NET WORK LISER

Discussion Paper Series

IZA DP No. 19036

October 2026

The Role of Employment and Redistribution for Lifetime Income Inequality in Denmark

Jonas Maibom
Aarhus University
and IZA@LISER

Trine Schack
Aarhus University

Rune Vejlin
Aarhus University
and IZA@LISER

The IZA Discussion Paper Series (ISSN: 2365-9793) ("Series") is the primary platform for disseminating research produced within the framework of the IZA@LISER Network, an unincorporated international network of labour economists coordinated by the Luxembourg Institute of Socio-Economic Research (LISER). The Series is operated by LISER, a Luxembourg public establishment (établissement public) registered with the Luxembourg Business Registers under number J57, with its registered office at 11, Porte des Sciences, 4366 Esch-sur-Alzette, Grand Duchy of Luxembourg.

Any opinions expressed in this Series are solely those of the author(s). LISER accepts no responsibility or liability for the content of the contributions published herein. LISER adheres to the European Code of Conduct for Research Integrity. Contributions published in this Series present preliminary work intended to foster academic debate. They may be revised, are not definitive, and should be cited accordingly. Copyright remains with the author(s) unless otherwise indicated.

IZA DP No. 19036 October 2026

The Role of Employment and Redistribution for Lifetime Income Inequality in Denmark*

Abstract

Using Danish administrative data from 1980–2023, we analyze lifetime income (both earnings and net-income) inequality and its evolution across cohorts. Earnings inequality rises with age from midlife onward and is highest among the low educated and lowest among those with medium education. Differences in employment attachment—such as non-employment and part-time work—account for 30–60 percent of lifetime earnings dispersion and are particularly important among the low educated. Weak employment attachment is a key driver of lifetime earnings inequality and is closely linked to exposure to adverse shocks such as unemployment and health-related events. Lifetime earnings inequality has risen across cohorts among the low educated, partly through growing dispersion in employment attachment. In moving from earnings to net-income, transfers account for roughly five times as much of the inequality reduction as taxes, but this equalizing effect has weakened over time. Our results highlight the role of employment dynamics and social insurance for lifetime inequality.

JEL classification

D31, J31, J64, H24

Keywords

lifetime earnings inequality, employment attachment, income redistribution, tax and transfer system

Corresponding author

Rune Vejlin
rvejlin@econ.au.dk

* We acknowledge comments and discussions from various seminars and conferences. We also thank Kristoffer Hvidberg and Torben M. Andersen for useful discussions and comments. The paper was previously circulated as "Lifetime Income Inequality in Denmark". The data access was obtained through the ECONAU project database (Department of Economics and Business Economics, Aarhus University). This paper was supported by the Danish Research Council grant "Causes of Lifetime Income Inequality", grant nr. 3099-00035B.

1 Introduction

A large and growing literature documents substantial inequality in earnings and income. Most of this evidence is based on cross-sectional earnings measures, which capture dispersion at a point in time. While informative, such measures provide only a partial view of inequality because they abstract from dynamics in earnings, employment, and mobility over the life-cycle. Individuals experience periods of employment and non-employment, wage growth, and shocks, and these trajectories accumulate into lifetime outcomes. Depending on the degree of mobility and persistence in trajectories, cross-sectional inequality may not be particularly informative about inequality in lifetime resources, see e.g. Friedman (1962), Björklund (1993), Deaton and Paxson (1994), Flinn (2002), Haider and Solon (2006) and Aaberge and Mogstad (2015). It would overstate inequality if there are, e.g. transitory shocks in earnings processes and it could understate it if, e.g. unemployed are excluded from the analysis. The latter is an additional complication, since many studies of cross-sectional income are confined to describing earnings inequality for individuals in employment.

This paper takes a lifetime perspective and studies inequality in accumulated income following individuals over their working life in Denmark. We construct lifetime income profiles for multiple cohorts and document how inequality evolves over the life cycle, differs across education groups, and changes across cohorts. Denmark is well suited for studying lifetime inequality. Rich population-wide administrative register data, and time-consistent variables, allow us to follow individuals over more than four decades and construct near-complete lifetime income and employment histories. Denmark also represents an interesting setting combining a flexible labor market with extensive redistribution.[1]

Our analysis contributes to the literature (which we discuss in depth further below) along two main dimensions. First, we focus on the role of lifetime employment attachment, defined as cumulative differences in time spent working, in shaping lifetime income inequality. The lifetime perspective, which accumulates income over the working life, easily incorporates periods of non-employment and therefore allows employment histories to contribute directly to measured inequality. Differences in employment attachment may reflect differences in labor supply and job opportunities, but also exposure to unemployment, adverse health shocks, and other disruptions that affect individuals' ability to remain employed throughout their careers. Existing work (which we discuss in more depth further below) differ in what dimensions they emphasize, we complement

[1]Thus, we study something which is in between existing evidence from high mobility/low redistribution (e.g. US based evidence) vs. lower mobility/larger redistribution (Central/Southern Europe: Germany/France/Italy). Bowlus and Robin (2012) show that earnings mobility and employment risk are higher in countries with weaker employment protection, and that this brings lifetime inequality levels in the United States, Canada, the United Kingdom, France and Germany closer together than cross-sectional comparisons suggest. OECD (2020) measures "Procedural requirements for individual dismissals of regular workers" and ranks Denmark as one of the easiest countries to dismiss workers in Europe. In terms of labor market transition rates, Denmark is comparable to the US, see Jolivet et al. (2006) and Engbom (2022).

this work by characterizing the states through which weak lifetime employment attachment materializes. The Danish registers allow us to decompose (non-)employment histories into voluntary and involuntary non-employment and quantify the role of e.g. part-time work, unemployment, and sickness. Overall, this analysis provides new empirical evidence on the mechanisms underlying persistent differences in employment attachment and lifetime outcomes in a sample that retains workers with weak labor market attachment.[2]

Second, the focus on employment attachment naturally raises the question of whether, and to what extent, the tax-and-transfer system insures individuals against lifetime earnings risks. By comparing inequality in lifetime earnings with inequality in net income (income after taxes, transfers and capital income, and thus a proxy for income at your disposal), we assess how redistribution mitigates inequalities in earnings. This leads to new evidence on the importance of this redistributive mechanism and the importance of taxes vs. transfers. In particular, transfers operate by offsetting inequality arising from differences in employment attachment, thereby substantially reducing the role of employment histories as a source of lifetime inequality in net income. We find that rising cohort inequality is partly driven by increasing dispersion in employment trajectories and that, while redistribution remains important, its capacity to offset these differences has weakened over time.

We structure our analysis in two parts. The first part of our analysis focuses on inequality in lifetime earnings across education levels and at different stages of the life cycle for cohorts born between 1960 and 1965. Our definition of a lifetime spans ages 20 to 60. We calculate average lifetime earnings up to a given age X (the average annual income based on cumulated income up to age X) and show that inequality as measured by the variance of logs in *realized* lifetime earnings is increasing steadily with age from midlife and onward. Lifetime inequality largely reflects inequalities present within education groups (the between-group variance share is around 10 percent), suggesting that understanding lifetime inequality requires going beyond education as a summary measure of workers earnings potential. Low educated workers have the highest level of lifetime inequality and the largest "average" contributions to aggregate inequality, while medium educated workers, which are workers with a vocational – practical or trade-oriented education programs – education, display the lowest. The rankings of lifetime earnings measured at age 45 and at age 60 are very similar, indicating that individuals largely maintain their relative positions in the earnings distribution from mid-life and onward. This highlights that drivers of lifetime inequality should primarily be sought in earlier stages of the life cycle, where differences in employment attachment and earnings trajectories are formed and subsequently persist and expand. This is consistent with findings in e.g. Huggett et al. (2011); Haan et al. (2025); Haider and Solon

[2]Empirical lifetime work often study individuals with relatively strong labor market attachment, thereby abstracting from longer term non-employment dynamics. Our sampling restrictions are weaker allowing us to incorporate individuals with longer or more frequent non-employment spells and bringing our sample closer to full population. Appendix A.4 explicitly compares our restrictions with those of related papers and documents how our main results change under alternative restrictions.

(2006).

Using a standard wage/hours variance decomposition adapted to the lifetime setting, we show that variation in employment attachment, capturing both non-employment and deviations from full-time work such as part-time work, is a key contributor to lifetime earnings inequality. It contributes around 30–60 percent of total inequality. The contribution from employment attachment is largest for low educated workers and it is increasing throughout the life cycle. For medium and high educated workers, the role of employment is constant or even decreasing. Splitting non-employment periods into voluntary (in our definition this includes e.g. studying and part-time work) and involuntary (e.g. unemployment) parts, we find that involuntary non-employment is more important than voluntary when explaining variation in lifetime income and employment attachment. Further disaggregating non-employment periods reveal that periods in unemployment insurance and social assistance (means-tested income support for individuals who are not eligible for unemployment insurance benefits) are key states leading to differences in employment attachment. A relatively small group with persistently weak employment attachment accounts for a disproportionate share of overall inequality in lifetime employment. Membership in this lower tail is strongly associated with potential shocks such as health-related events, mass layoffs, and recession exposure, while variables related to voluntary non-employment are far less predictive. This finding points toward labor-market and health shocks as important contributors to lifetime inequality.

As a final step in Part 1, we examine how inequality evolves once taxes and transfers are taken into account (net income). This provides a direct measure of how the welfare state affects long-run inequality. Contrasting lifetime inequality measures based on earnings versus net income, we show that inequality in lifetime net income is lower and that transfers are more important than taxes in accounting for this reduction. Inequality in net income is roughly similar to inequality in counterfactual earnings where variation in employment attachment have been accounted for (i.e., proxying a world without differences in employment). Combined with evidence that transfers are heavily concentrated among individuals with weak lifetime attachment, this suggests that, at least in the aggregate, the key re-distributive role of the Danish welfare state is to substantially reduce the role of dispersion in employment attachment as a driver of lifetime inequality. However, redistribution does not eliminate inequality and is less effective for higher-educated workers, where dispersion in earnings conditional on working plays a larger role.

Part 2 of our analysis focuses on the evolution in lifetime inequality over cohorts. We ask whether more recent cohorts have more or less inequality in lifetime earnings than earlier cohorts. Similar to what has been documented in, e.g. Germany (Bönke et al., 2015) and the US (Guvenen et al., 2022) – lifetime earnings inequality has increased for more recent cohorts in Denmark, however, only for low educated and (to some extent) workers with medium education. Building on the analysis from Part 1, we find that the increase is partly explained by an increase in the dispersion of employment attachment across cohorts. The ranking across cohorts is stable from

age 40 and onward. That is, the most unequal cohorts by age 40 remain the most unequal ones when aging further. This again suggests that the key drivers of increasing lifetime inequality (also between cohorts) seem to be in place early in the life cycle.

Inequality in net income across cohorts tends to be more increasing across cohorts than for earnings for low educated workers. The increase in net income inequality reflects increasing inequality in earnings and a lower ability of the transfer system to offset differences in employment attachment. Thus, while redistribution continues to reduce inequality, its equalizing effect has declined over time, allowing differences in labor market attachment to translate more directly into inequality in lifetime resources for more recent generations.

At least two implications of our findings emerge. First, employment attachment matters and detailed (and persistent) (non)employment dynamics is a key driver of lifetime inequality. These results tie in with recent empirical evidence which highlights particular margins of employment attachment. For example, Bick et al. (2024) show that heterogeneity in lifetime employment—driven largely by differences in preferences for work—can generate substantial inequality through both direct effects and human capital accumulation. Ozkan et al. (2023) find large ex ante differences in job-loss, job-finding and contact rates across workers, which account for 75 percent of the differences in lifetime wage growth in the bottom half of the lifetime earnings distribution. Similarly, Morchio (2020) documents large differences in lifetime unemployment – explained by information frictions and differences in job separation rates – across workers, while Hosseini et al. (2026) find that health shocks also contribute to lifetime earnings inequality.[3] Our analysis complements existing work by providing a unified (decomposition) analysis of lifetime inequality and the link to employment attachment using full-population administrative data. We are considerably less restrictive in terms of sample requirements on employment histories thereby also leaving more scope for employment history to matter. We quantify the role of employment attachment, document some of its key drivers, and provide new evidence on the importance of involuntary versus voluntary non-employment. Our empirical results suggest that structural models abstracting from unemployment risk, labor market frictions, or heterogeneity in employment stability may miss a central mechanism through which inequality is generated over the life cycle.

