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

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**Abstract.** This paper provides a formal decomposition analysis of rising lifetime earnings inequality in Germany using to-the-day 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 also 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 even aggravates when looking at changes within education groups.

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# 1 Introduction

The phenomenon of growing wage and earnings inequality in most developed countries around the world caused an increasing interest in the topic from both policymakers and academics. The latter have so far mainly focused on the increase in cross-sectional inequality over time as well-documented in a vast and ever-growing 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 affects the evolution of individual long-term or even 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 caused by the fact that observable differences in cross-sectional earnings are equally the consequence of individuals being observed at different points of their working life. Besides, studying lifetime earnings from a cohort perspective is likely to be more informative with regards to an individuals or cohorts 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 identifies different channels underlying the increase in cross-sectional inequality, most prominently skill-biased technological change (*SBTC*), demographical and institutional factors as well as internationalization or changes in individual earnings biographies.[2] However, it remains ex ante 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 from Germany. Methodologically, the paper uses state-of-the-art RIF decomposition (Firpo et al., 2014, 2018) which is used together with rich to-the-day information from individual employment biographies.

In a nutshell, the paper makes the following contributions to the literature: First, the present

[2]For a more comprehensive discussion, please refer to section 2

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 factors for the rise in inequality in the lower half of the distribution. Contrary to that, much of the rising inequality at the top of the distribution is associated with educational upgrading. To the best of my knowledge, this is the first study providing a comparable decomposition analysis that tries to explain the rising inequality in lifetime earnings. Second, the results confirm previous findings of Bönke et al. (2015a) who documented a sharp rise in lifetime earnings inequality. Going a step further, the present paper also shows that German men born between 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 educational groups which are counterbalanced by on average higher levels of educational attainment. The median of earnings up-to-age 40 (UA40) seems to follow an inverse U-shape across cohorts, with an increase among cohorts born until the mid 1960s and a gradual decline thereafter. The paper also provides first evidence that these trends tend to accelerate for the youngest cohorts. The rest of the paper structures as follows: Section 2 summarizes the related literature. Sections 3 and 4 describe the data and the econometric method used for the main analysis. Section 5 presents the empirical results and section 6 concludes with a discussion of the major findings.

## 2 Related Literature

The present paper relates to different strands in the literature. Most importantly, it 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 wages and lifetime earnings seem to show 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, earnings mobility is not identified as an important factor in explaining the rise in lifetime earnings inequality. As the study builds on a relatively short panel, the used measure 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 an increasing inequality in male long-term earnings, especially for the *baby-boomers* born after 1945. This trend is found in all stages of the career with the level of inequality being higher in later stages. More recently, Guevenen et al. (2017) document both a decline in median lifetime earnings of U.S. men, combined with an increasing earnings inequality when comparing individuals entering the labor market between 1967 and 1983. Hereby, they find the increasing lifetime earnings dispersion to be primarily caused by an increasing inequality in earnings in early years of the career. For Germany, Bönke et al. (2015a) document a dramatic increase in intragenerational lifetime earnings inequality. Using an Insurance Account Sample (*Versicherungskontenstichprobe*), the study compares 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 of individual long-term earnings, which is defined as the present value of all earnings before the individual is reaching a certain age.[3] By imputing earnings for periods of un- and non-employment, they show that parts of this increase can be assigned to changes in unemployment patterns of individuals at the lower tail of the respective distributions. Moreover, they establish two other results that are important for this paper. 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 evolution of earnings up to age 40. Hence, studying causes for the increasing inequality in up to age $\geq 40$ does not only offer important insights into changes in individual long-term earnings, but can most likely be generalized to inequality in lifetime earnings. 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 findings by trying to pin down the aforementioned increase in lifetime earnings across cohorts to different explanatory factors.

In this aspect, the present study also relates to the 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. Although not having reached a consensus yet, the respective literature finds several factors 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

[3] Despite minor methodological differences, the same terminology is used throughout the paper.

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). Moreover, institutional changes in the form of deunionization (Dustmann et al., 2009, Baumgarten et al., 2016, Biewen and Seckler, 2017) seem to explain much of the increase in inequality, whereas internationalization seems to to be another potential explanation (Baumgarten, 2013). In a recent contribution, Biewen et al. (2018) highlight the importance of an increasing heterogeneity regarding individuals' past labor market experience for the recent rise in cross-sectional wage inequality in Germany. Using inverse probability weighting, they account a substantial share to this increasing heterogeneity in individuals' labor market history (measured by episodes of full-time, part-time and non-employment), especially at the bottom of the distribution.

As the present studies identifies episode of part-time and non-employment as important factors, 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 earnings biographies among individuals born later. 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 being important results alone, both studies abstain from establishing a direct link to the evolution earnings inequality over time. Brehmer and Seifert (2008) and Wolf (2010) also show that part-time employment is associated with lower hourly wages relative to full-time employment. Finally, a number of studies provides direct evidence that both employment interruptions and part-time episodes tend to have adverse effects on future earnings growth (Beblo and Wolf, 2002, Görlich and Grip, 2008, Potrafke, 2012, Fernández-Kranz et al., 2015, Blundell et al., 2016, Paul, 2016).

# 3 Data

The further analysis is based on the *Sample of Integrated Employment Biographies (SIAB)* provided by the Research Data Center of the IAB. The data constitute a 2 percent random sample of all employees covered by social security records between the years 1975 and 2014. The data are the ideal basis for studying changes in lifetime earnings across cohorts due to the fact that complete individual employment histories (down to a daily basis) of approximately 1.75 million individuals are provided. Moreover, the *SIAB* includes much more covariates that can potentially explain the rise in intragenerational lifetime earnings inequality compared to the Insurance Account Sample of the Federal Pension Register (*Versicherungskontenstichprobe*) that has mostly been used in previous research. Hence, the subsequent analysis covers 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.

