towards a greater importance of composition effects (11.71 points), which are found to be more important than the overall returns effect (6.49 points) in explaining the overall increase of 20.01 points in terms of the 85-15 log wage differential. Most importantly, there seems to be a much stronger composition effect linked to education explaining up to 6.38 points (or approx. 32 percent) in terms of 85-15 and up to 87 percent at the top of the distribution. In fact, this finding does not come as a surprise given that this specification does not account for forgone earnings during times of education. Hence, the educational expansion has a mechanically stronger effect on inequality between age 25 and 40 (as opposed to UA40). This is accompanied by a reduction in the composition effect linked to non-employment, which likely reflects both a generally higher incidence of unemployment among very young individuals as well as the fact that parts of the increase in non-employment at young ages might be due to the additional time spent in education (though only non-employment spells after labor market entry are counted as non-employment). Note also that the overall share explained by the increasing incidence of part-time employment remains virtually unchanged. At the same time, there is a moderate increases in the relative importance of compositional effects linked to occupations and job mobility when compared to the decomposition of UA40.

As to the returns effect, the overall picture remains mostly unchanged with a persistently strong effect linked to non-employment (5.39 points in terms of 85-15). At the same time, the previously found returns effect linked to part-time employment becomes more pronounced, suggesting that it had an inequality-reducing effect of -2.13 points (or -18 percent in terms of 50-15) at the bottom of the distribution, but hardly any effect in the upper half of the distribution.

6 Summary and Discussion

This study has investigated potential determinants of increasing lifetime 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, 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 empirical results suggest that a lower labor market participation of younger cohorts explains some 20-30 percent of the overall increase in lifetime earnings inequality, with the effect being mostly limited to the lower half of the distribution. Compared to the findings in Bönke et al. (2015a), the analysis assigns a smaller part of this effect to non-employment periods and instead highlights the growing importance of part-time employment. Nevertheless, this results is not at odds with the results in Bönke et al. (2015a) due to the additional cohorts included in the present study. The findings presented in the preceding chapters 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 also adds substantially to the increasing inequality in lifetime earnings. At the same time, changing employment patterns can only partly explain the losses in UA40 earnings at the bottom of the distribution. Hence, this points towards some similarities with the development in the U.S. for which Guevenen et al. (2017) showed that losses in lifetime earnings among later cohorts are mostly due to a decline in earnings conditional on employment.

Beside changing employment patterns, composition effects linked to the educational upgrading of younger cohorts explain another 15-30 percent of the increasing dispersion in lifetime earnings. Importantly, these changes were favorable for all parts of the distribution but more favorable for individuals at the top, thereby increasing inequality in the upper half of the distribution. Beyond educational upgrading, the analysis finds only limited evidence of skill-biased technological change (SBTC). As such, only a moderate impact from changes in the composition of occupations in the range of 4-7 percent and mostly insignificant results regarding their returns are found.

The analysis also points towards a potentially important returns effect linked to episodes of non-employment, which had an adverse effect on long-term earnings for individuals in the lower half of the distribution. A natural interpretation of this result is that individuals in later cohorts found it increasingly difficult to re-integrate into the labor market after being non-employed, resulting in stronger long-term earnings losses. Possible mechanisms behind this finding may be a faster depreciation of human capital during periods of non-employment as well as a poorer job match quality following a period of non-employment.

The present study also provides evidence for a stagnation in UA40, i.e. during a major part of the career, among German men born between the years 1955 and 1974. In this regard, the development in Germany resembles the one in the U.S., though somewhat delayed and less pronounced, for which previous research by Guevenen et al. (2017) documented significant losses in lifetime earnings among men starting already with cohorts born in 1942. Importantly, the results of the present paper point towards moderate earnings losses within all educational subgroups (though being strongest for the lowest education group), which were counterbalanced by the educational expansion. This is an interesting finding given significant gains in hourly/daily earnings found in cross-sectional data during study period 1975-2014 (see, e.g. Dustmann et al., 2014). It suggests that the cross-sectional earnings gains were only beneficial to individuals of older cohorts, whereas younger cohorts suffered both a stagnation and increasing inequality in lifetime earnings.

7 References

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8 Figures

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Figure 1 – Indexed real growth in UA40