Second, by comparing inequality in earnings and net income, we shed light on the role of the welfare state in shaping and coping with lifetime earnings inequality. Most existing studies of lifetime inequality (e.g. Guvenen et al., 2022; Huggett et al., 2011; Bönke et al., 2015) focus on pre-tax earnings and therefore do not capture the extent to which taxes and transfers offset persistent (lifetime) differences in employment and earnings trajectories. A smaller literature studies

[3]Similarly, Guvenen et al. (2017) document large and persistent earnings losses following full-year non-employment, partly because non-employment increases the risk of future non-employment. This highlights the role of shocks and state dependence in generating persistent differences in employment attachment. See also Bowlus and Robin (2004) who show that labor market interruptions and differences in employment stability contribute significantly to disparities in lifetime income, independently of wage differences. Our contribution is to quantify the lifetime importance of different mechanisms and assess their relative importance.

redistribution directly. For example, Haan et al. (2025) estimate a life-cycle model on German survey data and find that the tax-and-transfer system offsets around 40-50 percent of the inequality in lifetime earnings through a combination of redistribution and insurance. In their model, taxes are more effective at redistribution than at insurance against shocks, because annual taxes cannot address differences in the number of years individuals work.[4] We complement this work with a full-population perspective based on administrative registers and by linking redistribution directly to the employment histories that generate lifetime earnings inequality. Following individuals' taxes and transfers over the life cycle, we separately quantify the contributions of the two components and show that transfers account for the lion's share of the reduction in inequality. The Danish tax system—which is relatively progressive compared with the OECD average (OECD, 2026)—plays a more limited redistributive role. This finding reflects the importance of employment attachment: transfers directly replace income during periods of unemployment, sickness, disability, and other forms of non-employment, whereas progressive taxation primarily compresses income differences among individuals with positive earnings.

Finally, a separate literature compares pre-tax and post-tax inequality in annual cross-sections and finds that differences in post-tax inequality across countries and over time mainly reflect differences in pre-tax inequality rather than differences in redistribution (see e.g. Bozio et al. (2024)). Our lifetime perspective complements this evidence. Across cohorts, inequality in lifetime net income in Denmark has increased relatively more than inequality in lifetime earnings, pointing to a weakening equalizing role of taxes and transfers alongside changes in pretax inequality.

Our paper proceeds as follows. In Section 2, we briefly discuss our data sources and our limited sample selection. We also document some key descriptives and institutional features. Section 3 contains the first part of our analysis where we focus on analyzing and documenting lifetime income inequality for a set of cohorts (1960–1965) where we observe almost the full life cycle. In Section 4, we extend the analysis by considering cohorts 1960–1983 and analyze changes in lifetime income inequality across cohorts. In Section 5, we discuss a number of robustness checks and finally we conclude.

2 Data and Institutional Setting

2.1 Institutional Setting

During our sample period of 1980–2023, Denmark experienced substantial changes in labor market performance and institutions. In the early part of the period, Denmark was characterized by relatively low employment rates and high unemployment, reflecting both cyclical conditions

[4]Bengtsson et al. (2016) follow a Swedish cohort over 42 years and find that the tax-and-transfer system is much less progressive over the lifetime than in virtually any single year, because a large share of transfers smooth temporary income losses within individuals' lifetimes.

and structural weaknesses. Employment rates increased markedly from the 1990s onward, while unemployment declined following a series of labor market reforms and broader structural changes such as rising educational attainment, increasing female labor force participation, and a shift from manufacturing toward services. Together, these developments contributed to higher aggregate employment and more dynamics in the labor market.

An important labor market reform was the introduction of the Danish "flexicurity" model through a series of labor market reforms during the 1990s and 2000s. The model combines flexible hiring and firing rules with a strong social safety net and increasing reliance on active labor market policies (see e.g. Andersen and Svarer, 2007). These reforms shifted the transfer system for non-employed from passive income support toward a model emphasizing rapid re-employment, tightened eligibility conditions, activation requirements, and labor market attachment (see e.g. Kreiner and Svarer, 2022). Throughout the data period, employment protection has been among the lowest in Europe, enabling high job turnover and rapid reallocation. This flexibility is balanced by strong collective bargaining institutions and a compressed wage structure, which ensures relatively high minimum wages[5] and few working poor. The welfare state provides universal access to education and social transfers, financed by (relatively) high taxes on labor income, and emphasizes activation through mandatory job-search programs and training as a condition for benefits. Unemployment insurance benefits duration was 7 years in the 1990s and has gradually been reduced to 2 years, with a relatively high but declining replacement rate over the years. If unemployment benefits expire, individuals are typically eligible for social assistance, which is a means-tested cash benefit paid to individuals who cannot support themselves through labor market income and who are not entitled to insurance-based benefits such as unemployment insurance. It constitutes the last-resort component of the Danish social safety net.

The personal income tax system is progressive and combines municipal and central government income taxes with a labor market contribution. Over the sample period, a sequence of major tax reforms took place. The reforms of 1987, 1994, and 1999 generally reduced marginal tax rates while broadening the tax base through e.g. restrictions on tax credits. Subsequent reforms in the 2000s continued this development with an increasing emphasis on strengthening labor supply incentives through earned-income tax credits (beskæftigelsesfradrag), higher thresholds for upper tax brackets, and reductions in marginal tax rates. In particular, the 2009 reform abolished the middle income tax bracket and substantially reduced marginal tax rates for higher-income workers. Thus, while Denmark has remained a high-tax country throughout the period, the tax system has gradually shifted toward lower marginal taxation of earned income and stronger incentives for labor market participation (Kleven and Schultz, 2014).

Lastly, in terms of earnings inequality, Leth-Petersen and Sæverud (2022) show that, cross-sectional earnings inequality has increased since the late 1980s, particularly at the bottom of the

[5]There is no formal minimum wage but there are wage floors set by occupational agreements in the decentralized bargaining system. The system is similar to the two-tiered bargaining system described in Bhuller et al. (2022).

distribution in Denmark. At the same time, net income (or disposable income) inequality has remained comparatively stable due to extensive redistribution through taxes and transfers. We return to these movements below.

2.2 Key Variables

We rely on administrative data from Statistics Denmark covering the full Danish population from 1980 to 2023. The panel data span nearly the full working life of individuals born around 1960, allowing us to observe a cohort's income from age 20 and onward. The data includes detailed information on income, employment and socioeconomic characteristics, enabling construction of accurate measures of lifetime income.

Information on personal income is obtained from the IND register, which contains comprehensive income data on all tax-paying individuals in Denmark. This includes information on income both before and after taxes, as well as income transfers such as unemployment benefits or sickness payments, interest payments, and other residual income. None of the data is top-coded. Labor market attachment is captured using mandatory pension payments and data from the registers IDAP and RAS. They cover different time periods and both contain data on wage conditions, employment status, unemployment spells, and earnings across multiple jobs. This allows us to follow individuals longitudinally across jobs and time. All registers are linked at the individual level via personal identification numbers. All monetary variables are deflated to 2015 values using the Danish CPI and winsorized within year and cohort at the 1st and 99th percentiles to reduce the influence of outliers.

The main variables used are (for further information see Appendix A.1 and A.2):

- **Earnings**: Includes wages, self-employment income, and certain smaller fees. This variable captures both salaried and self-employed income and is used as the pre-tax earnings measure.
- **Net income**: Defined as after-tax income adjusted for capital income and including income transfers. This variable gives a better indication of consumption potential. Importantly, we observe transfers, taxes, and residual income (interest income and realized gains/losses on securities, plus other miscellaneous income, net of deductible interest expenses) separately, allowing us to decompose the difference between earnings and net income.
- **Employment attachment:** The source on hours worked is from mandatory pension contributions from all employers during the year from 1980-2007. Based on these contributions, we obtain an estimate of annual hours worked, see Lund and Vejlin (2015). From 2008-2023 we have contracted hours in each employment relationship.[6] We convert this into a full-time-equivalent (FTE) measure. The measure captures full non-employment as well as part-time

[6]Mandatory pension contributions are a 4-step function of contracted hours worked. For each of the intervals of 0–10, 10–20, 20–30, and 30+ hours there is a different level of pension payment, which is paid by the firm for each worker. If the worker is in the lowest bracket (0–10 hours) the firm pays no contributions, the second lowest (10–20

work and partial-year employment. It is considerably more detailed than the binary or full-time/part-time classifications available in many other data sources.

- For each year in which the individual is not employed full-time, we further classify the deviation from full-time work as either involuntary (receipt of unemployment insurance, sickness or disability benefits, rehabilitation benefits, or social assistance) or voluntary (part-time work, or self-financed non-employment such as studying, retirement, or childbirth-related absence). Our classification complements existing literature, which typically infers involuntary non-employment from self-reported separation reasons in surveys (e.g. Haan et al., 2025) or infers the sources of labor supply variation through latent preference and productivity components in structural models (e.g. Bick et al., 2024), by distinguishing non-employment states through their type of benefit receipt for the full population and every year of non-employment.

Our data also contains demographic information, such as age, gender, municipality, and family structure and we also have information on educational attainment including highest degree and field of study. We measure educational attainment at age 30 throughout the paper in order to take into account the fact that individuals may finish education at various ages. We define three educational groups: 1) Low education: 10th grade or below (includes missings which are rare), 2) Medium education: High school degree or vocational degree, and finally 3) High education: Short tertiary, bachelor's, or master's degree.

2.3 Sample Selection

We impose two main sample restrictions. First, we restrict attention to men born between 1960 and 1983 who are alive and resident in Denmark for at least 75 percent of the potential observation years. Lifetime income is measured from age 20 until age 60 or the end of the sample period in 2023, whichever comes first. Consequently, the youngest cohort (born in 1983) can be observed for at most 20 years, from age 20 in 2003 to age 40 in 2023. Second, because a key variable in our analysis is earnings while employed, we require a minimum degree of labor market attachment. To allow for both low earnings and extended periods of non-employment, we base this restriction on accumulated employment attachment rather than earnings. Specifically, individuals must be employed in at least 25 percent of the years between ages 20 and 40. This threshold corresponds to approximately five years of employment and excludes only individuals with very limited or no labor market participation. In practice, the restriction implies that we exclude around 7–8 percent of our sample (see Table A.5) and primarily removes individuals with little or no labor market attachment,

hours) gets 1/3 of the contribution, the next bracket gets 2/3, while the final bracket gets a full contribution. In some special cases (e.g. for self-employed individuals) where we believe that the estimate of hours worked are not informative we use information on the employment status from individuals' primary work position in November, see Appendix A.1.

such as those spending most of their adult lives on social assistance, disability insurance, or early retirement. Some minimum attachment requirement is unavoidable since very low accumulated earnings (or no earnings at all) will disproportionately affect inequality measures and hence focus on a small selected group of individuals where the data at hand is rather uninformative. Our results are robust to increasing the threshold to 50 percent; see Section 5 and Figure D.6.

Our approach differs from much of the related literature, which often relies on annual earnings thresholds and focuses on individuals with relatively stable careers (e.g. Bönke et al., 2015; Guvenen et al., 2022). Our restriction is less stringent and retains a larger share of workers with weak labor market attachment (see Table A.5 for a direct comparison). As demonstrated in Appendix A.4, alternative sample definitions substantially affect both the level and composition of measured lifetime inequality. This distinction is particularly important in our setting because employment attachment is itself a central object of interest. Restricting the sample to highly attached (or higher income) workers would mechanically remove variation in the very dimension we seek to analyze and understate the contribution of employment attachment to lifetime inequality. It would also understate inequality for the broader population. For example, Ozkan et al. (2023) exclude men with earnings below a minimum threshold in at least one quarter of their working life or in two or more consecutive years, which retains less than half of their initial sample. Even in this selected sample, they find that heterogeneity in unemployment risk is the main driver of lifetime wage growth differences in the lower half of the distribution, which suggests that the role of employment attachment is likely to be larger in a sample that retains workers with weaker attachment. Overall, our sample selection strikes a balance between retaining individuals with weak attachment and excluding those with essentially no labor market connection.

Our final dataset includes 24 cohorts and more than 30 million observations, with between 20,000 and 40,000 individuals per cohort (see Table A.6). We use two analysis samples. The **lifetime sample** consists of birth cohorts 1960–1965, for whom we observe almost complete lifetime trajectories (ages 20–60);[7] it is the basis for the first part of our analysis in Section 3. The **cohort sample** consists of cohorts 1960–1983 and is used to analyze changes in lifetime inequality across cohorts in Section 4. In both parts, we present results for the full sample and separately by education group. Finally, we present some descriptives:

Aggregate Trends: Figure A.1 shows the development of average earnings and net income over time for the cohort sample. This comparison illustrates the role of income growth and taxes and transfers in shaping net incomes. Three patterns are worth noting. First, average real earnings have grown substantially over the period. Second, average net income lies below average earnings and displays a flatter profile, reflecting the combined effect of taxes and transfers. Third, the P10–P90 range is considerably narrower for net income than for earnings, illustrating the compression of the income distribution through redistribution.