The analysis in this study builds on a sample comprised of individuals with a sufficient attachment to the labor market. This is achieved by imposing the following restrictions[4]: First, to make sure 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 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

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

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 109194 (81271) respondents for which complete UA40 (UA45) earning biographies can be constructed. A more detailed overview on the number of observations for the different cohorts is provided in table A1 in the appendix.[5]

Due to censoring at the upper earnings limit for the statutory pension fund, earnings above this threshold are imputed following the procedure by Gartner (2005).[6] Depending on the year of observation, up to 15 percent of observations are affected by this right-censoring. Hence, as it is commonly the case in studies based on German administrative data, this paper focuses on the development of earnings inequality below the 85th percentile of the different UAX distributions. Due to this property, the subsequent analysis might in fact underestimate the true increase in long-run earnings given that much of the development at the very of the distribution will not be captured. Starting in 1984, one-time payments became part of the annual earnings measure resulting in both an increase in average daily wages as well as a spurious increase in annual earnings inequality between 1983 and 1984. To account for this structural break, the procedure introduced by Bönke et al. (2015) is used, which denotes a modification of the original procedure by Fitzenberger (1999) that works on panel data.[7]

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, this might result in individuals in the sample whose earnings biographies are partly unobservable. However, this does not affect the results of the subsequent decomposition of UA40 earnings due to the following reasoning: For the analysis, individuals that can be observed in the SIAB before 1989 are assumed to only consist of West Germans, given the fact that the Berlin Wall

[5]This paper does not discuss any results for 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.

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

[7]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

didn't come down 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 only consist of West Germans. Similarly, individuals born after 1970 are equally not affected by (relevant) unobservable employment spells in East Germany, given the fact that starting in 1991, the SIAB covers both East and West Germany and only earnings starting at age 20 are included in the earnings measures. Hence, the decomposition results comparing pooled cohorts 1955-57 to 1972-1974 are not diluted by individuals with unobservable employment spells in East Germany.[8]

## 3.1 Trends in lifetime earnings inequality

To measure inequality in individual long-term earnings, *up-to-age X earnings (UAX)* are computed for different ages. This is done, instead of directly examining lifetime earnings, due to the underlying 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 a first step, daily earnings are inflated/deflated to the level of 2010 using the German consumer price index (CPI). In a second, 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). Hereby, the measures only include payments from employment subject to social insurance contributions before tax, i.e. any form of social transfer-payments as well as earning from periods of self-employment are not part of the analysis. Hence, the earnings measure mirrors the price of labor paid in the market.[9] 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,

[8]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 major 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.

[9]Bönke et al. (2015) 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.

1999.

— (Figure 1 here ) —

Figure 1 illustrates the indexed (real) growth in UA40 earnings at different percentiles of the unconditional within cohort distribution for cohorts 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 lost 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%. This in turn suggests that gains/losses in UA40 are more pronounced than comparable figures found in studies on cross-sectional earnings (see, e.g. Dustmann et al., 2009). In fact, this result does not come as a surprise if individuals at the bottom of the cross-sectional earnings distribution do not only face pressure on hourly/daily wages (i.e. on earnings per unit of work), but also have a lower labor market participation via part- and non-employment. Second, over the entire period of study, the graph shows a stagnation in median UA40 earnings with the development following an inverse U-shape. More precisely, median earnings increased up to birth cohorts 1965 and gradually deteriorate thereafter. Third, the graphical analysis suggests that the increase in inequality is dramatically speeding up for 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 A2 in the appendix, the overall picture remains virtually unchanged when only earnings starting at age 25 are taken into account.

— (Figure 2 here ) —

Figure 2 summarizes the impact of this development on different inequality measures, also including UA45 earnings but for a smaller number of cohorts. 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 of UA40, this is mirrored by a sharp increase in the Gini coefficient from 0.168 to 0.226 (approx.+35%), which is affecting 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 line with previous findings by Bönke et al. (2015a), inequality as captured by the different measures is increasing over the life-cycle.[10] The presented graphical evidence suggests that the development in UA40 earnings seems be closely linked to the developments in UA45 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 convincing evidence that the evolution of lifetime earnings closely follows the development in UA40.[11]

— (Figure 4 here ) —

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.[12] The graph confirms that a large share of the previously documented increase in overall within-cohort inequality can in fact be attributed to an increasing dispersion of UA40 within educational groups. This increase seems to be strongest within 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. Once more, these losses are strongest for individuals without a degree (approx.-8%)

[10] One exeception 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.

[11] In this respect, the results confirm previous findings by Bönke et al. (2015a) who conclude that *the evolution of inequality of lifetime earnings is likely to mirror the evolution of inequality of earnings up to age 40* (p.186).

[12] Evidence on pooled cohorts (as opposed to results on a cohort-wise basis) are provided due to a relatively small size of the subgroup *No Degree*.

in contrast to rather marginal losses of approx. -1.5 percent and -1.3 percent for individuals with a vocational training and university background. This in turn 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.

## 3.2 Trends in employment patterns

Against the background of the outlined trends in UA40 earnings, it is insightful to look at some descriptive evidence on factors potentially explaining the outlined development. To evaluate observed changes in lifetime earnings, it is important to distinguish changes in an individual's labor market participation during the working life from changes in earnings during the time an individual was actually employed (i.e. changes in hours worked vs. changes in hourly earnings). Although the *SIAB* does not include precise information on hours worked, the data allows to consistently distinguish between full-time, part-time and non-employment episodes 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 (e.g. employment breaks due to further education) by exploiting information on benefits recorded in the *Benefit Recipient History (LeH)* and the *Unemployment Benefit II Recipient Histories (LHG and XLHG)* as well as information of the *Jobseeker-Histories (ASU and XASU)* provided by the Federal Employment Agency. However, the latter data sources suffer from both missing information as well as several reforms affecting the entitlement to unemployment benefits and hence, do not allow to recover a consistent measure across the cohorts used in this study.[13]

— (Figures 5 to 7 here ) —

Figure 5 compares the UA40 full-time duration for the pooled cohorts 1955-57 and 1972-74 at different quartiles of the UA40 earnings distribution. Although full-time employment remains by far the most frequent employment form among German men, there seems to be a considerable reduction in full-time employment spells which is found to be strongest at the bottom of the UA40

[13]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.