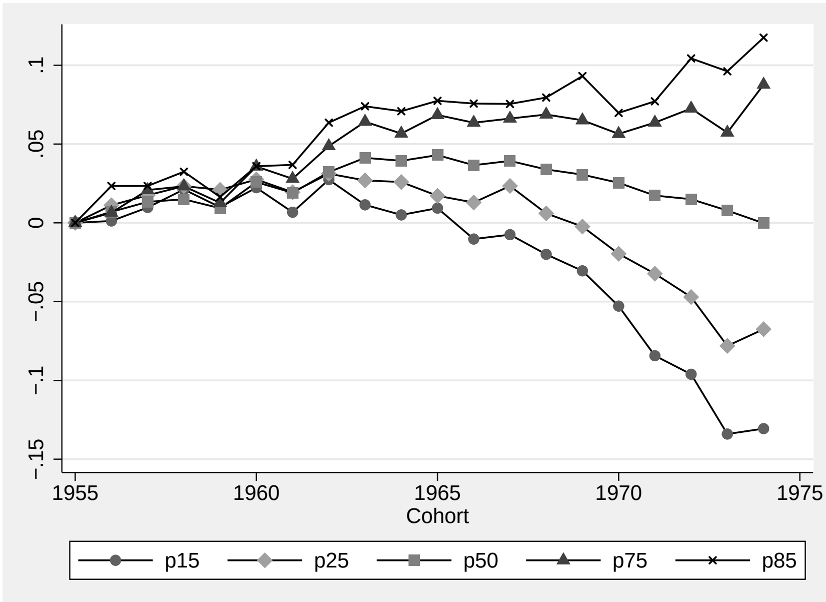


Figure 2 – Inequality in *up-to-age-X*

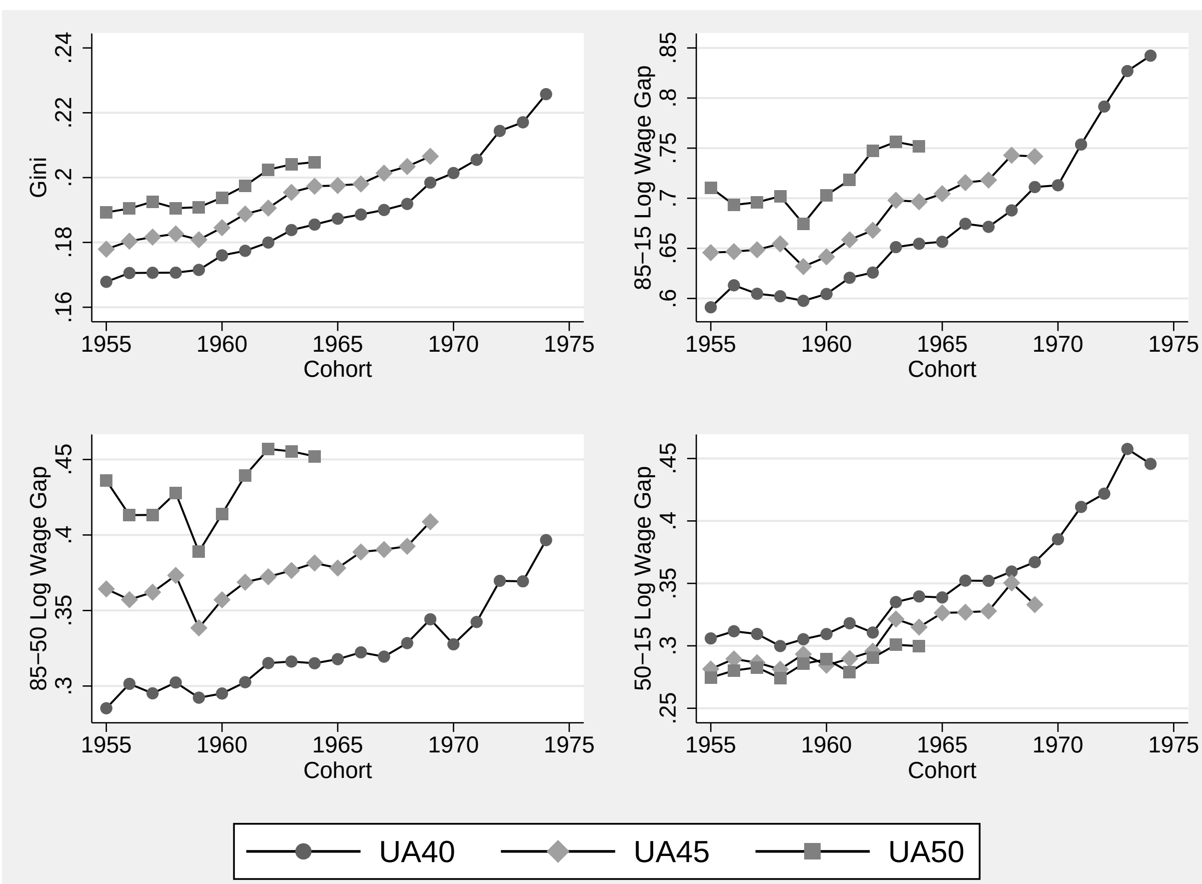


Figure 3 – Rank correlations of UA40 with selected UAX

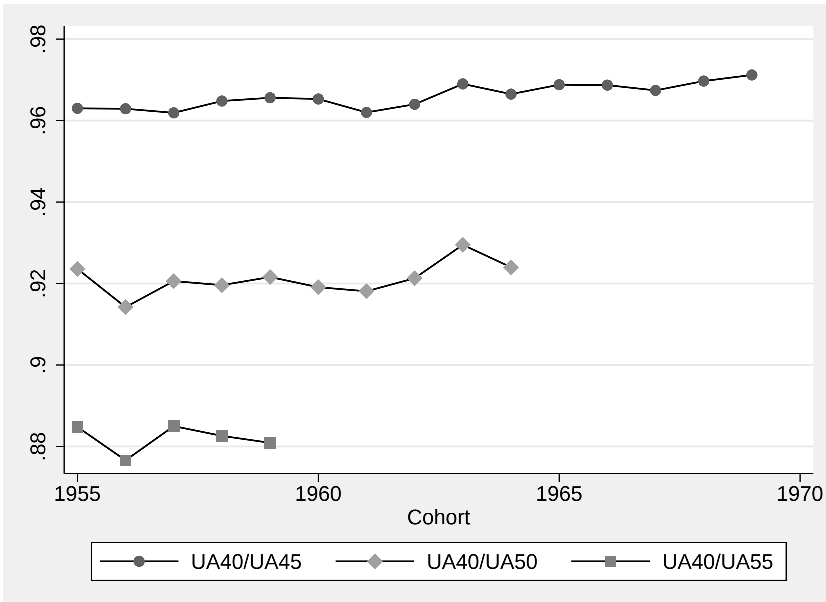


Figure 4 – Evolution of UA40 within education groups, cohorts 1955-57 vs. cohorts 1972-74