Composition: The distribution of schooling levels has shifted markedly across cohorts, as

[7]For the 1965 (1964) cohort, we can only follow until age 58 (59).

depicted in Figure A.2, with younger cohorts being substantially more educated. The steady increase in educational attainment motivates analyzing lifetime inequality separately by education, since differences in schooling affect both wage potential and labor market attachment.

Employment History: Figure A.3 (and Table A.4) in the Appendix shows the distribution of lifetime employment attachment up to age 45. Based on our employment measure accumulated over the data window for each individual (Equation (2) below), average employment attachment is around $75-85$ percent (of the lifetime) with a standard deviation of $0.14-0.21$. There are also clear educational differences where higher educated workers have more employment attachment and less dispersion. These numbers illustrate substantial heterogeneity in employment histories, even within education groups, a theme that plays a central role in the subsequent analysis.

2.4 Lifetime Income up to Age X and Inequality Measures

We define "lifetime income up until age X" , LI^i_{UAX}, for individual i as the sum of annual incomes scaled by the period length:

$$LI^i_{UAX} = \frac{1}{X-20}\sum_{a=20}^{X} Y^i_{at}. \tag{1}$$

Annual income, Y^i_{at} at age a at calendar time t, can be either earnings or net income. We scale by the period length to ease comparability across ages X by removing the mechanical component from longer periods. As explained earlier, individuals enter our sample at age 20 and we follow them for as long as possible given the sampling window ending in year 2023.[8] Since the longest time period over which we follow individuals is 40 years, our LI^i_{UAX} measures will range from ages $X = 30$ to 60. Of course, the higher the age, X, the fewer the cohorts we have to characterize LI^i_{UAX} for.

As is clear from Equation (1), we are not discounting income when determining LI^i_{UAX},but yearly income, Y^i_{at}, is CPI adjusted prior to calculating LI^i_{UAX}. First, discounting with a common rate would prioritize some parts of the life cycle over others, which we see no immediate reason to do ex ante. Second, in practice, discounting would require taking a stand on what discounting to use (market rate, shadow rate, etc.). For a non-common rate, differences in discounting across cohorts could then itself be a driver of differences in lifetime inequality.

We also define lifetime employment up until age X, LH_{UAX}, as the cumulative sum of employment:

[8]The only exceptions are the limited variations in years where individuals are not present in the sample (e.g. missing due to temporary migration). In these cases, X is adjusted to reflect the number of years actually observed rather than the number of calendar years since age 20, so that LI^i_{UAX} is not mechanically understated for individuals with brief absences from the sample. This at-risk correction allows us to retain individuals with incomplete observation histories without imputing missing years or excluding them from the sample.

$$LH^i_{UAX} = \frac{1}{X-20}\sum_{a=20}^{X} H^i_{at}, \tag{2}$$

where H^i_{at} (employment attachment in Section 2.2) is the full-time equivalent for worker i in year t where the worker is age a. This measure takes account of periods of non-employment as well as part-time work and other periods with reductions in employment. We use this measure later to quantify the importance of employment attachment in lifetime earnings inequality.

Inequality Measure and Groupings Our baseline inequality measure is the variance of logs. This metric is scale-invariant and less sensitive to outliers than raw variances. In addition, the variance of logs is often used in both the empirical and theoretical literature, which makes our results directly comparable to related work, e.g. Deaton and Paxson (1994); Heathcote et al. (2010); Huggett et al. (2011); Song et al. (2019). While the variance of logs is our preferred inequality measure, Section 5 also repeats some of our key results using alternative inequality metrics such as the Gini coefficient.

Inequality in our full sample, which we also refer to as aggregate inequality, is calculated as:

$$Var(\ln LI_{UAX}) = \frac{1}{N}\sum_{i=1}^{N}\left(\ln LI^i_{UAX} - \hat{\mu}_f\right)^2 \tag{3}$$

where $\hat{\mu}_f = \frac{1}{N}\sum_i^N \ln LI_{UAX}$, i.e. the mean of log lifetime income for the full sample. As mentioned above, and shown in Figure A.2, there are some large educational shifts over our sample period. We therefore also analyze inequality by education. First, we decompose aggregate inequality into education-specific contributions. For a given educational subgroup $e \in \{low, medium, high\}$, we define lifetime inequality up to age X as

$$Var(\ln LI_{UAX})^e = \frac{1}{N_e}\sum_{i\in e}\left(\ln LI^i_{UAX} - \hat{\mu}_f\right)^2 \tag{4}$$

where N_e is the number of individuals in educational group e and $\hat{\mu}_f$ is the mean of log lifetime income for *the full sample*. This ensures that each group's contribution to inequality is evaluated relative to the same overall mean, such that group-level measures map directly back to the full-sample variance (aggregate inequality).[9]

Second, it is natural to decompose aggregate inequality into within-group and between-group components to understand the relative role of changes within education groups relative to between groups. The within-group variance part is now calculated relative to the education group mean instead of the full-sample mean:

[9]In other words, inequality in the three education samples can be mapped back to full-sample inequality by: $Var(\ln LI_{UAX}) = \left(\frac{N_L}{N}\right) Var(\ln LI_{UAX})^L + \left(\frac{N_M}{N}\right) Var(\ln LI_{UAX})^M + \left(\frac{N_H}{N}\right) Var(\ln LI_{UAX})^H$.

$$Var(\ln LI_{UAX}) = \sum_e \frac{N_e}{N} \underbrace{\left[\frac{1}{N_e} \sum_{i \in e} \left(\ln LI^i_{UAX} - \hat{\mu}_e \right)^2 \right]}_{within-group} + \underbrace{\sum_e \frac{N_e}{N} \left(\hat{\mu}_e - \hat{\mu}_f \right)^2}_{between-group} \quad (5)$$

The first term captures dispersion among individuals within each education group, while the second term captures differences in mean log lifetime income across groups. Together, they sum to the total variance in the full population and provide a natural way to assess how much of overall lifetime inequality is explained by differences between education levels versus differences within groups. Thereby this decomposition also provides a framework for how much of the evolution in lifetime inequality that is "lost" when we focus on within-education-groups inequality.

3 Part 1: Inequality in Lifetime Income

In the first part of our analysis, we focus on the sample of birth cohorts 1960–1965 (the lifetime sample). We focus on four different samples: the full (pooled) sample, and three education subsamples where we distinguish individuals by their education level obtained at age 30, see Section 2.2. As we return to later, these findings reported below are not specific to the selected cohorts, but extend to later cohorts as well.

3.1 Lifetime Inequality over the Life Cycle

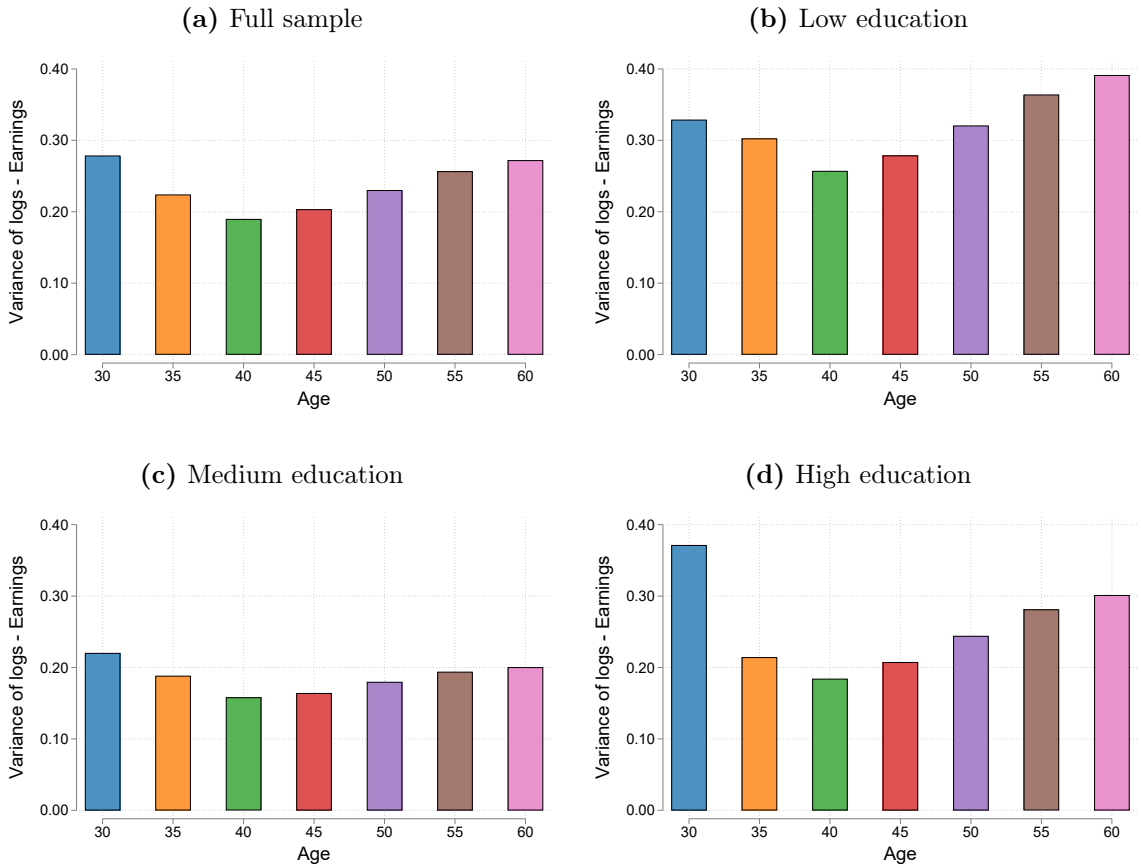
Figure 1 shows the variance of log lifetime earnings up to different ages X for the full sample and separately for each education group in Panels (a) and (b)–(d), respectively. As outlined earlier, we report the "average-group contribution to the full-sample variance" which, when weighted with relative group sizes, maps into the full-sample variance, see Equation (4).

Figure 1 reveals that inequality in lifetime earnings (up to age X) is first decreasing and then it increases steadily from age 40 and onward in all samples. This concurs with evidence in the literature that differences in shocks and labor market histories accumulate over time, producing greater dispersion in outcomes at older ages.[10] The initial decrease from age 30 to 40 is around 0.1 log points while the increase from age 40 to age 60 is of similar magnitude. The initial decrease in inequality is largest among the high educated workers, likely also reflecting differences in actual entry into the labor market due to differences in time spent in education or other non-work (gap/travel years). The increase in inequality from age 40 and onward could be explained by the presence of more permanent shocks (of either earnings or employment status) which amplify earnings differences further over the life cycle, see e.g. Deaton and Paxson (1994). Similarly,

[10] In work on cross-sectional inequality, there is a well-known problem of separating cohort, age, and time effects from each other (see e.g. discussions in Deaton and Paxson, 1994). Our interpretation below implicitly discards time effects (as in e.g. Deaton and Paxson, 1994) when ascribing lifetime inequality changes to the life cycle (age). While it is of course possible that increasing inequality from age 40 onward reflects time effects, we note that we find the same patterns when looking across cohorts (and thus time periods) in part 2 of the paper (see Section 4).

the decline from age 30–40 could be explained by a higher relative frequency of transitory shocks (potentially via e.g. randomness in initial job allocations and gradual subsequent convergence). This creates inequality initially, which then slowly smooths out as individuals age and these shocks are less frequent.

Figure 1: Inequality over the Life Cycle



Note: This figure shows the variance of log lifetime earnings, $Var(\ln LI_{UAX})$, at different ages X (horizontal axis) for the pooled 1960-1965 cohorts. Lifetime earnings are defined in Equation (1) as cumulative earnings up to age X. For the full sample the inequality measure is defined in Equation (3) while for each education sub-sample it is given by Equation (4). For education shares see Figure A.2.

Figure 1 Panels (b)–(d) also display clear level differences across education groups. At age 40, inequality among low educated workers is around 0.08–0.10 log points higher than for medium and high educated workers. For the low educated, inequality is not only at a higher level, but it also increases more sharply with age (around 0.14 log points) especially compared to medium educated workers (0.04 log points). In contrast, medium and high educated workers show lower levels of lifetime inequality, suggesting more common earnings trajectories and therefore less within-group dispersion.

Focusing on the full sample at age 45, Figure 1 shows a variance of log lifetime earnings of approximately 0.2. For comparison, Leth-Petersen and Sæverud (2022) report a cross-sectional variance of log earnings of around 0.3–0.4 for Danish men during the 1990s, while Huggett et al.