Figure 7 illustrates the evolution of part-time employment. Starting from a very low level among individuals of birth cohorts 1955-57, the graph documents a dramatic increase in the average duration spent in part-time employment in all parts of the UA40 distribution. The graph also reveals that individuals in the bottom quartile of the UA40 distribution are by far most affected by this part-time expansion, with the average time spent in part-time employment increasing by on average 11.6 months. This shift in part-time employment durations across cohorts mirrors a growing importance during the last decades in Germany. Against common perceptions, there has also been a large increase in part-time employment among 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 has also been enforced by several legal changes, such as the *Teilzeit und Befristungsgesetz (TzBfG)*, which increased the relative attractiveness of part-time employment. The outlined development has a potentially twofold effect on lifetime earnings. Besides a simple reduction in lifetime working hours, and the resulting earning losses due to a reduction in total hours worked, it also has potentially adverse effects on future earnings growth as argued in the review of the previous literature in section 2

## 3.3 Trends in Education

— (Figure 8 here ) —

The cohorts included in the study also differ substantially in terms of their educational attainment. For illustrative purposes, figure 8 includes 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 mirrors 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% for those born in 1974. This development was accompanied by corresponding declines in both the share of medium skilled workers (i.e. individuals holding a high school degree and/or having pursuit 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 includes a more fine-grained educational measure which distinguishes six categories, i.e. *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. (2005) is used.

### 3.4 Trends in other covariates

— (Figure 1 here ) —

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 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), which are firm changes within the same industry or occupation (job changes) as opposed to firm changes where both the industry and occupation are changed (career changes). Gius (2014) shows this to be an important distinction given that the first type of job change is linked to an increase in earnings, whereas the latter one is found to have adverse effect on earnings. 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 an 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 1 shows that job changes are generally more frequent than career changes and the mean of both type of firm changes moderately increased among individuals born 1972-74.

To capture the potential impact of migration, a dummy variable indicating whether a person is native German or not is included. According to the definition used in this paper, a person is classified as native German if he or she does not have any observable employment spell with foreign nationality throughout the working life. During the observation period, there seems to be 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. As the previous research on cross-sectional earnings inequality points towards an increasing importance of between firm difference (see section 2), the analysis includes a number of firm characteristics that can be calculated 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) firms. 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 on the number of engineers and natural scientists (*Techies*) working in an establishment as provided by the Establishment History Panel. 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. Differences across industries are captured by the inclusion of the the primary sector an individual worked at up to a certain age (44 categories). In an analogues way, regional heterogeneities are accounted for by the inclusion of federal state dummies (10 categories). Lastly, the occupation (32 categories) a person worked in mostly is included.

# 4 Econometric methods

The subsequent decomposition analysis builds on RIF decomposition to disentangle the increasing inequality in different *up-to-age X earnings(UAX)* measures across cohorts. Compared 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. The method itself is based on unconditional quantile regression which goes back to the seminal contribution by Firpo et al. (2009). The main idea is to run regressions of the recentered influence function (RIF) of some distributional statistic of interest $\nu$ (e.g. the Gini coefficient) on explanatory variables. The RIF in turn is defined as $RIF\left(y,\nu\right)=\nu+IF\left(y;\nu\right)$ which integrates to the statistic of interest $\int RIF\left(y;\nu\right)dF(y)=\nu\left(F_y\right)$, where $F_y$ is the distribution function of the dependent variable. In the simplest form, the RIF is modeled as a linear function of the explanatory variables, i.e. $E\left[RIF\left(Y;\nu\right)|X\right]=X\gamma$, where $\gamma$ can be estimated by means of OLS. Ultimately, an Oaxaca-Blinder decomposition is used to decompose the overall change in a certain distributional statistic $\Delta_O^\nu$ between two cohorts 0 (e.g. cohort 1955-57) and 1 (e.g. cohort 1972-74) into a composition effect $\Delta_X^\nu$ and returns effect $\Delta_S^\nu$, i.e.

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

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

Due to their linear specification, the RIFs are only a local approximation which might potentially yield biased results in case of large changes in the distribution of characteristics. To circumvent this problem, Firpo et al (2014, 2018) suggest a *hybrid version* which includes inverse probability weighting (see DiNardo et al, 1996) into the original decomposition procedure. Hereby, the main idea is to create some artificial cohort 01 in which the cohort 0 distribution of characteristics $X$ is reweighted to that of the target cohort 1. Afterwards, two separate Oaxaca-Blinder decompositions are used to split up the overall change into four components

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

Accordingly, the estimate for the composition effect $(\Delta_X^\nu)$ is split up into a pure composition effect $(\Delta_{X,p}^\nu)$ and a specification error $(\Delta_{X,c}^\nu)$. Similarly, the estimate for the returns effect $(\Delta_S^\nu)$ is divided into a pure returns effect $(\Delta_{S,p}^\nu)$ and a reweighting error $(\Delta_{S,c}^\nu)$. Ultimately, detailed composition effects which reflect the contribution from changes in the distribution of a particular set covariates, e.g. changes in the part-time duration across different cohorts, to the overall change in the statistic of interest are provided. Likewise, the detailed returns effects $(\Delta_{S,p}^\nu)$

capture the effect from changes in $\gamma$ for a certain group of covariates. The specification error $\Delta^{\nu}_{X,c}$ mirrors differences in the estimated RIF coefficients between the cohorts 01 and 0, whereas the reweighting error 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.

Among others, Fortin et al. (2011) 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 following the approach in Gardezabal and Ugidos (2004) such that they sum up to zero within a group of categorical variables J, i.e. $\sum_{j \in J} \gamma_j = 0$. Hence, this approach effectively makes the results independent of the chosen reference group (see Biewen and Seckler, 2017 for a more rigorous discussion).

Finally, it is worth mentioning that the findings from this sort of decomposition analysis should not be interpreted causally as general equilibrium effects are not taken into account. Moreover, the method does not account for the fact that different explanatory factors might by dynamically related. As an example, compositional changes across cohorts with respect to different occupations and industries might, rather than being exogenously given, in fact be both be a consequence of technological change.

# 5 Decomposition results

This section presents RIF decomposition results comparing pooled cohorts 1955-57 and 1972-74. For reasons of clarity, the previously presented covariates are pooled into seven groups in line with table 2. These are *Non-employment*, *Part-time employment*, *Education*, *Occupation*, *Job mobility* and *Firm*. In the presentation of results, it is insightful to start with a graphical analysis. Results of an alternative specification using German nationals is provided in table A2 in the appendix. As results are mostly unchanged, they are not discussed in greater detail at this point.