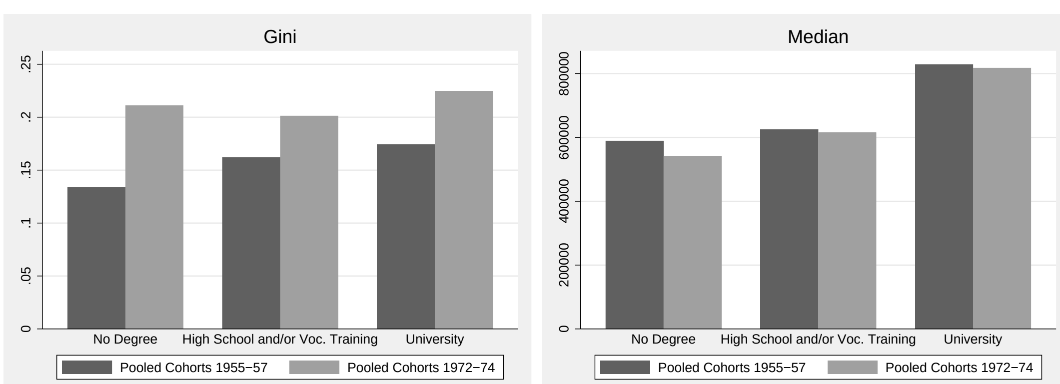


Figure 5 – Changes in UAX, cohorts 1955-57 vs. 1972-74

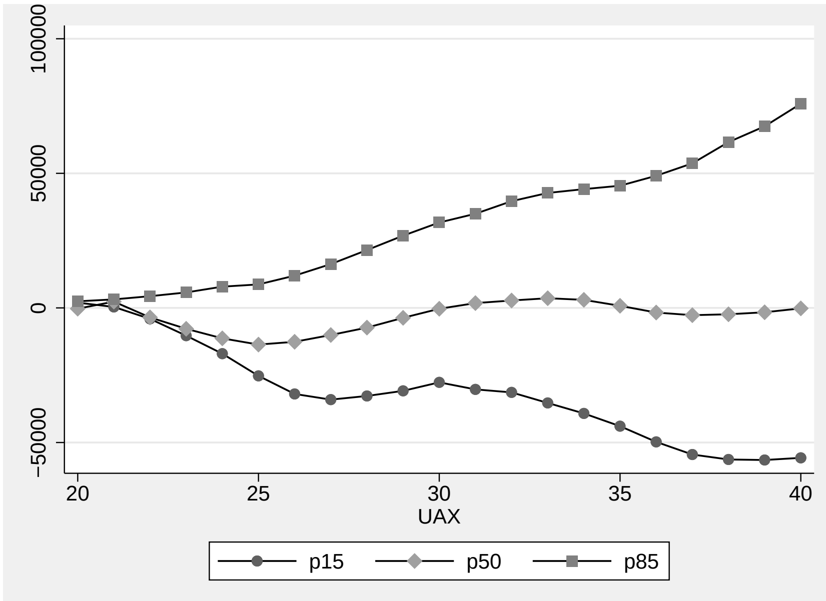


Figure 6 – Full-time employment UA40 in months, cohorts 1955-57 vs. cohorts 1972-74

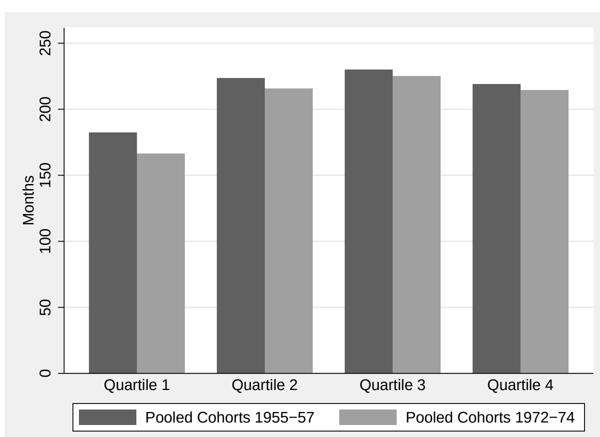


Figure 7 – Non-employment UA40 in months, cohorts 1955-57 vs. cohorts 1972-74

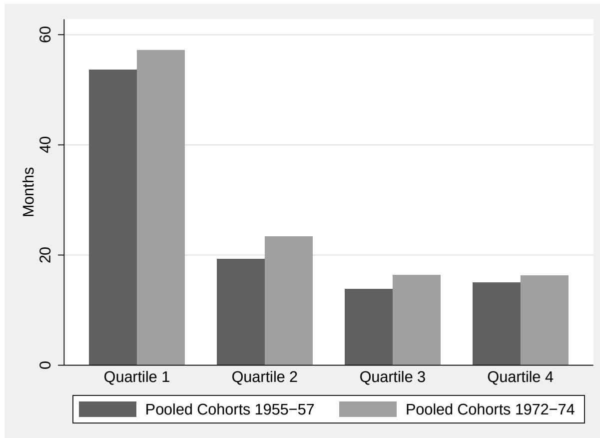


Figure 8 – Part-time employment UA40 in months, cohorts 1955-57 vs. cohorts 1972-74