(2011) report a variance of approximately 0.4 for US men around age 45. The difference in inequality levels reflect the distinction between cross-sectional and lifetime inequality. The magnitude of this gap is also in line with earlier evidence. Björklund (1993) reports that lifetime income dispersion among Swedish men is 35–40 percent below annual dispersion, and Bowlus and Robin (2004) find a gap of around 40 percent for the United States. However, since our baseline sample generally impose less restrictive earnings requirements, the comparisons with existing estimates actually understates the difference that would arise in our sample.[11]

The lower level of lifetime inequality relative to cross-sectional inequality reflects that some of the earnings differences observed in a given year are transitory and average out when earnings are accumulated over the career. A central distinction is the persistence of individuals' positions in the earnings distribution. Cross-sectional inequality age profiles measures the dispersion of earnings at particular ages, whereas lifetime inequality age profiles also depends on whether those with relatively low or high earnings remain in the same part of the distribution over time. Two economies can consequently display identical cross-sectional inequality at every age but very different lifetime inequality age profiles: cross-sectional differences largely wash out when earnings ranks are transitory, but accumulate when relative earnings positions are persistent. Changes in cross-sectional inequality are therefore difficult to interpret in terms of lifetime inequality without information on earnings mobility and rank persistence. This is why long administrative panels (and ageprofiles as in Figure 1) provide an important addition to the inequality debate: they reveal that the observed earnings differences do (at least to some extent) represent persistent differences in economic resources over the career. In our data cross-sectional inequality and lifetime inequality do in fact exhibit similar age profiles. They both decline until around age 40 and increase thereafter. The decline in cross-sectional inequality at younger ages is also consistent with Leth-Petersen and Sæverud (2022), as well as related evidence from Norway (Halvorsen et al., 2022) and Sweden (Friedrich et al., 2022). Figures A.4 and B.7 in the Appendix shows that we reproduce this pattern within cohorts.[12]

A natural question is to what extent lifetime earnings measured by mid-life (age 45) provides a useful approximation to the relative ordering of lifetime earnings based on the full working life (age 60). In our data, the rank-rank correlation (between earnings ranks age 45 and 60) is always around 0.9 across groups. Furthermore, when plotting earnings ranks for the distribution of lifetime earnings measured at age 45 against the mapping at age 60, the realized mapping is close to the 45-degree line, indicating that the average individual within each percentile of the age-45 distribution largely maintain their position also in the distribution at age 60 (see Figure B.2 in Appendix Section B.2). This stability reflects a broader decline in cross-sectional earnings

[11]Using the same earnings restrictions as in Leth-Petersen and Sæverud (2022) in our data, we obtain a cross-sectional variance of 0.34 at age 45, closely replicating their result (see Appendix B.7).

[12]Notice that while (cross-sectional) hourly wage variation systematically increases with age, see Heathcote et al. (2005), the literature on variation in earnings across ages is less clear, see Guvenen et al. (2024), who show that variation in earnings can both increase and decrease by age.

mobility with age, see Figure B.1. Rank correlations between annual (cross-sectional) earnings at age 40 and later ages are high—on the order of 0.85–0.95 across education groups—thus implying limited re-ranking after mid-life. Thus, while lifetime earnings continue to accumulate after age 45, the relative ordering of individuals is largely established by that age.

Overall, one interpretation of these findings is that a part of early-career dispersion in earnings translates into persistent differences that are only weakly offset later in life. Consequently, lifetime earnings accumulated up to age 45 provides a strong proxy for full lifetime outcomes at least in relative ranking. This stability is consistent with evidence from the broader literature. Haider and Solon (2006) show that the association between current and lifetime earnings strengthens markedly with age (also found in Björklund (1993); Aaberge and Mogstad (2015)), while Bönke et al. (2015) document that earnings mobility declines substantially after the early and mid-career stages. Taken together, these findings suggest that the key determinants of lifetime inequality (or at least the determinants which determine the rankings) —such as wage trajectories, employment attachment, and exposure to shocks—are largely realized by mid-life.

This result has two important implications for the analysis that follows. First, it justifies focusing on measures of lifetime earnings up to age 45 when comparing across cohorts in Section 4. This allows us to include a larger set of cohorts without sacrificing too much information about eventual lifetime inequality. Second, it highlights that the key determinants of lifetime inequality should primarily be sought in earlier stages of the life cycle, where differences in employment attachment and earnings trajectories are formed and subsequently persist. For these reasons, we will focus on inequality up to age 45 whenever we have to choose one particular age to look at.

3.2 Employment Attachment and Lifetime Inequality

We now turn to the role of dispersion in employment attachment as a driver of inequality in lifetime earnings. For expositional clarity we focus on within-group inequality.[13] This focus is empirically well justified: our within–between variance decomposition (Equation (5)) shows that most aggregate inequality arises from within-group differences. In our sample, the within-group component accounts for 96 percent of total variance at age 30 from which it decreases but only to 88 percent at age 60, see Appendix Table B.1. This is an important finding in itself, as it highlights that heterogeneity within education groups is the dominant source of inequality.

Using the definitions of LI_{UAX} and LH_{UAX}, we can now express lifetime earnings as the product of lifetime employment and another term which we (loosely) refer to as a lifetime wage following the terminology from normal cross-sectional analysis (see e.g. Mogstad et al., 2025):

$$LI^i_{UAX} = LH^i_{UAX} \cdot \left(\frac{\sum_{a=20}^{X} Y^i_{at}}{\sum_{a=20}^{X} H^i_{at}} \right) = LH^i_{UAX} \cdot LW^i_{UAX}. \tag{6}$$

[13]Thus, we subtract the sub-group mean instead of the grand mean as we did in Figure 1, see Equation (5). As a result, the education-specific decompositions no longer aggregate to total inequality in the full sample.

This representation allows us to analyze the role of differences in employment attachment across individuals as a potential driver of lifetime inequality in LI^i_{UAX}. LW^i_{UAX} can be thought of as the weighted yearly wage if the worker had worked full-time up to age X ($LW^i_{UAX} = \frac{\sum_{a=20}^{X} W^i_{at} H^i_{at}}{\sum_{a=20}^{X} H^i_{at}}$) where W^i_{at} represents the respective yearly hourly wage and H^i_{at} hours in FTE in a given year (in practice LW^i_{UAX} is of course defined by the accounting identity in Equation (6)). Importantly, variation across individuals in LW^i_{UAX} can thus arise from a number of cases such as e.g. differences in the level of age-specific wages (W_{at}) throughout the life cycle, different time specific shocks t to W_{at}, as well as similar life-cycle profiles of wages but different timing of non-employment (variation in H_{at}).[14] By definition, our life-cycle wage measure is silent on such dynamics except to the extent that they lead to differences in lifetime wages.

Using the definition of LW^i_{UAX}, we can now construct a standard ensemble variance decomposition (see e.g. Card et al., 2018) to analyze the relative role of dispersion in employment attachment versus wages in lifetime inequality. The ensemble variance decomposition is as follows:

$$\begin{aligned} Var(\ln LI^i_{UAX}) &= Cov(\ln LI^i_{UAX}, \ln LI^i_{UAX}) \\ &= Cov\left(\ln LI^i_{UAX}, \ln LH^i_{UAX} + \ln LW^i_{UAX}\right) \\ &= Cov\left(\ln LI^i_{UAX}, \ln LH^i_{UAX}\right) + Covar\left(\ln LI^i_{UAX}, \ln LW^i_{UAX}\right) \end{aligned} \tag{7}$$

The first term in this decomposition, $Cov\left(\ln LI^i_{UAX}, \ln LH^i_{UAX}\right)$, quantifies the importance of dispersion in lifetime employment attachment for dispersion in lifetime earnings across individuals. The second term, $Cov\left(\ln LI^i_{UAX}, \ln LW^i_{UAX}\right)$, quantifies the role of dispersion in lifetime wages as a driver of the observed dispersion in lifetime earnings across individuals. As discussed above, LW^i_{UAX} may be shaped by many factors including differences in e.g. the timing of employment and wages. For this reason, we mainly think of the second term as an accounting term representing the role of factors not directly accounted for by (accumulated) employment attachment (see also footnote 14).

In Figure 2, we report each of the components in our variance decomposition of Equation (7) across our four samples.[15] The figure reveals that variation in employment attachment across individuals is an important driver of lifetime earnings inequality. Our measure of employment attachment explains around 0.10 log points of the 0.23 log points difference at age 50 in the full sample thereby accounting for more than 40 percent of lifetime earnings differences. Across edu-

[14] Of course, to the extent that prior non-employment periods directly affect future W^i_{at}'s, our decomposition would mainly decompose the direct effect from non-employment periods (fluctuations in hours worked) from the more indirect effects (subsequent wage effects). In this view, we can think of our decomposition below as providing a conservative benchmark on the importance of employment attachment.

[15] Note that as an alternative decomposition, we can also directly decompose $Var(\ln LH^i_{UAX} + \ln LW^i_{UAX})$ into variance and covariance terms. We do this in Appendix Section B.3. The ensemble decomposition method is attractive for our decomposition agenda because it quantifies how inequality changes when a component is equalized across individuals, thereby capturing its overall contribution to lifetime inequality, including effects arising from its correlation with other determinants.

Figure 2: Variance Decomposition



Note: Decomposition of lifetime earnings inequality using Equation (7) into two components: employment attachment (blue) and wages (red). Each part of the bar represents the contribution to total lifetime earnings inequality attributable to each component at a given accumulation age.

cation groups we see large differences. For workers with low education, dispersion in employment attachment accounts for more than half of lifetime inequality at all ages, and the importance of employment attachment is increasing over the life cycle from age 40 onward. Given the results on rank preservation earlier, this suggests that employment shocks from earlier in the life cycle display persistence and lead to expanding differences in lifetime employment attachment. By contrast, for medium and even more so for high educated workers, variation in lifetime wages is the dominant source of inequality and the role of employment attachment is more stable over time. Across all education levels, we see that employment attachment is the largest contributor to inequality early in the life cycle and that reductions in the dispersion of employment attachment from age 30 to 40 map almost one-to-one into reductions in overall earnings inequality as well.

Overall, this decomposition exercise underlines the importance of dispersion in employment attachment in shaping lifetime earnings inequality. These results suggest that modeling lifetime earnings processes without emphasizing (non)employment dynamics (e.g. heterogeneity in job

stability, unemployment risk, labor market segmentation, or part-time availability) may miss a very important channel through which inequality materializes. Life-cycle models that distinguish employment risk from productivity risk (Low et al. (2010)) and models with ex ante heterogeneity in job-ladder risk (e.g. Ozkan et al. (2023)) move in this direction. Our results suggest that persistent differences in employment risk across individuals are quantitatively important over the full working life, and that models abstracting from this heterogeneity (or its persistence) are likely to understate the role of employment attachment in lifetime inequality. In order to shed further light on the drivers of heterogeneity in employment attachment, the next subsection explores different types of non-employment further.

3.3 Sources of Variation in Lifetime Employment Attachment

We now examine the underlying sources of these differences further. The literature emphasizes several potential mechanisms: some studies highlight heterogeneity in preferences for work (Bick et al., 2024), and others emphasize labor market frictions and adverse shocks that may generate prolonged periods of non-employment (Krusell et al., 2020; Morchio, 2020; Hosseini et al., 2026). There is also work which illustrates the importance of prior work histories, including occupation- and industry-specific experience and broader career dynamics (Groes et al., 2015; Huggett et al., 2011). We conduct two complementary analyses. First, we decompose differences in lifetime employment attachment into contributions from different types of employment and non-employment histories. Second, we examine whether specific adverse life- and labor market events are associated with being in the lower tail of the lifetime employment-attachment distribution.

3.3.1 Decomposition of Employment Attachment

Our measure of lifetime employment attachment is based on annual full-time-equivalent employment, constructed primarily from mandatory pension contributions (see Section 2.2). The detailed Danish register data allow us to characterize the employment and non-employment histories underlying this aggregate measure. However, we do not observe the exact daily status associated with every period of reduced or zero employment. We therefore combine annual information on earnings and transfer receipts with information on employment status and job type in November, which is the standard reference month used by Statistics Denmark. Using this information, we can classify 76 percent of the years with some deviation from full-time work (and thus with some non-employment history) into more detailed non-employment statuses. We provide more information about the exact procedure and definitions in Appendix A.2.

We use these constructed histories in two empirical models:

Model 1: takes an aggregate approach by distinguishing between deviations from full-time work classified as either voluntary or involuntary non-employment based on the status in the last week of November and accumulate across the lifetime. The voluntary category includes years of

part-time work as well as years of self-sufficiency (i.e. no earnings or income transfers), and finally years with income transfers associated with education, retirement, or childbirth-related absence (leave). The involuntary category includes years associated with income transfers such as sickness benefits, disability benefits, unemployment insurance, social assistance, rehabilitation, and other transfers intended to compensate for a temporarily or permanently reduced capacity to work. These labels should be interpreted as empirical classifications based on observed income transfers.