— (Figures 9 to 11) —

Figure 9 includes the total change in unconditional quantiles together with the aggregate composition and return effect. The total change in unconditional quantiles is characterized by a very 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 cross-sectional wage inequality in Germany (e.g. Dustmann et al., 2009, Biewen and Seckler, 2017). However, note once more that the losses in the lower half of the within-cohort UA40 distribution are far more pronounced than those known from studies on increasing cross-sectional wage inequality in the last decades. The aggregate composition effect reveals a similar monotonic pattern but is negative for most of the distribution and only reveals a weakly positive effect above the 75th percentile. Being similarly monotonic, the aggregate returns effect is found to be positive above the 40th percentile and negative in the lower part of the distribution.

Figure 10 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 plays an important role at the bottom of the UA40 distribution. Interestingly, the effect of part-time employment seems to be even slightly stronger than the effect from the increasing incidence of non-employment. Note also that both effects, despite being strongest at the bottom of the distribution, have a negative effect for most of the distribution. Being the strongest individual composition effect (but weaker than the joint effect from changing employment patterns), compositional changes in education lead to an upward shift of the UA40 distribution across all quantiles. As it is, however, monotonically increasing over the distribution, it is found to be the most important single factor for inequality at the top of the distribution. In this regard, both the results on changing employment patterns and educational upgrading are in line with the general trends described in the preceeding chapters. Further, the analysis reveals a moderate composition effect linked to a changing composition of the workforce and a minor effect linked to changes in job mobility with the other factors being rather negligible.

Figure 11 provides detailed results for the return effects, that seem to be similarly important when compared to the overall composition effect. Besides the constant term, return effects linked to non-employment are found as the single most important factor. This effect lead to a downward shift of the lower half of the distribution and does not seem to have any impact on the upper half of the distribution. A possible interpretation for this finding would be that 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. This points towards increasing difficulties to re-integrate into the labor market which might potentially reflect the difficult labor market conditions in the late 1990s as wells as other factors such as a faster human capital depreciation or a lower job match quality. Note that this finding should be interpreted with some caution due to the relatively large standard error (also see table 3). Finally, the picture also suggests a positive return effect linked to education which is however insignificant (see, table 3).

— (Table 3 here ) —

Table 3 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) are found to contribute 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 are due to changes in educational attainment (3.17 points) as well as changes in non-employment (2.03 points) and part-time (2.51 points) patterns. Further, there seem 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 the detailed results of the return effects, show that the estimated effects are generally less precise. However, it equally reveals a moderate inequality-reducing effect linked to the returns to part-time employment at the bottom of the distribution.

Regarding the question of whether increasing inequality in lifetime earnings is driven by changes in labor market participation as opposed to changes in earnings received during employment, this result suggests that some 21 percent of the overall increase are linked to a lower labor market participation among individuals of later cohorts. Note that the baseline decomposition does not control for 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 does not capture the delayed labor market entry of later cohorts. An alternative model specification that equally accounts for the age at labor market entry suggests that up to 31 percent of the increase in 85-15 might in fact be due the overall lower lifetime labor market participation. As the detailed return effects are less intuitive in this specification, the results are provided in table A3 of the appendix only and not discussed in greater detail at this point.

— (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.[14] Overall, the results point towards a greater importance of composition effects (11.71 points), which are found to be more important than return effects (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 as this specification does not account for forgone earnings during times of education.

At the same time, there is a further reduction in the composition effect linked to non-employment. This 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 in fact reflect additional time spent in education. Note also that the overall share explained by the increasing incidence of part-time employment remains virtually unchanged. Simulatenously, this development is accompanied by moderate increases in the relative importance of compositional effects linked to occpuations and job mobility when compared to the decomposition of UA40. With respect to the return effects, the overall picture remains mostly unchanged with a persistently strong effect linked to non-employment. Simultaneously, the results for the return effects remain mostly unchanged with the strongest positive contribution linked to changes in the non-employment penalty (5.39 points in terms of 85-15). At the same time, the previously found return effect linked to part-time employment is found to be more pronounced, suggesting that it reveals 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 on the upper half.

[14] In fact, this definition is closer to the one used in Guevenen et al. (2017) who only consider earnings starting at age 25.

# 6 Conclusion

This study investigates potential determinants of increasing lifetime earnings inequality using detailed, down to a daily-basis employment biographies of West German men born between the years 1955 and 1974. By taking on a cohort perspective, the paper relates to a comparatively small literature documenting an increasing inequality in lifetime earnings not only in the U.S., but also in Germany among younger cohorts (Bönke et al., 2015a, Guevenen et al., 2017). As the major contribution, the paper formally disentangles these changes by means of a detailed decomposition analysis using state-of-the-art RIF Decomposition.

The detailed 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 of 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 finding is not at odds with their previous results due to the different cohorts included in the study. Hence, the oldest cohort in the present paper entered the labor market after the first oil price shock and was already confronted with higher levels of unemployment. 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.

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 in education were favorable to 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 potentially important return effects linked to episodes of non-employment, which seems to have lowered long-term earnings for individuals mostly 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 earning losses. Hence, this finding might mirror a faster depreciation of human capital during periods of non-employment as well as a poorer job match quality. However, this effect should rather be seen as first evidence and requires a more sophisticated evaluation that goes beyonds this paper.

The analysis also provides evidence for a stagnation in earnings until age 40, 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 seems to be similar to the U.S., where previous research of Guevenen et al. (2017) documented significant losses in lifetime earnings among men of later birth cohorts. Importantly, the results of the present paper point towards earnings losses within all educational subgroups (though being strongest for the lowest education group), which are counterbalanced by an increasing average educational attainment. Overall, this is another remarkable results against the background of significant gains in cross-sectional earnings during the study period 1975-2014 (see, e.g. Dustmann et al., 2014). Hence, the increase in cross-sectional earnings observed in the last decades did not seem to have benefited the younger cohorts, which suffered from both an increase in inequality and a stagnation in long-term earnings.