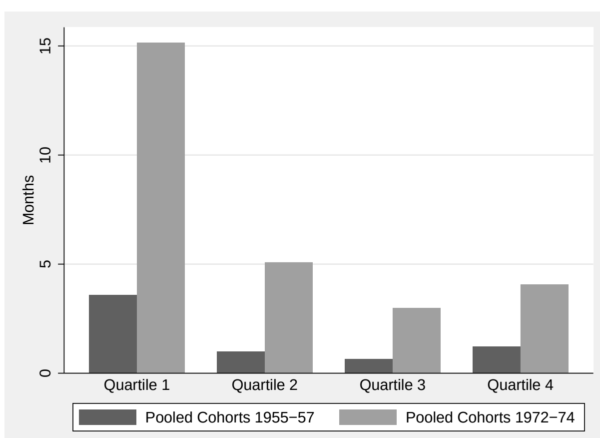


Figure 9 – Share of different education groups

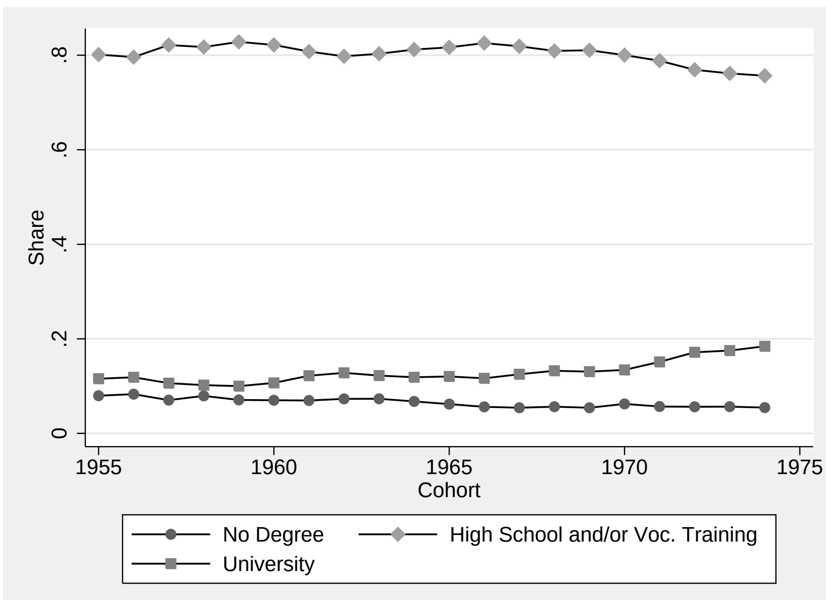


Figure 10 – Aggregate decomposition, cohorts 1955-57 vs. 1972-74

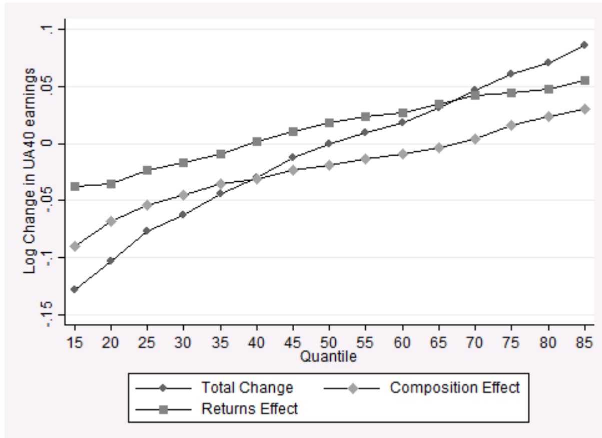


Figure 11 – Detailed composition effect, cohorts 1955-57 vs. 1972-74

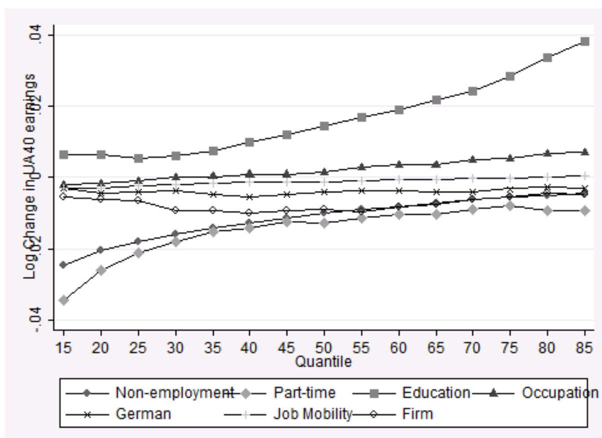
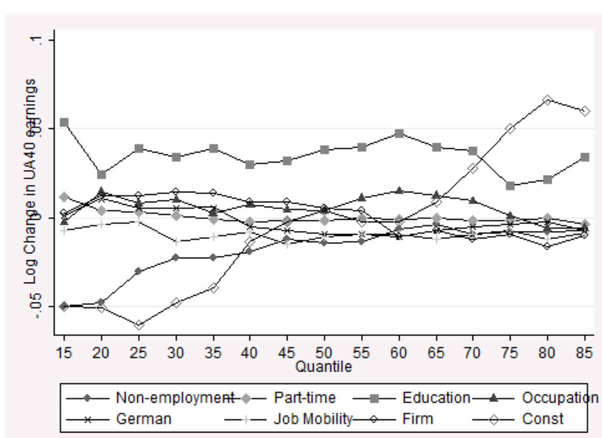


Figure 12 – Detailed returns effect, cohorts 1955-57 vs. 1972-74



9 Tables

Table 1 – Groups of covariates

Group	Covariates
1. Non-employment	Years of non-employment UA40 (= days of full-time employment/365)
2. Part-time employment	Years of part-time employment UA40 (= days of part-time employment/365)
3. Education	Highest educational degree UA40 (6 categories)
4. Occupation	Most frequent occupation UA40 (32 categories)
5. Nationality	German by birth (binary, no spells with foreign nationality)
6. Job mobility	Number of firm changes UA40 (with change in both occupation/industry)
	Number of firm changes UA40 (without change in both occupation/industry)
7. Firm	Most frequent firmsize UA40 (3 categories)
	Mostly in high-tech firm UA40 (binary)
	Most frequent sector UA40 (44 categories)
	Most frequent federal state UA40 (10 categories)

Table 2 – RIF decomposition results, UA40

Inequality measure	85-15	85-50	50-15	Gini	Log Variance
Total change	21.35***	8.58***	12.77***	4.91***	7.25***
	(1.13)	(0.58)	(0.98)	(0.18)	(0.31)
Total composition	9.05***	4.53***	4.52***	2.24***	3.19***
	(0.68)	(0.40)	(0.47)	(0.17)	(0.33)
Non-employment	2.03***	0.55***	1.48***	0.55***	0.95***
	(0.31)	(0.09)	(0.23)	(0.09)	(0.15)
Part-time	2.51***	0.34**	2.18***	0.69***	1.33***
	(0.34)	(0.16)	(0.26)	(0.09)	(0.23)
Education	3.17***	2.35***	0.82***	0.62***	0.46***
	(0.33)	(0.26)	(0.19)	(0.07)	(0.09)
Occupation	0.92***	0.57***	0.35**	0.19***	0.26***
	(0.21)	(0.15)	(0.16)	(0.04)	(0.06)
Nationality	0.00	0.10	-0.10	0.08**	0.15*
	(0.19)	(0.13)	(0.19)	(0.04)	(0.08)
Job Mobility	0.38***	0.19***	0.19***	0.08***	0.08**
	(0.10)	(0.05)	(0.07)	(0.02)	(0.04)
Firm	0.04	0.42*	-0.38	0.03	-0.04
	(0.28)	(0.23)	(0.22)	(0.06)	(0.09)
Total effect returns	9.09***	3.61***	5.47***	2.70***	4.04***
	(1.40)	(0.73)	(1.23)	(0.19)	(0.40)
Non-employment	4.22*	0.69	3.53*	0.57**	3.13***
	(2.24)	(0.81)	(1.90)	(0.29)	(0.74)
Part-time	-1.51**	-0.19	-1.32**	-0.24**	-0.09
	(0.69)	(0.25)	(0.59)	(0.12)	(0.29)
Education	-1.97	-0.46	-1.51	-1.06	-4.27
	(4.95)	(2.77)	(4.03)	(0.92)	(2.23)
Occupation	-0.33	-0.95	0.62	-0.17	-0.11
	(1.67)	(1.06)	(1.46)	(0.31)	(0.89)
Nationality	-0.84	0.20	-1.04	-0.08	0.20
	(1.15)	(0.82)	(1.11)	(0.22)	(0.56)
Job Mobility	-0.16	0.24	-0.40	0.00	-0.15
	(1.95)	(0.91)	(1.51)	(0.34)	(0.83)
Firm	-1.29	-1.54	0.25	-0.38	-1.05
	(1.99)	(1.41)	(1.51)	(0.36)	(0.67)
Constant	10.96*	5.61	5.35	4.05***	6.37**
	(5.93)	(3.73)	(4.80)	(1.10)	(2.73)
Specification Error	2.95***	0.33	2.62***	-0.07	-0.03
	(0.86)	(0.39)	(0.87)	(0.05)	(0.11)
Reweighting Error	0.27	0.11	0.15	0.04	0.06
	(0.42)	(0.14)	(0.33)	(0.09)	(0.16)