Model 2: disaggregates the broad categories into their underlying components by cumulating the number of times individuals are classified in each of the underlying states separately. On the involuntary side, we separately consider unemployment insurance, social assistance, rehabilitation, sickness, and disability. On the voluntary side, we distinguish part-time work, education, retirement, and childbirth-related absence. This specification allows us to assess which particular employment and non-employment histories account for the aggregate patterns identified in Model 1.[16]

For each exercise, we take a simple linear projection of lifetime employment on the constructed set of regressors, X_{ik}, where k indexes each individual regressor in the model:

$$\ln LH^i_{UAX} = y_i = \alpha + \sum_k \beta_k X_{ik} + \epsilon. \tag{8}$$

To analyze implications for dispersion in lifetime employment, we again form an ensemble assessment of the importance of each component to dispersion[17]:

$$Var(\ln LH^i_{UAX}) = Cov(\ln LH^i_{UAX}, y_i) = \sum_k \beta_k Cov(\ln LH^i_{UAX}, X_{ik}) + Cov(\ln LH^i_{UAX}, \epsilon_i). \tag{9}$$

This decomposition describes each of the regressors' importance in accounting for dispersion in lifetime employment attachment in our sample. We also repeat the same decomposition for lifetime earnings to analyze the extent to which these patterns also materialize here. The results are presented in Table 1 for both lifetime earnings and employment measured up to age 45 (we report the respective variance shares in square brackets). For expositional reasons, we only report the four most important predictors and the residual in Model 2 in Table 1, but Appendix Table

[16]We provide more information about the specific states and the exact definitions of variables in Appendix A.2. In Model 1, voluntary and involuntary non-employment events are mutually exclusive at the yearly level (to produce an upper bound of the importance of part-time non-employment we give this state priority over involuntary non-employment). Model 2 instead cumulates the years spent in each of the underlying states separately allowing for more than one event every year. That is, an individual who is part-time employed in a given year but also experiences unemployment is recorded with two events during that same year in Model 2. See further discussion in Appendix A.2.

[17]Overall, this exercise is closely related to the wage-hours decomposition above (Equation (7)). The key difference is that the wage-hours decomposition starts from the exact accounting identity $\ln LH^i_{UAX} + \ln LW^i_{UAX} = \ln LI^i_{UAX}$ (see Equation (6)). In contrast, the present exercise first projects lifetime employment onto the explanatory variables in Equation (8) and then applies the same ensemble decomposition methodology to the fitted components.

B.2 shows the estimates for the other predictors. Two caveats apply to the decompositions below. First, years with e.g. unemployment insurance or social assistance are by construction years with reduced employment, so part of their predictive power is to some extent mechanical. The decomposition therefore tells us through which states weak attachment materializes (and thus their relative importance), and less about why it arises. Second, our classification is based on benefit receipt, which also depends on eligibility rules and search behavior, and it does not directly identify preferences or constraints.

In **Model 1**, involuntary non-employment makes a larger contribution than voluntary histories to dispersion in both lifetime earnings and employment attachment. This difference is most pronounced among low-educated workers. For this group, the contribution of involuntary non-employment is approximately 50 percent larger for lifetime earnings (variance shares are 18 vs. 28 percent) and 75 percent larger for employment attachment (19 vs. 33 percent). Among medium-educated workers, the difference is more modest. For high-educated workers, the pattern depends on the outcome: involuntary non-employment contributes more to earnings dispersion, whereas voluntary non-employment contributes more to dispersion in employment attachment. These results reveal substantial education-specific differences in the sources of unequal employment histories. This is consistent with existing evidence that employment stability and career dynamics vary systematically across education groups, reflecting differences in job mobility, job stability, and the accumulation of human capital over the career (Bagger et al., 2014; Doniger, 2026).

Model 2 provides a more detailed decomposition by allowing the individual components within the voluntary and involuntary categories to have separate contributions. Together, these components account for between 56–73 percent of the variation in lifetime employment attachment across education groups, compared with 34–53 percent in Model 1. This indicates that the disaggregated employment histories contain more information than the aggregate voluntary–involuntary distinction. Social assistance makes the largest contribution in the full sample and among low- and medium-educated workers. In the full sample, it accounts for approximately 20 percent of lifetime earnings dispersion and 29 percent of employment-attachment dispersion. Among low-educated workers, the corresponding shares increase to 24 and 36 percent. Unemployment insurance makes the second-largest contribution in the full sample, accounting for approximately 13 percent of earnings dispersion and 14 percent of employment-attachment dispersion. These results connect to the recent literature on the determinants and persistence of long-term unemployment (Mueller and Spinnewijn, 2025) and emphasize the importance of modeling heterogeneous and persistent unemployment dynamics when studying lifetime inequality. In particular, Morchio (2020) shows directly that a standard search-and-matching model with homogeneous workers cannot reproduce the observed concentration and persistence of unemployment over the life cycle. Our findings point in the same direction: models of lifetime inequality need to allow for persistent heterogeneity in job-finding and separation rates if they are to generate the large differences in employment attachment accumulated by age 45. Recently, a similar point has been made by Gregory et al.

Table 1: Decomposing Earnings and Employment Differences

		Model 1			Model 2				
	Total	Voluntary	Involuntary	Residual	Part-time	Disability	UI	Soc. assist.	Residual
Earnings									
Full Sample	.2036	.0259	.0571	.1205	.0067	.0127	.0272	.0401	.1034
	[100]	[12.72]	[28.06]	[59.22]	[3.31]	[6.25]	[13.38]	[19.72]	[50.72]
Low Education	.2473	.0457	.0685	.1331	.0181	.0247	.0228	.0600	.1101
	[100]	[18.47]	[27.71]	[53.81]	[7.32]	[9.99]	[9.22]	[24.26]	[44.52]
Medium Education	.1638	.0292	.0341	.1005	.0097	.0078	.0185	.0241	.0907
	[100]	[17.82]	[20.81]	[61.37]	[5.89]	[4.77]	[11.30]	[14.73]	[55.35]
High Education	.1686	.0095	.0322	.1269	.0013	.0033	.0366	.0234	.0939
	[100]	[5.65]	[19.09]	[75.26]	[0.75]	[1.97]	[21.68]	[13.92]	[55.69]
Employment									
Full Sample	.0753	.0148	.0186	.0418	.0080	.0063	.0106	.0221	.0248
	[100]	[19.73]	[24.71]	[55.56]	[10.64]	[8.42]	[14.48]	[29.34]	[32.39]
Low Education	.1165	.0222	.0390	.0553	.0088	.0133	.0147	.0421	.0314
	[100]	[19.05]	[33.47]	[47.48]	[7.57]	[11.41]	[12.65]	[36.11]	[26.87]
Medium Education	.0589	.0115	.0144	.0331	.0068	.0047	.0095	.0164	.0185
	[100]	[19.49]	[24.36]	[56.15]	[11.50]	[8.00]	[16.12]	[27.77]	[31.40]
High Education	.0465	.0102	.0057	.0307	.0051	.0012	.0104	.0073	.0205
	[100]	[21.85]	[12.22]	[65.92]	[11.05]	[2.56]	[22.32]	[15.71]	[43.98]

Note: Table 1 decomposes lifetime earnings and lifetime employment variation (up to age 45) into contributions from observable factors, following the decomposition in Equation (9). Model 1 reports the covariance contribution of voluntary and involuntary non-employment histories (see Appendix A.2 for definitions), plus an unexplained residual. Model 2 reports the corresponding decomposition using the individual non-employment states as separate regressors: part-time work, childbirth-related absences, education, retirement, sickness, disability, unemployment insurance, social assistance, and rehabilitation benefits, plus a residual (we only report the estimates from the four most important predictors, but see Appendix Table B.2 for all the estimates). For each predictor, the first panel (Earnings) reports the covariance contribution to total lifetime earnings inequality, and the (cov)variance share in square brackets. The second panel (Employment) reports corresponding numbers for employment-attachment. As Model 1 and Model 2 are separate regressions with different sets of regressors, the individual covariance shares in Model 2 need not sum to the aggregate voluntary or involuntary shares reported in Model 1. Results are reported for the full sample and for each education group.

(2025).

Part-time work also makes an important contribution to the employment-attachment dispersion, accounting for approximately 11 percent in the full sample, followed by disability at approximately 8 percent. The importance of part-time work alongside histories of benefit receipt indicates that both reduced working hours and periods of non-employment contribute to differences in lifetime employment attachment. The decomposition also reveals clear differences across education groups. Social assistance makes the largest contribution among low- and medium-educated workers. Among high-educated workers, unemployment insurance instead makes the largest contribution, accounting for approximately 22 percent of both earnings and employment-attachment dispersion and exceeding the contribution of social assistance for this group.

3.3.2 Lower Tail of the Employment-Attachment Distribution

The preceding decomposition considers variation across the entire distribution of lifetime employment attachment. However, Figure B.4 in Appendix B.5 shows that the bottom 20 percent of the attachment distribution accounts for roughly 75 percent of the variance in lifetime employment. This concentration suggests that overall inequality is largely driven by individuals with persistently weak labor market attachment. We therefore focus on this group and examine the importance of employment histories and adverse life events. We define an indicator variable, $Bottom20_i$, for whether an individual belongs to the lower tail of the cohort-specific distribution of lifetime employment attachment (up to age 45).[18] We disregard individuals with the 20 percent highest employment attachment such that in all exercises below, the reference group consists of individuals in the middle of the distribution.

We consider a simple linear OLS regression of the form:

$$Bottom20_i = \alpha + \sum_k \beta_k X_{ik} + \epsilon_i. \tag{10}$$

As above, we run different regressions distinguished by what we include in the set of explanatory variables.

First, Table 2 reports the R^2 from specifications where the regressors are the voluntary and involuntary non-employment histories used above (Section 3.3.1). The table reports the R^2 from the full specification and from specifications that separately exclude either voluntary or involuntary non-employment histories. The decline in explanatory power when involuntary histories are excluded is substantially larger than when voluntary histories are excluded. Involuntary non-employment is therefore the dominant predictor of membership in the bottom 20 percent of the lifetime employment-attachment distribution. This pattern is especially pronounced among low-educated workers, for whom involuntary histories account for approximately 90 percent of the explanatory power attributable to the two aggregate employment-history measures. These findings suggest that particularly weak lifetime employment attachment is more closely associated with states classified as involuntary than with part-time work and other states classified as voluntary. Although the results are descriptive and our classification does not directly identify preferences or constraints, they are more consistent with an important role for labor-market and health-related constraints than with an explanation based primarily on differences in preferences for work.

Second, while the preceding analysis shows that involuntary non-employment histories are strongly associated with membership of the lower tail, these histories are defined largely by benefit receipt and therefore describe the states through which weak attachment materializes rather than

[18] For completeness and in order to maximize the prevalence of e.g. recessions, the analysis in this part includes all cohorts for which UAX45 is available. $Bottom20_i$ is constructed within each cohort. The reported results are estimated without birth-cohort fixed effects; including them leaves the results virtually unchanged (available upon request).

Table 2: Bottom 20: Voluntary vs. Involuntary

R^2	Full model	Excluding voluntary	Excluding involuntary
Full sample	0.1118	0.0877	0.0144
Low education	0.1545	0.1205	0.0127
Medium education	0.1016	0.0801	0.0123
High education	0.0571	0.0394	0.0153

Note: Table 2 reports the R^2 based on Equation (10) with regressors voluntary and involuntary employment history. The outcome is an indicator for whether the individual is in the bottom 20 percent of the employment-attachment distribution (up to age 45). Columns 'Excluding voluntary' and 'Excluding involuntary' report the R^2 when voluntary and involuntary non-employment histories, respectively, are excluded from the regression.

the underlying events that produce it. To shed light on these underlying events, we next examine a set of specific adverse events that may disrupt employment over the life cycle. These include exposure to mass layoffs, sickness, disability, and recessions. We also include childbirth-related absences as an important life event that may affect employment trajectories.[19] Appendix Table B.3 assesses the predictive importance of these events for membership of the bottom 20 percent of the lifetime employment-attachment distribution. As above, we interpret the variables as predictors rather than causal effects and we assess variable importance by comparing the full model R^2 to the R^2 when a given regressor is excluded from the regression. We obtain a full model R^2 of around 20 percent across all samples except for the high educated where it is 9 percent. This highlights that despite our relatively crude approach in selecting and identifying only a few selected set of "shocks", these measures are still highly relevant in identifying individuals with weak employment attachment.