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# 8 Figures

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**Figure 1** – Indexed real growth in UA40

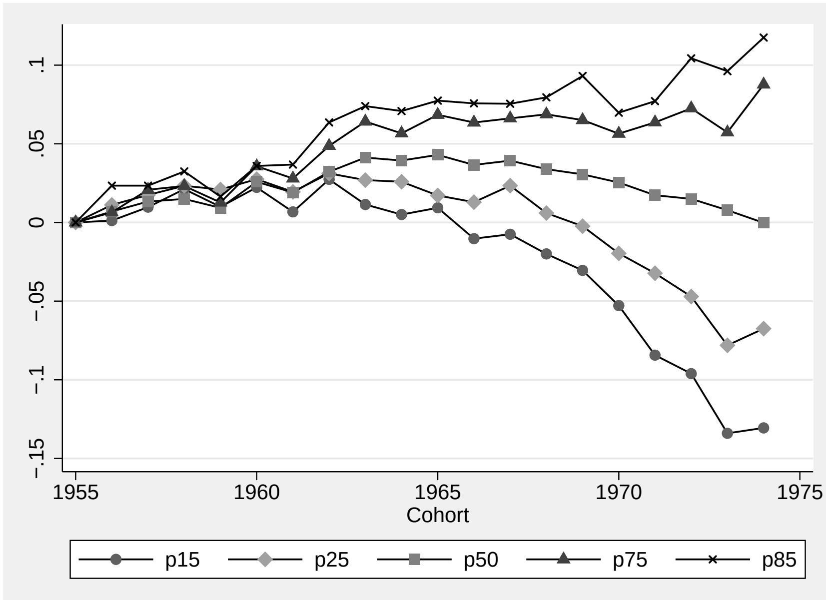



**Figure 2** – Inequality in *up-to-age-X*, cohorts 1955-1974

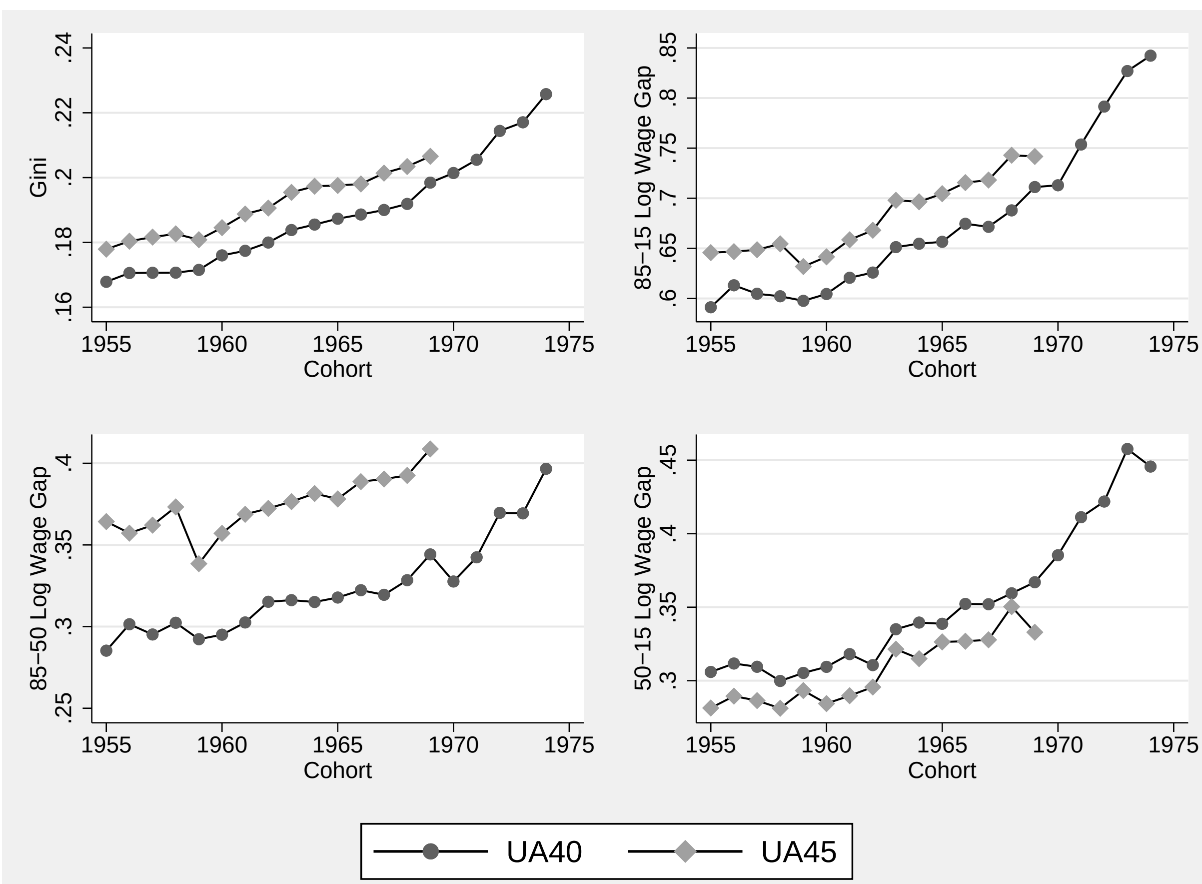


**Figure 3** – Rank correlations of UA40 with selected UAX

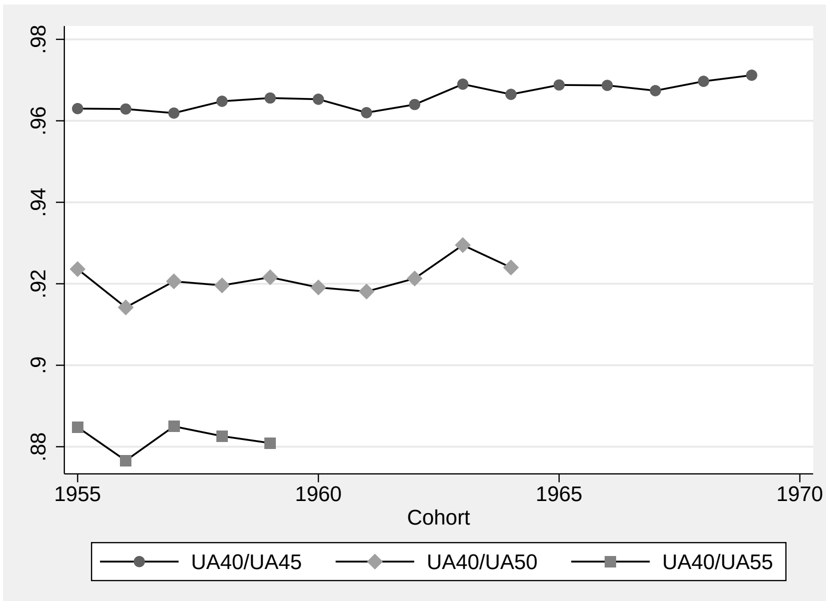



**Figure 4** – Evolution within education groups

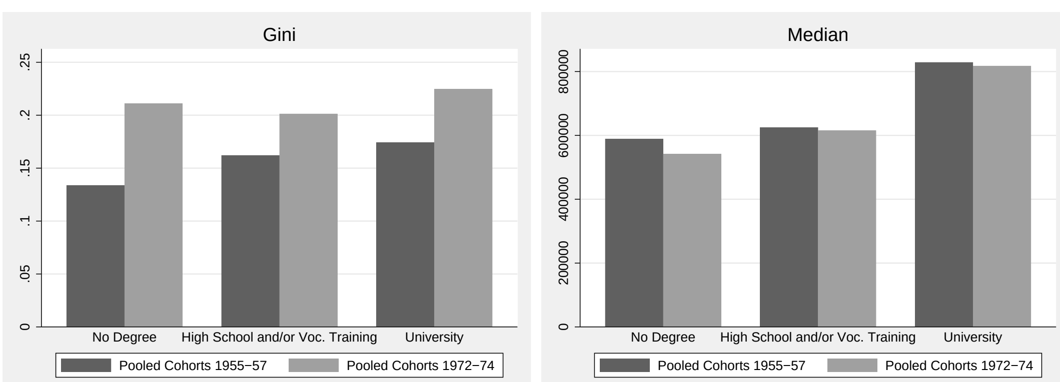


**Figure 5** – Full-time employment UA40 in months, cohorts 1955-57 vs. cohorts 1972-74

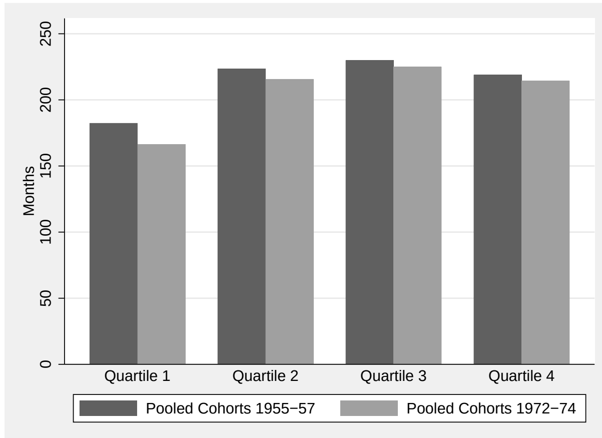



**Figure 6** – Nonemployment UA40 in months, cohorts 1955-57 vs. cohorts 1972-74

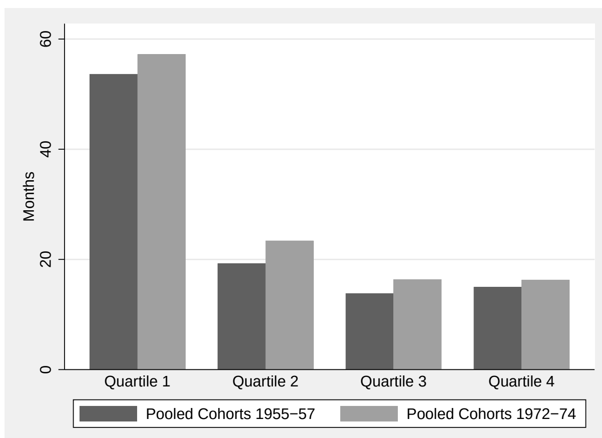



**Figure 7** – Part-time employment UA40 in months, cohorts 1955-57 vs. cohorts 1972-74

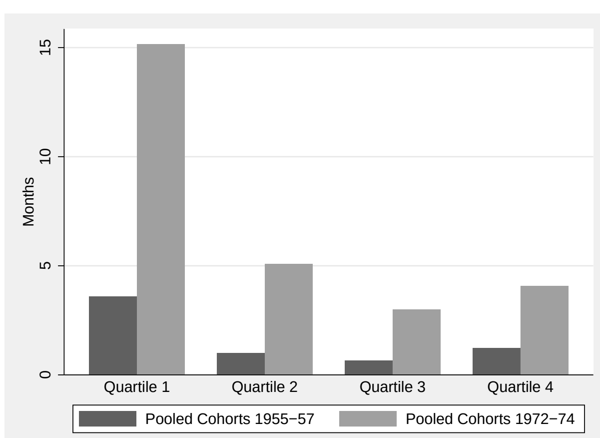


**Figure 8** – Share of different education groups

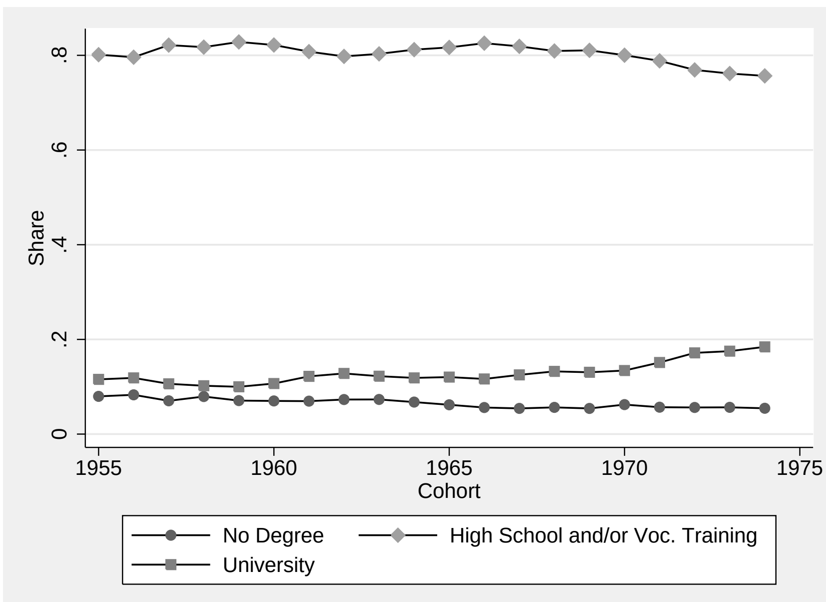


**Figure 9** – Aggregate decomposition cohorts 1955-57 vs. 1972-74

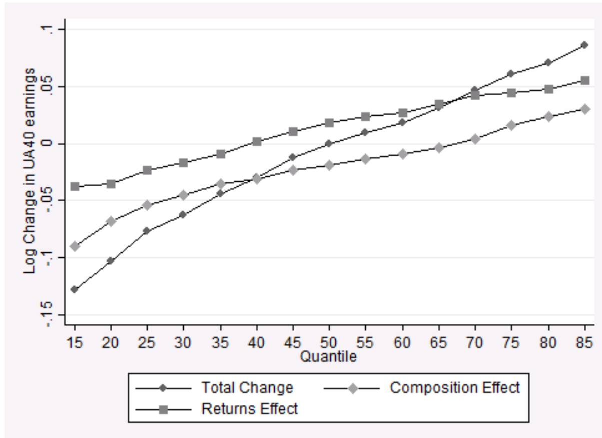