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

Log wage differentials×100. Bootstrapped standard errors (100 replications) in parentheses

*** / ** / * statistically significant at 1%/5%/10%-level

Table 3 – RIF decomposition results, UA40, including age at labor market entry

Inequality measure	85-15	85-50	50-15	Gini	Log Variance
Total change	21.35***	8.58***	12.77***	4.91***	7.25***
	(1.13)	(0.58)	(0.98)	(0.18)	(0.31)
Total composition	9.63***	4.83***	4.80***	2.36***	3.37***
	(0.70)	(0.41)	(0.47)	(0.17)	(0.34)
Non-employment	2.05***	0.57***	1.49***	0.55***	0.96***
	(0.33)	(0.10)	(0.24)	(0.09)	(0.16)
Part-time	2.38***	0.28*	2.11***	0.67***	1.28***
	(0.33)	(0.16)	(0.26)	(0.09)	(0.23)
Age at labor market entry	2.27***	0.97***	1.30***	0.47***	0.85***
	(0.29)	(0.19)	(0.20)	(0.06)	(0.11)
Education	1.91***	1.87***	0.04	0.36***	-0.05
	(0.35)	(0.28)	(0.22)	(0.08)	(0.11)
Occupation	0.84***	0.54***	0.30*	0.17***	0.22***
	(0.22)	(0.16)	(0.16)	(0.05)	(0.06)
Nationality	-0.15	0.04	-0.19	0.05	0.09
	(0.18)	(0.13)	(0.18)	(0.04)	(0.08)
Job Mobility	0.37***	0.19***	0.19***	0.08***	0.08**
	(0.10)	(0.05)	(0.07)	(0.02)	(0.04)
Firm	-0.05	0.38	-0.43*	0.02	-0.07
	(0.29)	(0.24)	(0.22)	(0.06)	(0.09)
Total effect returns	8.63***	3.66***	4.97***	2.68***	3.98***
	(1.36)	(0.75)	(1.20)	(0.19)	(0.41)
Non-employment	3.70	0.82	2.87	0.57**	3.09***
	(2.31)	(0.78)	(1.97)	(0.29)	(0.74)
Part-time	-1.43**	-0.16	-1.27**	-0.22*	-0.05
	(0.68)	(0.25)	(0.59)	(0.12)	(0.29)
Age at labor market entry	23.39	30.01*	-6.62	6.47*	9.30
	(19.98)	(12.19)	(16.11)	(3.71)	(7.30)
Education	-1.00	0.41	-1.41	-0.77	-3.83*
	(4.87)	(2.70)	(4.05)	(0.89)	(2.19)
Occupation	0.61	-0.86	1.46	-0.11	-0.07
	(1.68)	(1.09)	(1.43)	(0.31)	(0.88)
Nationality	-1.83	0.23	-2.06*	-0.42*	-1.01*
	(1.18)	(0.82)	(1.11)	(0.22)	(0.58)
Job Mobility	-1.56	-2.41***	0.85	-0.22	-0.24
	(1.92)	(0.92)	(1.48)	(0.33)	(0.82)
Firm	1.04	1.04	-0.00	0.25	0.35
	(2.02)	(1.41)	(1.55)	(0.36)	(0.66)
Constant	-14.28	-25.43	11.15	-2.87	-3.57
	(21.76)	(13.42)	(17.56)	(4.02)	(8.17)
Specification error	3.30***	0.13	3.16***	-0.09*	-0.02
	(0.86)	(0.40)	(0.86)	(0.05)	(0.12)
Reweighting error	-0.21	-0.04	-0.16	-0.04	-0.08
	(0.44)	(0.15)	(0.35)	(0.09)	(0.16)

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

Log wage differentials×100. Bootstrapped standard errors (100 replications) in parentheses