Regarding the relative predictive importance of the different adverse events, Appendix Table B.3 shows that recession exposure accounts for a substantial share of the model's explanatory power for membership in the bottom 20 percent part of the lifetime employment-attachment distribution. This contribution reflects both the association between recession exposure and lower-tail membership and the amount of variation in exposure across individuals. In addition, sickness and/or disability events are important for explanatory power. On the contrary, children or mass layoffs do not appear as core components for presence in the lower tail. Mass layoffs, however, constitute only a small share of involuntary separations more broadly (Cederlöf, 2024), which may help explain their limited role in predicting weak lifetime employment attachment relative to the broader involuntary non-employment measures documented in Table 2. This interpretation is reinforced when looking at the actual estimates in the regression model. The estimates for the

[19] All variables are coded as event counts (so the scale is common). Recession events are indicators for recession years interacted with the individual's lifetime industry (the 1-digit NACE industry in which they worked most years). Recession exposure thus combines the number of recession years an individual experiences with the industry in which he worked most years, and it therefore partly reflects cohort and industry sorting. We view it as a summary measure of exposure to cyclical risk and not as an isolated effect of recessions. We discuss the precise variable definitions further in Appendix A.2.

recession events are roughly similar in magnitude (and on a similar scale, namely as event counts) to the estimate of mass-layoffs suggesting that the difference in predictive power comes from the differences in frequency by which these events occur.

Overall, these results highlight the importance of cyclical and health-related labor market risks for understanding long-run employment outcomes. Such adverse events may have cumulative consequences when employment trajectories exhibit persistence or state dependence. This interpretation is consistent with the job-displacement literature, which documents persistent employment and earnings losses following job loss, with particularly large losses during recessions (Jacobson et al., 1993; Davis and von Wachter, 2011; Schmieder et al., 2023). The predictive importance of these events also differs across education groups: collectively, they account for more of the variation in lower-tail membership among low-educated than among high-educated workers. This may reflect differences in exposure to adverse events, their persistence, or their consequences for subsequent employment.

Taken together, the evidence indicates that weak lifetime employment attachment is more closely associated with involuntary non-employment histories and adverse events (e.g. unemployment, health-related shocks, and recession exposure) than with states classified as voluntary. Although part-time work and other voluntary margins contribute to dispersion across the full distribution, they have relatively limited predictive importance for particularly weak lifetime employment attachment.

3.4 Lifetime Inequality in Earnings vs. Net Income

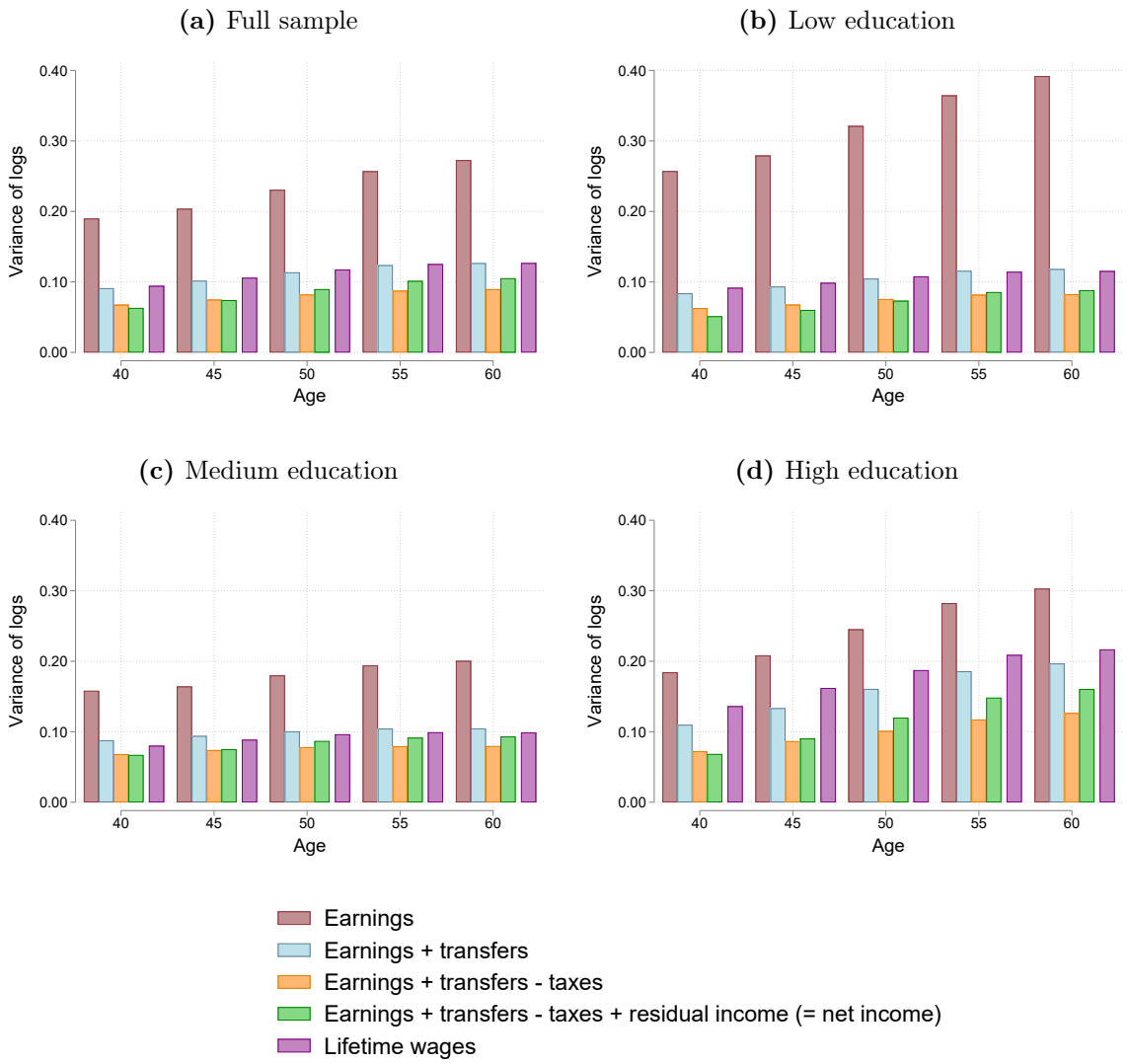
We now examine how inequality in earnings translates into inequality in the economic resources available to individuals after government intervention. To do so, we compare lifetime earnings with lifetime net income and sequentially introduce the components of net income. Starting from earnings, we first add transfers, then subtract taxes, and finally add residual income. Residual income comprises interest and other capital income, tax-deductible interest expenses, and other income, including child-support payments. Figure 3 presents the results.

Across all ages and education groups, lifetime inequality is substantially lower in net income than in earnings, demonstrating the importance of the Danish welfare state for long-run redistribution. The central result is that this equalization occurs mainly through transfers rather than through progressive taxation. For the full sample, the reduction in inequality associated with adding transfers is approximately five times as large as the reduction associated with subtracting taxes. Residual income has only a modest effect: it slightly reduces inequality at younger ages but increases it later in the life cycle, when differences in capital income become more important.

Moving across the life cycle in Figure 3, we see that lifetime inequality in net income, as in the case of gross earnings, is increasing from ages 40 and onward. However, the increase is more modest, at least in absolute terms. For low educated workers, the increase in gross earnings is

around 0.14 log points (Figure 1) but only 0.04 log points in net income. Among highly educated workers, the corresponding increases are 0.12 and 0.09 log points. The tax-and-transfer system therefore offsets the accumulation of earnings inequality much more strongly among low-educated workers. This differential redistribution pattern across education groups reverses the educational ranking of inequality: low-educated workers have the greatest inequality in lifetime earnings but, from approximately age 45 onward, the lowest inequality in lifetime net income. Highly educated workers display the opposite pattern: despite having more equal earnings, they have the highest net-income inequality at older ages. Hence, conclusions about which groups are most unequal depend fundamentally on whether inequality is measured before or after taxes and transfers.

Figure 3: Bar Plot on Redistribution



Note: Figure 3 contrasts the role of taxes and transfers vs employment attachment for lifetime inequality by moving sequentially from earnings to net income. The purple bar (lifetime wages) represents the level of lifetime inequality if variation in employment attachment is eliminated (that is, LW^i_{UAX} in Equation (6)).

The finding that transfers are a key driver of redistribution in net income also leads to an important link to our earlier results on employment attachment. A large share of lifetime earnings inequality reflects differences in accumulated employment, including periods with low or zero earnings. Most transfers directly insure against these periods by replacing part of their lost earnings through programs such as unemployment insurance and social assistance. Progressive taxation, by contrast, primarily compresses differences in earnings among individuals with taxable income and therefore provides less direct insurance against extended periods of non-employment. The modest role of taxes should thus not be interpreted as evidence that the Danish tax system is unimportant or insufficiently progressive. Rather, it reflects the nature of the underlying inequality: when inequality is generated primarily along the extensive employment margin, transfers are the policy instrument most directly targeted at that source of dispersion.

The purple bars in Figure 3 provide a useful benchmark by reporting inequality in lifetime wages (via the accounting identity in Equation (6)). This measure shows the inequality in (LI_{UAX}) that remains after mechanically removing differences in lifetime labor market attachment, (LH_{UAX}). A striking result is that adding transfers to earnings reduces lifetime earnings inequality to approximately the level of lifetime wage inequality. Thus, in an accounting sense, the transfer system offsets a substantial part of the inequality associated with differences in employment attachment, while leaving more of the inequality associated with earnings conditional on employment intact.[20] The results by education reinforce this interpretation. Transfers reduce inequality most strongly among workers with low education, for whom dispersion in lifetime employment attachment is also greatest, see Figure 2. Transfers remain the largest source of equalization also among highly educated workers, but taxes play a relatively more important role for this group. Overall, transfers are particularly important where employment risk is central, whereas progressive taxes matter relatively more where inequality primarily reflects differences in wages among individuals with strong employment attachment.

The targeting of transfers toward weak employment histories can also be seen directly in how transfers are distributed across the employment-attachment distribution. In Figure B.5 in the Appendix, we rank individuals by lifetime employment attachment and show the cumulative share of aggregate lifetime transfers (a Lorenz type curve). We show that those in the bottom of the employment distribution receive substantially larger transfers than those in the top for all four groups. For the full sample, 55.5 percent of aggregate lifetime transfers are received by the bottom quintile of the employment-attachment distribution. The same within-group pattern holds by education, ranging from 47.7 percent among the medium educated to 65.4 percent among the low educated. As a complementary illustration, Figure B.6 in Appendix B.6 reports a bin scatter plot of the same relationship (grouping by employment-attachment deciles and plotting against

[20] As transfers are also taxed an alternative order would first increase inequality (that is, subtracting taxes from earnings without accounting for transfers) and would further increase the inequality reduction when accounting for transfers. Our conclusion is thus robust to the ordering: the transfer system accounts for the large majority of the difference between lifetime earnings inequality and lifetime net-income inequality.

transfers) together with the corresponding rank correlations. Both figures clearly illustrate that moving from earnings to net income compresses differences between individuals with strong and weak employment histories particularly strongly. Together, these results show that a key redistributive function of the Danish welfare state is not simply to compress the earnings distribution generally, but more specifically to insure the long-run income consequences of unequal employment attachment and that the latter feature is by far the most important in terms of reducing income inequality. These results complement the evidence from Bengtsson et al. (2016), who show that for Sweden a large share of the redistribution observed in annual data reflects transfers to individuals with transitory income losses and therefore largely cancels out over the life cycle. Our analysis speaks to the redistribution that remains on a lifetime basis. Our results suggest that the redistribution which remains on a lifetime basis is targeted at individuals whose employment losses are persistent. Transfers to workers with occasional spells of non-employment mainly smooth income within the life cycle, whereas transfers to workers with repeated spells of unemployment, sickness, or social assistance compress differences in lifetime income across individuals.

These findings also illustrate an important policy trade-off. Policies that, via transfer reductions, improve employment stability, facilitate re-employment, or prevent prolonged health-related absence may reduce the underlying dispersion in lifetime earnings. But transfers also provide insurance against the income consequences of employment losses that are not prevented. Reforms that strengthen employment incentives may improve employment attachment, but reductions in benefit generosity or tighter eligibility can simultaneously increase the extent to which adverse employment histories translate into lifetime income inequality. Assessing such reforms solely by their effects on employment or annual income distributions may therefore miss an important part of their long-run distributional consequences.

Although the role of net income may be particularly pronounced in Denmark given the scale of taxes and transfers, the comparison between earnings and net income is informative beyond the Danish context. Contrasting lifetime earnings with net income allows us to analyze how redistribution and insurance mechanisms shape inequality, how much inequality remains after taxes and transfers, and the extent to which redistribution offsets rising earnings inequality across cohorts. This also provides lessons for countries with less extensive welfare states.