**Figure 10** – Composition effects cohorts 1955-57 vs. 1972-74

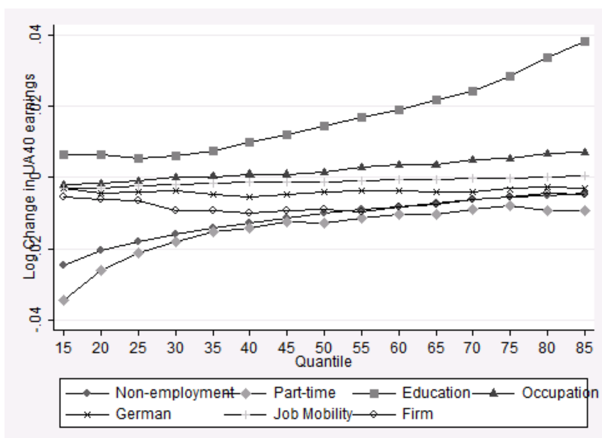
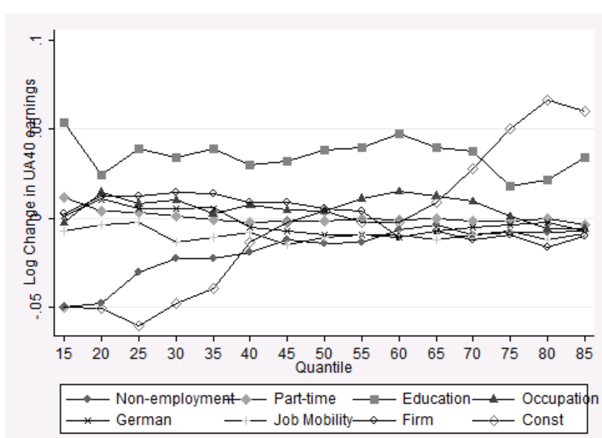



**Figure 11** – Return effects cohorts 1955-57 vs. 1972-74



# 9 Tables

**Table 1** – 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 |
| 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 2 –** Groups of covariates

| Group | Covariates |
|---|---|
| 1. Non-employment | Years of non-employment UAX (= Days of full-time employment/365) |
| 2. Part-time employment | Years of part-time employment UAX (= Days of part-time employment/365) |
| 3. Education | Highest educational degree UAX (6 categories) |
| 4. Occupation | Most frequent occupation UAX (35 categories) |
| 5. German | German by birth (= no spells with foreign nationality) |
| 6. Job mobility | Number of firm changes UAX (with change in both occupation/industry) |
| | Number of firm changes UAX (without change in both occupation/industry) |
| 7. Firm | Most frequent firmsize UAX (3 categories) |
| | Mostly in high-tech firm UAX (binary) |
| | Most frequent sector UAX (57 categories) |
| | Most frequent federal state UAX (9 categories) |

**Table 3** – Results RIF Decomposition 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) | (0.4) | (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) |
| German | 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 Return Effects | 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) | (1.9) | (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) |
| German | -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) | (4.8) | (1.1) | (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 4 –** Results RIF Decomposition, 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) |
| German | -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 Return Effect | 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) |
| German | -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** | 7.00 |
| | (0.68) | (0.49) | (0.44) | (0.05) | (0.13) |
| Reweighting error | 0.55 | 0.28 | 0.27 | 7.00 | 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 $\times$100. Bootstrapped standard errors (100 replications) in parentheses