*** / ** / * statistically significant at 1%/5%/10%-level

Table 4 – RIF decomposition results, earnings age 25-40

Inequality measure	85-15	85-50	50-15	Gini	Log Variance
Total change	20.01***	7.84***	12.17***	4.82***	7.31***
	(1.21)	(0.90)	(0.97)	(0.20)	(0.36)
Total composition	11.71***	7.88***	3.83***	2.08***	2.66***
	(0.99)	(0.66)	(0.63)	(0.17)	(0.36)
Non-employment	1.40***	0.02	1.38***	0.34***	0.71***
	(0.39)	(0.03)	(0.39)	(0.10)	(0.20)
Part-time	2.17***	-0.47*	2.64***	0.49***	1.07***
	(0.45)	(0.26)	(0.34)	(0.09)	(0.21)
Education	6.38***	6.79***	-0.41**	0.92***	0.62***
	(0.62)	(0.60)	(0.19)	(0.09)	(0.11)
Occupation	1.40***	0.92***	0.47***	0.18***	0.26***
	(0.34)	(0.25)	(0.17)	(0.05)	(0.07)
Nationality	-0.52**	-0.23	-0.29	-0.06	-0.11
	(0.22)	(0.17)	(0.19)	(0.04)	(0.09)
Job Mobility	1.04***	0.54***	0.49***	0.20***	0.23***
	(0.18)	(0.10)	(0.13)	(0.03)	(0.08)
Firm	-0.15	0.30	-0.46**	0.00	-0.13
	(0.42)	(0.34)	(0.20)	(0.07)	(0.11)
Total effect returns	6.49***	-0.24	6.73***	2.79***	4.42***
	(1.42)	(0.94)	(1.07)	(0.21)	(0.45)
Non-employment	5.39**	2.29***	3.10	0.38*	2.34***
	(2.55)	(0.85)	(2.30)	(0.23)	(0.82)
Part-time	-2.31***	-0.17	-2.13***	-0.31***	-0.26
	(0.71)	(0.31)	(0.65)	(0.10)	(0.28)
Education	2.47	-1.72	4.19	-0.29	-2.91
	(5.87)	(3.75)	(4.31)	(0.86)	(1.95)
Occupation	-1.62	-3.34**	1.73	-0.48	-0.41
	(2.29)	(1.44)	(1.62)	(0.31)	(0.81)
Nationality	-0.55	0.42	-0.97	-0.11	0.30
	(1.46)	(1.11)	(1.14)	(0.22)	(0.68)
Job Mobility	-2.15	-0.89	-1.26	-0.33	-1.32
	(2.31)	(1.24)	(1.44)	(0.36)	(1.16)
Firm	-3.01	-0.45	-2.56	-0.24	-1.03
	(2.51)	(1.75)	(1.82)	(0.38)	(0.67)
Constant	8.27	3.63	4.64	4.17***	7.71***
	(6.97)	(4.70)	(5.68)	(1.04)	(2.50)
Specification error	1.27*	-0.08	1.35***	-0.12**	0.07
	(0.68)	(0.49)	(0.44)	(0.05)	(0.13)
Reweighting error	0.55	0.28	0.27	0.07	0.16
	(0.52)	(0.23)	(0.44)	(0.09)	(0.18)

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

Log wage differentials×100. Bootstrapped standard errors (100 replications) in parentheses

*** / ** / * statistically significant at 1%/5%/10%-level

10 Appendix

Correction for structural break 1983/1984

As outlined in the main part, the information on daily earnings in the *SIAB* is subject to a structural break between the years 1983 and 1984. More precisely, one-time payments (e.g. annual bonues, christmas/holiday allowances) were not included before 1984 which results in a spurious increase in both the level and dispersion of earnings between both years. The literature suggests different correction methods (see, e.g. Dustmann et al., 2009, Bönke et al., 2015a) which usually build on the technique by Fitzenberger (1999). Being most closely related to the present study, daily earnings are corrected following the procedure suggested in Bönke et al. (2015a). Accordingly, log earnings growth in year t is estimated by a random effects (RE) model of the following form

$$\Delta w_t = \alpha_0 + \alpha_1 D_{1984} + \alpha_2 age_t + \alpha_3 age_t^2 + \alpha_4 age_t^3 + \alpha_5 D_{1984} age_t$$
$$+ \alpha_6 D_{1984} age_t^2 + \alpha_7 D_{1984} age_t^3 + \boldsymbol{D_q'}\boldsymbol{\beta} + \boldsymbol{D_q'}\boldsymbol{\gamma} D_{1984} + \boldsymbol{D_q'}\boldsymbol{\delta} age_t + \epsilon$$

where Δw_t denotes the growth in log earnings between time periods t and t+1 and D_{1984} a dummy variable indicating the structural break. The model also includes a set of dummy variables D_q for an individual's average rank in the earnings distribution between age 35 and 40, which intends to approximate an individual's permanent position in the earnings distribution and accounts for the previous finding by Fitzenberger (1999) that the effect of one-time payments is more important for the upper part of the earnings distribution. Moreover, three polynomials of age as well as their interactions with the structural break dummy D_{1984} are included. Finally, the model includes interactions between the rank dummies D_q and both the structural break dummy D_{1984} and age. These are used to estimate an age and quantile specific spurious growth factor to correct observations before the year 1984.

Imputation of earnings above the contribution limit

The imputation of daily earnings above the contribution limit is done following the procedure suggested in Gartner (2005). Hence, wages above the censoring point are estimated by a series of tobit models which are computed separately for each year. The regressions include two polynomials of age, six education categories as wells as interactions between age and education. Instead of solely using the expected values from the tobit model, which suffer from a too high correlation with the covariates and downard-biased standard errors in later estimations, daily earnings above the threshold are drawn from a truncated normal distribution. The lower limit of this distribution is given by the censoring threshold, its standard deviation is estimated from the tobit model.

Table A1 – Observations per cohort

Year	(1) UA40	(2) UA45	(3) UA50
1955	4602	4192	3751
1956	4894	4480	4023
1957	4961	4525	4091
1958	5003	4588	4158
1959	5283	4775	4374
1960	5253	4801	4394
1961	5516	5053	4592
1962	5736	5258	4864
1963	5845	5368	4911
1964	5869	5397	4918
1965	5795	5340	-
1966	5948	5484	-
1967	5634	5256	-
1968	5351	5007	-
1969	5252	4798	-
1970	4863	-	-
1971	4555	-	-
1972	4086	-	-
1973	3624	-	-
1974	3517	-	-
Total	109194	81271	49864

Source: SIAB 1975-2014 and own calculations.