4 Part 2: The Evolution of Inequality in Lifetime Income across Cohorts

In the second part of our analysis, we focus on changes in lifetime inequality across birth cohorts 1960–1983 (the cohort sample). In Section 3, we saw that lifetime inequality metrics early in the life cycle can fluctuate a lot but that measures from age 40 and onward are rank stable. Therefore, we focus on measures based on earnings up to age 40 and onward. The evidence in the first part

of our analysis highlights three findings that are important for the cohort analysis in this section. First, employment attachment is a major determinant of lifetime inequality, particularly among low-educated workers. Second, the drivers of employment attachment appear to be established relatively early in the life cycle and remain persistent. Third, taxes and transfers substantially reduce inequality by offsetting differences in employment attachment, although they do not eliminate them completely. We now turn to whether these findings have changed across cohorts.

4.1 Lifetime Earnings Inequality across Cohorts

As a starting point we look at inequality across cohorts at different stages of the life cycle by reporting the variance of log lifetime earnings accumulated up to different ages for each birth cohort permitted by the sample window. Figure 4 displays the profiles. In the full sample, inequality measured up to age 40 is broadly stable across cohorts, although measures based on earnings accumulated to age 50 and beyond indicate a modest upward trend.

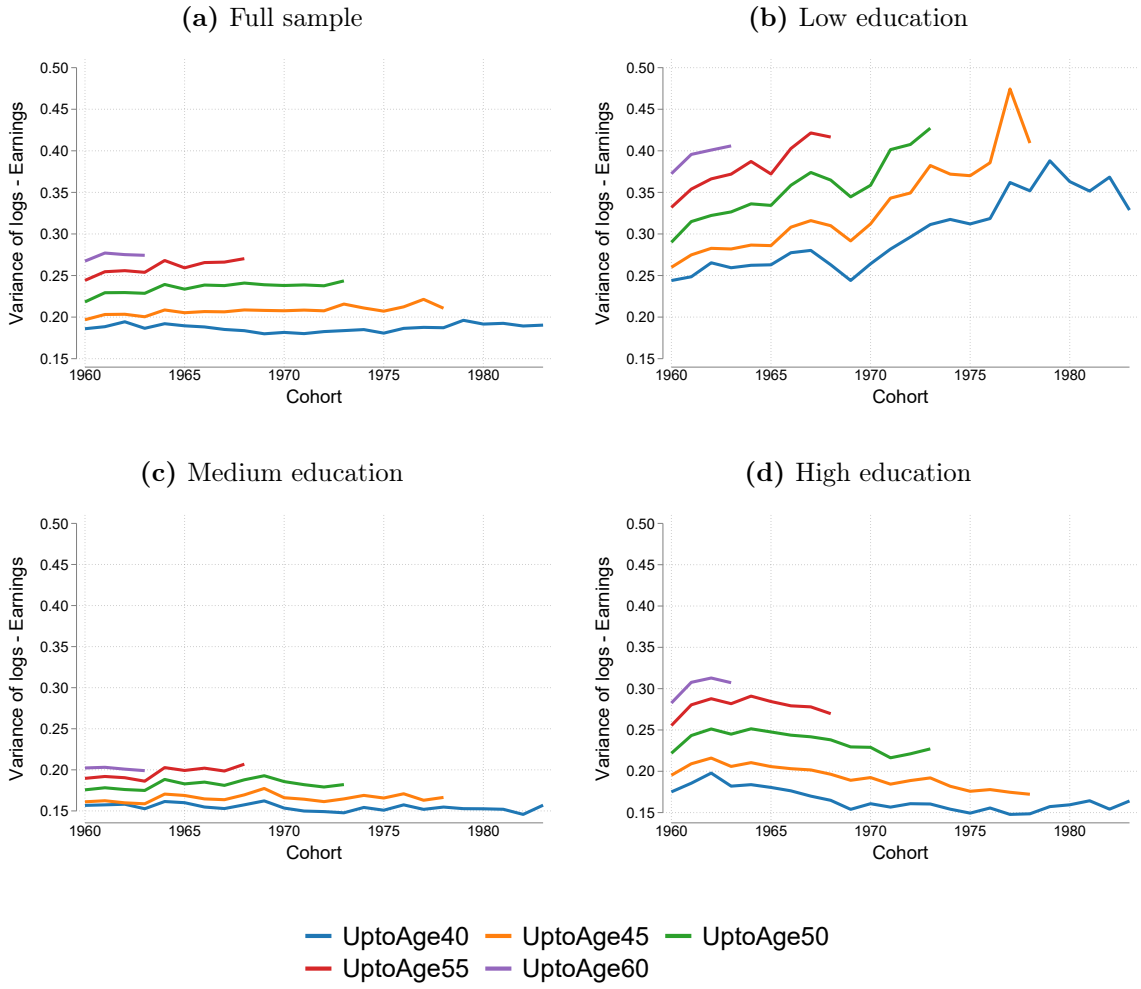
The cohort patterns differ markedly within education groups. Among low-educated workers, lifetime earnings inequality is substantially higher for more recent cohorts at all observed accumulation ages. At age 45, for example, inequality is approximately 0.11 log points higher for the 1975 cohort than for the 1960 cohort.[21] The corresponding increase among medium-educated workers is only around 0.01 log points, while inequality declines among the high educated. Cohort rankings are relatively stable from age 40 and onward: cohorts that are more unequal at that age generally remain so as the accumulation window expands. This suggests that cohort differences emerge relatively early and persist over the remainder of the observed working life.[22]

The increase in lifetime earnings inequality across cohorts among low-educated workers is qualitatively consistent with the rise in cross-sectional earnings inequality documented for Denmark (see Leth-Petersen and Sæverud (2022)). However, the two inequality measures capture different dimensions of inequality. Rising cross-sectional inequality need not imply rising lifetime inequality, since transitory earnings differences may average out over time. Indeed, we find a clear increase in lifetime inequality only among low-educated workers, while the increase is modest among the medium educated and inequality declines among the high educated. Our results thus identify the extent to which the cross-sectional developments are reflected in persistent differences across

[21] One concern when comparing low-educated workers across cohorts is that our sample restriction affects later cohorts differently. The share of low-educated men excluded by the 25 percent employment requirement rises from 14.5 percent in the 1960 cohort to 20.7 percent in the 1975 cohort and 28.1 percent in the 1983 cohort (Appendix Table A6), whereas exclusion rates for the medium and high educated remain at 2–4 percent. Excluded individuals typically have lifetime employment far below the threshold and are disproportionately observed on disability pension, social assistance or unemployment insurance. The restriction thus removes a growing part of the weakly attached lower tail among more recent cohorts of low-educated men. All else equal, this lowers measured lifetime inequality in later cohorts, and we therefore view the increase we document for the low educated as conservative. Consistent with this, the increase persists when we raise the threshold to 50 percent (Figure D5).

[22] Some individual cohort-age observations are affected by common calendar-time shocks. Most notably, the spike around the 1977 cohort in the up-to-age-45 measure for low-educated workers coincides with the COVID-19 period in 2020–2021.

Figure 4: Lifetime Inequality across Cohorts



Note: Figure 4 plots lifetime earnings inequality across birth cohorts (horizontal axis) for different accumulation windows. The vertical axis shows the variance of log lifetime earnings. The lines measure inequality when earnings are accumulated from age 20 up to the indicated age. Among low-educated, later cohorts exhibit higher lifetime inequality, and cohort rankings are stable from about UptoAge40 onward.

lifetime earnings trajectories.

Using U.S. Social Security records, Guvenen et al. (2022) also document that lifetime inequality has increased across successive cohorts. Bönke et al. (2015) document a substantial increase for West German men, while Garbinti et al. (2023) find a U-shaped pattern in France with a much smaller increase than in the United States. The increase we document appears more moderate and more concentrated: whereas Bönke et al. (2015) find that West German men born in the early 1960s face about 85 percent more lifetime inequality than the 1935 cohort, the Danish increase emerges mainly at higher accumulation ages and among the low educated (on the order of 30–60 percent relative to the 1960 cohort, cf. Figure C.3). Interestingly, Bönke et al. (2015) attribute 20–40 percent of the German increase to longer unemployment spells at the bottom of the distribution, consistent with the employment attachment channel we emphasize. Direct

comparisons of magnitudes should be made with caution, however, given differences in inequality measures, cohort coverage, and sample restrictions.

4.2 The Role of Employment Attachment

We now decompose lifetime earnings inequality for each cohort into contributions from lifetime employment attachment and lifetime wages. This allows us to assess which margin accounts for the observed cohort patterns. We focus on inequality within education groups and on earnings accumulated up to age 45.[23]

Figure C.2 in the Appendix shows that differences in employment attachment make a substantial contribution to lifetime earnings inequality in every cohort, but their importance varies markedly across education groups. Among low-educated workers, employment attachment accounts for approximately 60 percent of lifetime earnings inequality, compared with around 30 percent among the high educated. Lifetime wage differences consequently play a larger role among high-educated workers, who generally have stronger and more stable employment attachment.

Changes in employment attachment also account for an important part of the increase in lifetime earnings inequality across cohorts, particularly among low- and medium-educated workers. This is shown more directly in Figure C.3, which expresses each variance component relative to its value for the 1960 cohort. Among low-educated workers, the employment-attachment component increases by approximately 30–40 percent, whereas it changes little in the full sample. Thus, the aggregate stability masks a marked increase in employment-related inequality among workers with low education.

4.3 Lifetime Net Income Inequality across Cohorts

Figure 5 decomposes the transition from earnings to net income by sequentially incorporating transfers, taxes, and residual income for different cohorts. Several interesting findings emerge. First, lifetime inequality in net income (the green bars, second y-axis) is consistently lower than in earnings (the red bars) for all cohorts and education groups, confirming the redistributive role of the tax-and-transfer system. However, net income inequality has increased across cohorts far more (in relative terms) than the increase in earnings.[24]

Second, the cohort gradient in inequality for net income is different from the cohort gradient in earnings. Among highly educated individuals, where lifetime earnings inequality declines slightly

[23]As before, we focus on within-group inequality: Figure C.1 confirms that the within-group share accounts for around 90 percent of total variance across cohorts, implying that differences in aggregate inequality are largely driven by changes within education groups rather than between them. The share seems relatively stable across cohorts.

[24]For completeness Figure C.5 in Appendix compares inequality in lifetime earnings and net income up to ages 45 and 50, while Figure C.4 in the Appendix reports inequality profiles for other age-groups as well. The same patterns emerge. Notice that if we use ages higher than 50 we start to lose many cohorts.

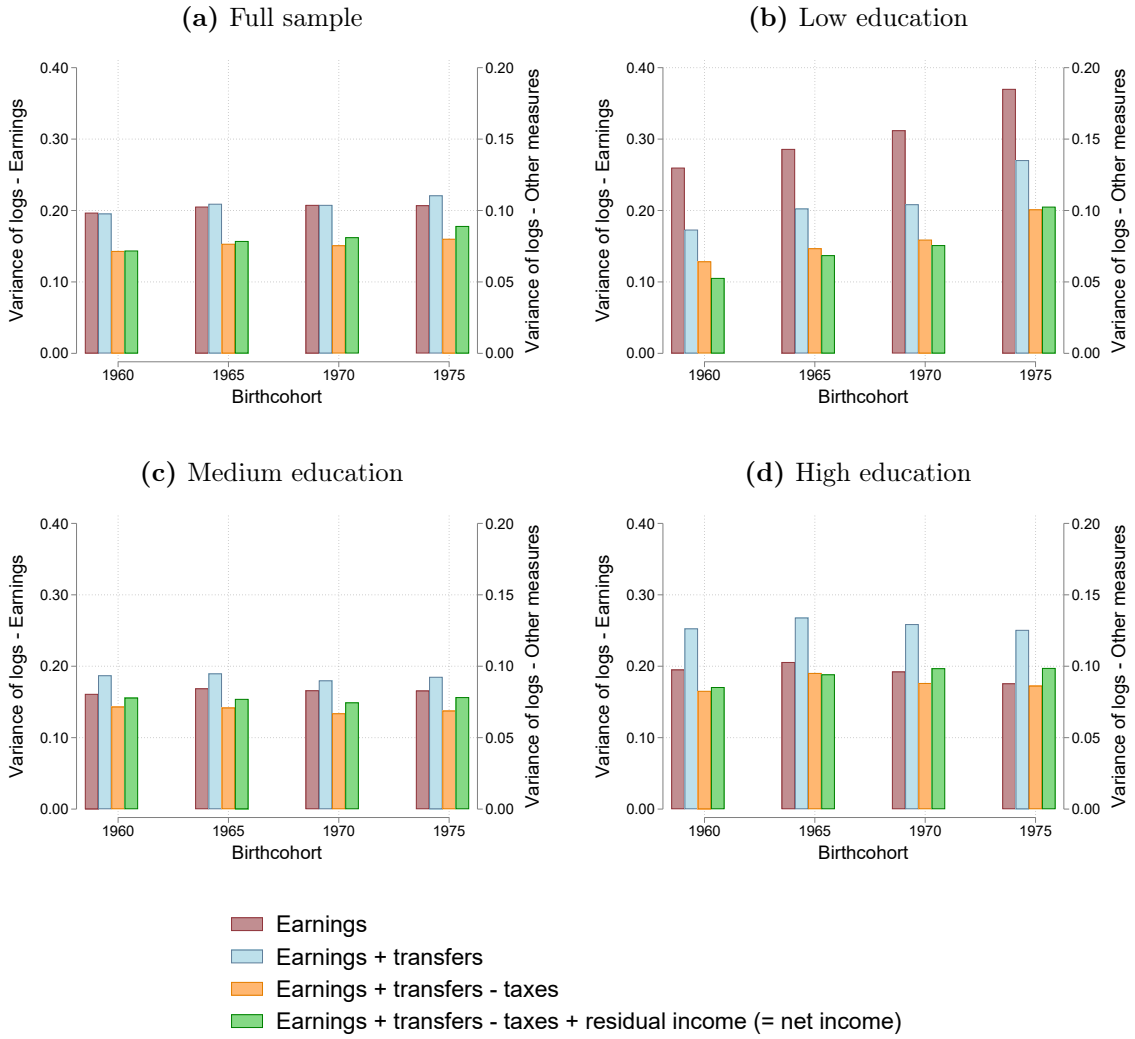
across cohorts, net income inequality rises slightly (around 0.02 log points). Among low-educated workers, lifetime earnings inequality increases by roughly 0.11 log points (from about 0.26 to 0.37 between the 1960 and 1975 cohorts), while the corresponding increase in net income inequality is around 0.05 log points (increases from about 0.05 to 0.10 between the 1960 and 1975 cohorts). This is smaller in levels, but the relative increase is larger given the lower baseline level of net income inequality. Thus, for low educated workers, inequality in net income has increased relatively more than in earnings. Figure 5 also shows that the role of transfers varies significantly across cohorts and education groups. For low-educated individuals, transfers generate larger reductions in inequality in the later cohorts (this reflects that later cohorts also display more variation in lifetime employment attachment) in absolute terms. However, in relative terms inequality after controlling for transfers grew more than earnings inequality across cohorts. This indicates that the transfer system has been less able to counteract inequality for low-educated in later cohorts.[25]