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

# 10 Appendix

**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.

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

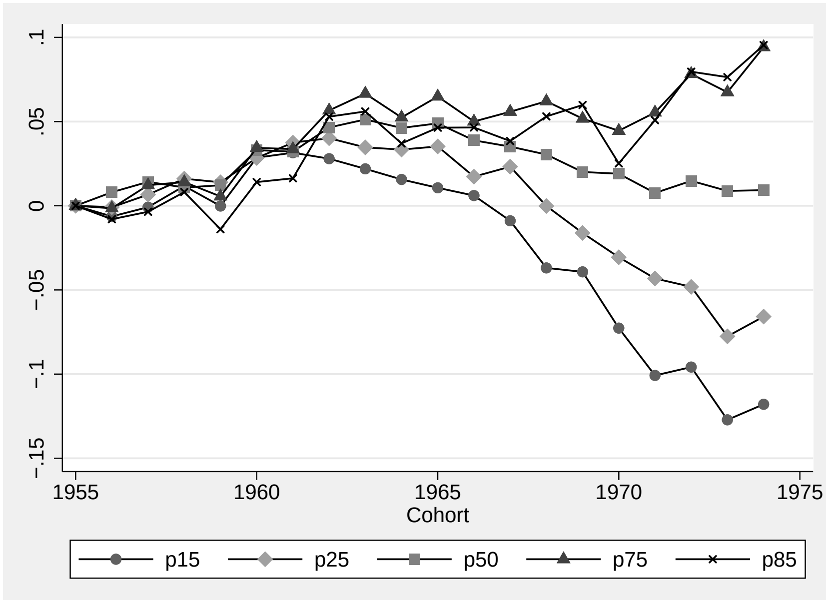



**Figure A2** – Inequality in earnings age 25-40, cohorts 1955-1974

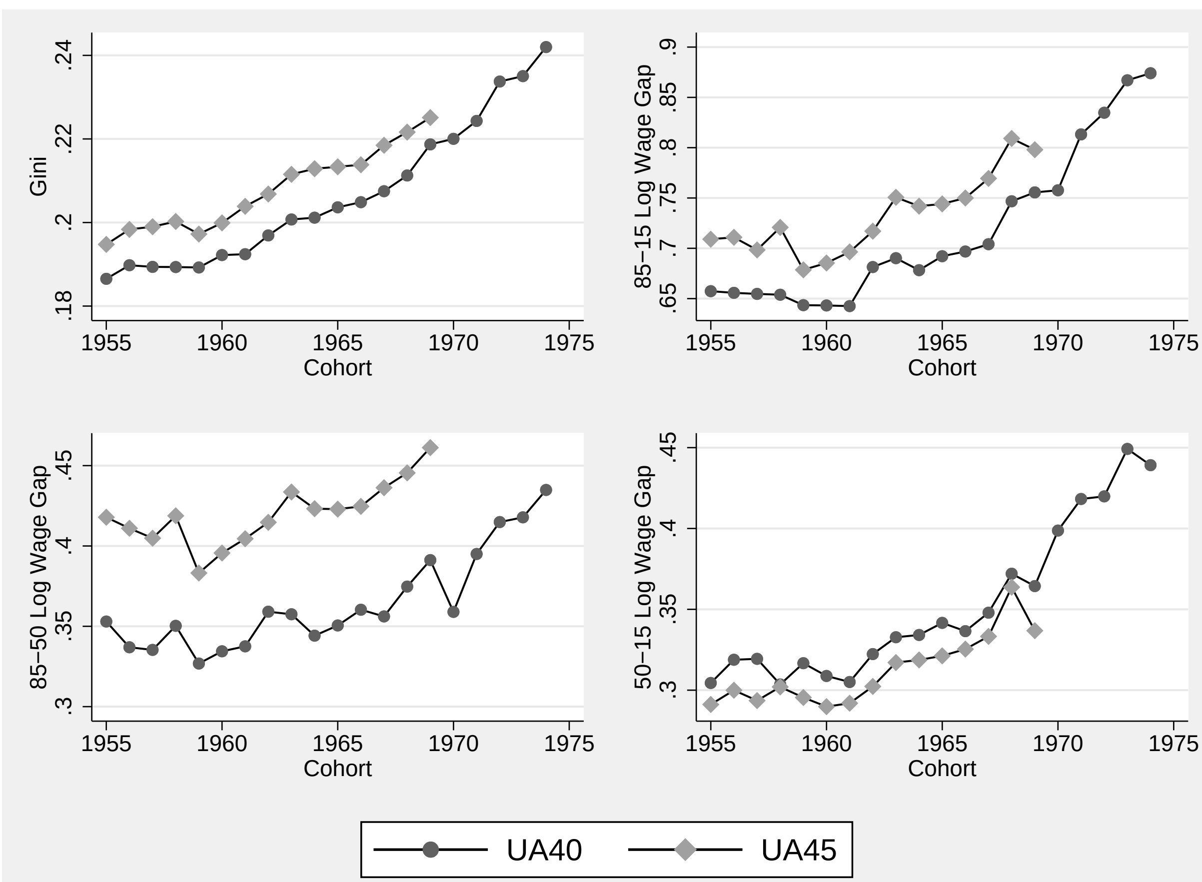


**Table A2** – Results RIF Decomposition UA40, German nationals

| 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) |
| German | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| 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 Return Effect | 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 | 4.4** | 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) |
| German | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| 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

**Table A3** – Results RIF Decomposition UA40, alternative specification explicitly controlling for 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 |
| Total composition | 9.63 | 4.83 | 4.80 | 2.36 | 3.37 |
| Non-employment | 2.05 | 0.57 | 1.49 | 0.55 | 0.96 |
| Part-time | 2.38 | 0.28 | 2.11 | 0.67 | 1.28 |
| Education | 1.91 | 1.87 | 0.04 | 0.36 | -0.05 |
| Occupation | 0.84 | 0.54 | 0.30 | 0.17 | 0.22 |
| German | -0.15 | 0.04 | -0.19 | 0.05 | 0.09 |
| Job Mobility | 0.37 | 0.19 | 0.19 | 0.08 | 0.08 |
| Firm | -0.05 | 0.38 | -0.43 | 0.02 | -0.07 |
| Age at labor market entry | 2.27 | 0.97 | 1.30 | 0.47 | 0.85 |
| Total Return Effect | 8.63 | 3.66 | 4.97 | 2.68 | 3.98 |
| Non-employment | 3.70 | 0.82 | 2.87 | 0.57 | 3.09 |
| Part-time | -1.43 | -0.16 | -1.27 | -0.22 | -0.05 |
| Education | -1.00 | 0.41 | -1.41 | -0.77 | -3.83 |
| Occupation | 0.61 | -0.86 | 1.46 | -0.11 | -0.07 |
| German | -1.83 | 0.23 | -2.06 | -0.42 | -1.01 |
| Job Mobility | -1.56 | -2.41 | 0.85 | -0.22 | -0.24 |
| Firm | 1.04 | 1.04 | -0.00 | 0.25 | 0.35 |
| Age at labor market entry | 23.39 | 30.01 | -6.62 | 6.47 | 9.30 |
| Constant | -14.28 | -25.43 | 11.15 | -2.87 | -3.57 |
| Specification error | 3.30 | 0.13 | 3.16 | -0.09 | -0.02 |
| Reweighting error | -0.21 | -0.04 | -0.16 | -0.04 | -0.08 |

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

Log wage differentials $\times$100. Bootstrapped standard errors (100 replications) in parentheses

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

## Correction for structural break 1983/1984

As outlined in the main text, 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 allowance) 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., 2015) which usually build on the technique by Fitzenberger (1999). Being most related to this study, daily earnings are corrected following the procedure suggested by Bönke et al. (2015). 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 $\Delta w_t$ 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 individuals permanent position in the earnings distribution and considers the previous finding by Fitzenberger (1999) that the effect of one-time payments are 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 which is used 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 estimated separately for each year. Hereby, these regressions include two polynomials of age, six education categories as wells as interactions between age and education.

Instead of solely using 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.