Table A2 – Descriptive statistics UA40

	1955-57		1972-74	
	Mean	SD	Mean	SD
Non-employment (= days of non-employment/365)	2.120	2.435	2.361	2.505
Part-time employment (= days of part-time employment/365)	0.135	0.857	0.569	1.784
Age at labor market entry	21.069	1.950	21.557	2.045
Lower/middle secondary without vocational training	0.078	0.268	0.056	0.230
Lower/middle secondary with vocational training	0.765	0.424	0.644	0.479
Upper secondary without vocational training	0.002	0.047	0.006	0.078
Upper secondary with vocational training	0.040	0.195	0.112	0.315
University/Fachhochschule	0.113	0.317	0.177	0.381
Missing information	0.002	0.049	0.005	0.068
Number of firm changes (with change in both occupation/industry)	1.731	2.621	1.929	2.441
Number of firm changes (without change in both occupation/industry)	2.183	2.712	2.475	3.427
German nationality	0.890	0.314	0.779	0.415
Firmsize 1-50	0.338	0.473	0.352	0.477
Firmsize 51-500	0.330	0.470	0.377	0.485
Firmsize 500+	0.331	0.470	0.271	0.444
Mostly in high-tech firm	0.304	0.460	0.294	0.455
Most frequent federal state:				
Schlewsig-Holstein	0.032	0.177	0.029	0.168
Hamburg	0.028	0.165	0.030	0.169
Lower Saxony	0.103	0.304	0.104	0.306
Bremen	0.015	0.121	0.012	0.110
North Rhine-Westphalia	0.290	0.454	0.269	0.444
Hesse	0.093	0.291	0.098	0.298
Rhineland-Palatinate	0.060	0.238	0.052	0.228
Baden-Wuerttemberg	0.169	0.374	0.179	0.383
Bavaria	0.187	0.390	0.209	0.407
Saarland	0.022	0.148	0.017	0.129
Most frequent sector:				
Agriculte and Forestry	0.006	0.076	0.010	0.097
Mining	0.022	0.146	0.004	0.067
Food products, beverages and tobacco products	0.026	0.158	0.025	0.156
Textiles	0.010	0.010	0.005	0.073
Wood and wood products	0.007	0.085	0.010	0.097
Pulp, paper, paper product	0.009	0.094	0.010	0.098
Publishing, printing and reproduction of recorded media	0.019	0.135	0.012	0.110
Coke, refined petroleum products and nuclear fuel	0.003	0.051	0.002	0.043
Chemicals and chemical products	0.032	0.175	0.024	0.152
Rubber and plastic products	0.022	0.147	0.021	0.145
Other non-metallic mineral products	0.014	0.117	0.011	0.105
Basic metals	0.028	0.164	0.021	0.145
Fabricated metal products, except machinery and equipment	0.043	0.202	0.039	0.193
Machinery and equipment n.e.c.	0.081	0.273	0.065	0.247
Office machinery and computers	0.006	0.080	0.003	0.057
Electrical machinery and apparatus	0.026	0.159	0.024	0.153
Radio, television and communication equipment and apparatus	0.009	0.097	0.012	0.107
Medical, precision and optical instruments, watches and clocks	0.024	0.154	0.020	0.140

Motor vehicles, trailers and semi-trailers	0.055	0.229	0.060	0.238
Other transport equipment	0.009	0.093	0.008	0.088
Furniture; manufacturing n.e.c.	0.013	0.115	0.012	0.107
Electricity, Water, Recycling	0.015	0.122	0.011	0.105
Construction	0.107	0.309	0.094	0.292
Sale, maintenance, repair of motor vehicles	0.029	0.169	0.045	0.208
Wholesale trade	0.064	0.246	0.063	0.243
Retail trade	0.044	0.204	0.047	0.211
Hotels and restaurants	0.012	0.108	0.015	0.123
Transportation	0.027	0.161	0.024	0.152
Supporting and auxiliary transport activities	0.026	0.158	0.032	0.175
Post and telecommunications	0.011	0.104	0.011	0.106
Financial intermediation	0.031	0.172	0.031	0.175
Insurance and pension funding	0.008	0.091	0.008	0.089
Activities auxiliary to financial intermediation	0.002	0.048	0.003	0.059
Real estate activities, Renting of machinery and equipment	0.005	0.067	0.008	0.088
Computer and related activities	0.005	0.072	0.028	0.150
Research and development	0.004	0.059	0.006	0.074
Other business activities	0.034	0.180	0.078	0.269
Public administration and defence; compulsory social security	0.046	0.210	0.028	0.166
Education	0.009	0.094	0.010	0.100
Health and social work	0.031	0.174	0.041	0.199
Sewage and refuse disposal, sanitation and similar activities	0.006	0.076	0.006	0.075
Activities of membership organizations n.e.c.	0.008	0.089	0.006	0.076
Recreational, cultural and sporting activities	0.006	0.077	0.007	0.083
Other service activities	0.008	0.089	0.004	0.064
Most frequent occupation:				
Occ. in agriculture, forestry, and farming	0.005	0.073	0.004	0.066
Occ. in gardening and floristry	0.006	0.080	0.008	0.090
Occ. in production and processing of raw materials, glass- and ceramic-making and -processing	0.016	0.127	0.008	0.087
Occ. in plastic-making and -processing, and wood-working and -processing	0.035	0.184	0.041	0.199
Occ. in paper-making and -processing, printing, and in technical media design	0.024	0.152	0.018	0.132
Occ. in metal-making and -working, and in metal construction	0.103	0.304	0.090	0.286
Technical occ. in machine-building and automotive industry	0.147	0.354	0.144	0.351
Occ. in mechatronics, energy electronics and electrical engineering	0.055	0.227	0.037	0.188
Occ. in technical research and development, construction, and production planning and scheduling	0.045	0.207	0.050	0.218
Occ. in textile- and leather-making and -processing	0.007	0.080	0.005	0.072
Occ. in beverage production	0.022	0.147	0.028	0.164
Occ. in construction scheduling, architecture and surveying	0.011	0.106	0.009	0.093
Occ. in building construction above and below ground	0.044	0.205	0.032	0.176
Occ. in interior construction	0.021	0.144	0.020	0.142
Occ. in building services engineering and technical building services	0.026	0.160	0.029	0.167
Occ. in mathematics, biology, chemistry, physics, geography, geology etc	0.031	0.174	0.026	0.158
Occ. in computer science, information and communication technology	0.018	0.133	0.035	0.184
Occ. in traffic and logistics (without vehicle driving)	0.064	0.245	0.072	0.259
Drivers and operators of vehicles and transport equipment	0.071	0.257	0.049	0.216
Occ. in safety and health protection, security and surveillance	0.009	0.092	0.010	0.098
Occ. in cleaning services	0.004	0.064	0.008	0.089
Occ. in purchasing, sales and trading	0.028	0.164	0.028	0.164
Sales occ. in retail trade	0.018	0.133	0.028	0.164

Occ. in tourism, hotels and restaurants	0.006	0.074	0.007	0.083
Occ. in business management and organisation	0.086	0.280	0.103	0.303
Occ. in financial services, accounting and tax consultancy	0.046	0.209	0.048	0.213
Occ. in law and public administration	0.003	0.053	0.008	0.081
Medical and health care occupations	0.015	0.120	0.024	0.155
Occ. in non-medical healthcare, body care, wellness and medical technicians	0.006	0.077	0.003	0.058
Occ. in education and social work, housekeeping, and theology	0.012	0.109	0.012	0.110
Occ. in teaching and training	0.005	0.073	0.005	0.068
Occ. in humanities, social sciences, economics, media etc.	0.012	0.109	0.014	0.116

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

Numbers refer to individuals with valid UA40 biography

Table A3 – RIF decomposition results, UA40, German nationals

Inequality measure	85-15	85-50	50-15	Gini	Log Variance
Total change	19.07***	8.33***	10.74***	4.53***	6.49***
	(1.15)	(0.67)	(0.91)	(0.19)	(0.33)
Total composition	9.22***	4.76***	4.46***	2.14***	2.82***
	(0.69)	(0.39)	(0.47)	(0.16)	(0.27)
Non-employment	1.94***	0.52***	1.42***	0.54***	0.94***
	(0.31)	(0.09)	(0.23)	(0.09)	(0.15)
Part-time	2.48***	0.35**	2.13***	0.68***	1.18***
	(0.34)	(0.16)	(0.26)	(0.09)	(0.18)
Education	3.42***	2.60***	0.82***	0.64***	0.44***
	(0.35)	(0.28)	(0.22)	(0.07)	(0.10)
Occupation	1.12***	0.67***	0.45***	0.20***	0.29***
	(0.22)	(0.16)	(0.17)	(0.05)	(0.06)
Job Mobility	0.30***	0.16***	0.14**	0.06**	0.06
	(0.11)	(0.05)	(0.07)	(0.03)	(0.05)
Firm	-0.04	0.45*	-0.49**	0.02	-0.09
	(0.30)	(0.25)	(0.24)	(0.07)	(0.09)
Total effect returns	7.75***	3.22***	4.53***	2.61***	3.89***
	(1.28)	(0.76)	(0.96)	(0.20)	(0.39)
Non-employment	5.06**	0.67	4.40**	0.69**	3.23***
	(2.09)	(0.83)	(1.75)	(0.31)	(0.73)
Part-time	-1.27*	-0.26	-1.01*	-0.21*	0.09
	(0.65)	(0.25)	(0.56)	(0.12)	(0.25)
Education	0.81	-1.12	1.93	-1.09	-4.38*
	(6.30)	(4.05)	(4.90)	(1.05)	(2.65)
Occupation	-1.88	-2.18**	0.30	-0.41	-0.50
	(1.87)	(1.06)	(1.59)	(0.32)	(0.73)
Job Mobility	-1.66	0.42	-2.08	-0.11	-0.32
	(2.00)	(0.94)	(1.46)	(0.38)	(0.83)
Firm	-1.43	-2.07	0.64	-0.34	-0.58
	(1.92)	(1.59)	(1.39)	(0.35)	(0.64)
Constant	8.11	7.77	0.34	4.08***	6.35**
	(6.99)	(4.73)	(5.60)	(1.21)	(3.10)
Specification error	2.20***	0.30	1.90***	-0.16***	-0.12
	(0.67)	(0.40)	(0.62)	(0.05)	(0.09)
Reweighting error	-0.10	0.05	-0.14	-0.06	-0.11
	(0.38)	(0.13)	(0.29)	(0.08)	(0.13)

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

Log wage differentials×100. Bootstrapped standard errors (100 replications) in parentheses

*** / ** / * statistically significant at 1%/5%/10%-level

Figure A1 – Indexed real growth in earnings age 25-40

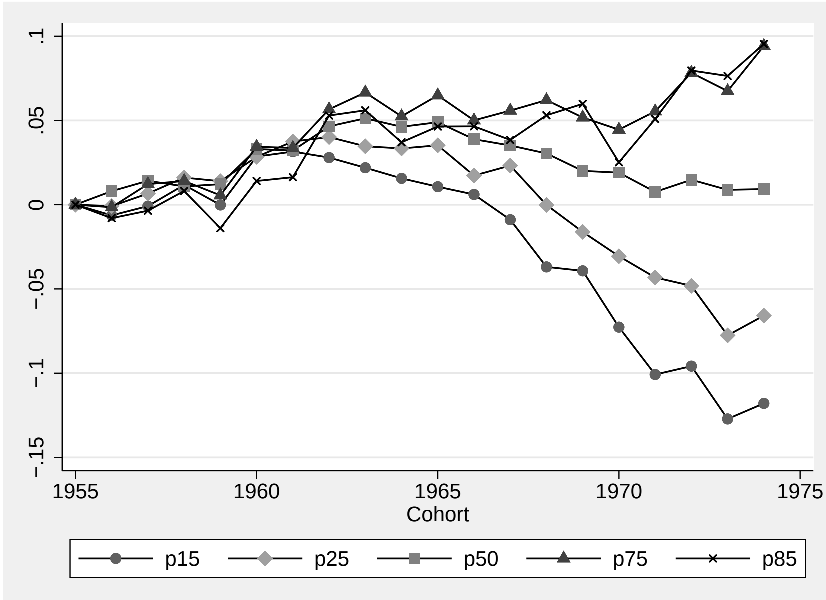


Figure A2 – Inequality in earnings age 25-40