On the contrary, the equalizing effect of taxation (i.e. moving from the blue to the orange bars in the figure) is relatively stable across cohorts within each education group. Taxes reduce inequality more strongly among higher-educated individuals, reflecting the progressive nature of the tax system, but this contribution has not changed markedly over time.

To look closer at the role of transfers, Appendix C.3 provides a complementary decomposition where we group individuals within each cohort by their lifetime employment attachment. With ten employment groups (i.e. classifying individuals by their position in the lifetime employment distribution within each cohort), the within- and between-group components of earnings inequality are of roughly similar magnitude, see Figure C.6. For net income, however, the between-group contribution is substantially smaller—more than 50 percent lower. However, the difference in between-group shares for earnings vs. net income is declining across cohorts. This comes from an increasing between-group share for net income. For example, the between-group share for net income in the full sample increases from 12.6 percent for the 1960 cohort to 27.6 percent for the 1978 cohort. This suggests that the redistributive compression of between-group inequality through transfers declines across cohorts, indicating that the tax-and-transfer system has become less effective at offsetting income differences between individuals with strong and weak labor market attachment. Overall, these results imply that although redistribution continues to reduce inequality within each cohort, its equalizing capacity has somewhat weakened over time in Denmark.

[25] As emphasized by Bozio et al. (2024), the measured reduction in inequality from pretax to post-tax income mechanically increases with the level of pretax inequality, all else equal. For low-educated workers, the relative reduction in inequality from earnings to net income *falls* from roughly 81 to 73 percent between the 1960 and 1975 cohorts, even though lifetime earnings inequality *increases* over the same period. The weakening of redistribution we document is therefore not an artifact of changes in pretax inequality.

Figure 5: From Earnings to Net Income across Cohorts



Note: Figure 5 plots the variance of log lifetime income (UAX45) when moving from earnings to net income, by cohort (horizontal axis). Earnings are measured on the left axis and all other measures on the right axis. Transfers account for the largest reduction in inequality, but their relative role varies across cohorts and education groups. The tax effect is smaller and relatively stable across cohorts.

5 Robustness Checks

Our baseline results rely on at least three modeling choices: (i) measuring inequality using the variance of log lifetime income, (ii) requiring individuals to be employed in at least 25 percent of the possible years up to age 40, and (iii) winsorizing annual income at the 1st and 99th percentiles. To ensure that our conclusions are not sensitive to these specific choices, we conduct three robustness checks—each reproducing a key life-cycle result from Section 3 and the cohort analysis in Figure 4 under an alternative specification.

Alternative Inequality Metric: First, we replace the variance of logs with the Gini coefficient as our measure of dispersion. Figure D.1 shows that the life-cycle profile from Figure

1 is preserved: the Gini of lifetime earnings declines until around age 40 and increases steadily thereafter. Across cohorts, Figure D.2 for earnings and Figure D.3 for net income show that the evolution of lifetime inequality closely mirrors the baseline. For earnings, the Gini is broadly stable in the full sample and the increase is concentrated among the low educated; for net income, it rises across cohorts in all education groups.

We also revisit the importance of the bottom 20 percent of the employment-attachment distribution (Section 3.3.2 and Appendix B.5) using the Gini coefficient, which is less sensitive to the lower tail than the variance of logs. Figure D.4 shows that winsorizing lifetime employment attachment at the 20th percentile within each cohort still leads to a large reduction in employment-attachment inequality: around one third in the full sample and 40–50 percent among the low educated. As expected, this is smaller than the roughly 75 percent obtained with the variance of logs (Figure B.4), but it confirms that the lower tail is a key source of dispersion in lifetime employment attachment. Moreover, among the low educated, the winsorized series increases only marginally across cohorts, so the rise in employment-attachment inequality remains concentrated in the lower tail. This confirms that our main findings do not depend on the chosen inequality metric.

Stricter Employment-Attachment Requirement: Second, we increase the minimum labor market attachment threshold from 25 to 50 percent of potential working years up to age 40. This stricter requirement excludes around 15–18 percent of each cohort, compared with 6–9 percent under our baseline requirement (see Table A.6), so the baseline sample is considerably closer to the full population. Figure D.5 repeats the ensemble decomposition from Figure 2 on this more attached sample. The contribution of employment attachment to lifetime earnings inequality is somewhat smaller, as expected when individuals with weak attachment are excluded, but it remains a key driver especially among the low educated. Across cohorts, Figure D.6 (Figure D.7 for net income) shows that overall inequality levels fall, but inequality still increases across cohorts among the low educated, and the relative ranking by education remains virtually unchanged. This demonstrates that our results are not driven by the inclusion of marginally attached workers.

Alternative Winsorizing: Finally, we winsorize annual income at the 5th and 95th percentiles instead of the 1st and 99th. Figure D.8 shows that the ensemble decomposition from Figure 2 is essentially unaffected: inequality levels are slightly lower, while the age profile and the differences across education groups remain. Likewise, Figure D.9 (Figure D.10 for net income) shows that trimming the distribution more aggressively only marginally lowers overall inequality levels, while the cohort pattern and education gradient remain intact. Hence, outliers in the income distribution do not drive our conclusions.

Taken together, these exercises confirm that our main findings are robust to alternative inequality metrics, sample definitions, and winsorizing thresholds. This holds for the life-cycle profile of lifetime inequality and the role of employment attachment, as well as for the increase in lifetime inequality across cohorts and its concentration among the low educated.

6 Conclusion

This paper uses Danish administrative data from 1980-2023 to examine how employment histories, earnings, and the tax-and-transfer system jointly shape lifetime income inequality. We document three main findings: First, employment attachment is a major determinant of lifetime earnings inequality, accounting for between 30 and 60 percent of the observed dispersion in lifetime earnings. Particularly among low-educated workers, repeated unemployment, part-time employment, and other periods of low or zero employment are strongly associated with inequality in lifetime earnings. Second, persistent differences in employment attachment are concentrated among a relatively small group of workers who experience disproportionately many episodes of unemployment, sickness, disability, and other adverse labor market events. Third, the welfare state substantially attenuates these differences. Transfers, rather than progressive taxation, account for most of the compression from lifetime earnings to lifetime net income because they directly replace income during periods of weak employment attachment.

Our interpretation of these results is that persistently weak employment attachment is more closely linked to labor-market and health-related risks than to voluntary reductions in labor supply. Weak lifetime attachment is concentrated in years with unemployment insurance, social assistance, sickness and disability, and lower-tail membership is predicted by health events and recession exposure, while part-time work and self-financed non-employment have limited predictive power. Because the analysis is descriptive, it does not identify the causal effects of these events or rule out a role for unobserved individual heterogeneity, including differences in preferences that shape both benefit receipt and employment.

Finally, we show that lifetime inequality has increased across cohorts for low educated workers, driven in part by rising dispersion in employment attachment. Importantly, while redistribution continues to compress inequality within each cohort, but its equalizing capacity has weakened over time. As a result, inequality in lifetime net income has increased more than inequality in earnings alone. These findings should not be interpreted as identifying the causal effects of particular reforms: cohort differences also reflect changing labor market conditions, demographics, and institutions. They nevertheless show that changes in both employment trajectories and the degree of social insurance must be considered when explaining the evolution of lifetime inequality.

The results point to two complementary policy margins: preventing persistent employment losses and insuring the income consequences of losses that cannot be prevented. Policies that improve job stability, speed up re-employment, or facilitate continued employment following health problems can reduce inequality at its source. Relevant policy margins include early re-employment assistance, retraining and occupational mobility, workplace accommodation, rehabilitation, and arrangements that allow a gradual return to work. Because disadvantages in employment and income are already highly persistent by mid-career, interventions may be particularly valuable before repeated spells of non-employment become entrenched. Our evidence does not identify a partic-

ular optimal intervention or age, but it suggests that policy evaluations should consider whether temporary employment disruptions develop into persistent differences in lifetime attachment.

At the same time, prevention cannot eliminate all employment risk. Transfers provide insurance against the remaining risk and are especially important for workers whose lifetime earnings inequality is generated primarily by periods of low or zero employment. The prominent role of transfers relative to taxes therefore reflects an important distinction between policy instruments.

References

Aaberge, R. and Mogstad, M. (2015). Inequality in current and lifetime income. *Social Choice and Welfare*, 44(2):217–230.

Andersen, T. M. and Svarer, M. (2007). Flexicurity–Labour Market Performance in Denmark. *CESifo Economic Studies*, 53(3):389–429.

Bagger, J., Fontaine, F., Postel-Vinay, F., and Robin, J.-M. (2014). Tenure, experience, human capital, and wages: A tractable equilibrium search model of wage dynamics. *American Economic Review*, 104(6):1551–1596.

Bengtsson, N., Holmlund, B., and Waldenström, D. (2016). Lifetime versus annual tax-and-transfer progressivity: Sweden, 1968-2009. *The Scandinavian Journal of Economics*, 118(4):619–645.

Bertheau, A., Acabbi, E. M., Barcelo, C., Gulyas, A., Lombardi, S., and Saggio, R. (2023). The unequal consequences of job loss across countries. *American Economic Review: Insights*, 5(3):393–408.

Bhuller, M., Moene, K. O., Mogstad, M., and Vestad, O. L. (2022). Facts and fantasies about wage setting and collective bargaining. *Journal of Economic Perspectives*, 36(4):29–52.

Bick, A., Blandin, A., and Rogerson, R. (2024). Hours worked and lifetime earnings inequality. Working Paper 32997, National Bureau of Economic Research.

Björklund, A. (1993). A comparison between actual distributions of annual and lifetime income: Sweden 1951–89. *Review of Income and Wealth*, 39(4):377–386.

Böhlmark, A. and Lindquist, M. (2006). Life-cycle variations in the association between current and lifetime income: Replication and extension for sweden. *Journal of Labor Economics*, 24(4):879–900.

Bönke, T., Corneo, G., and Lüthen, H. (2015). Lifetime earnings inequality in germany. *Journal of Labor Economics*, 33(1):171 – 208.

Bowlus, A. J. and Robin, J.-M. (2004). Twenty years of rising inequality in U.S. lifetime labour income values. *Review of Economic Studies*, 71(3):709–742.

Bowlus, A. J. and Robin, J.-M. (2012). An international comparison of lifetime inequality: How continental Europe resembles North America. *Journal of the European Economic Association*, 10(6):1236–1262.

Bozio, A., Garbinti, B., Goupille-Lebret, J., Guillot, M., and Piketty, T. (2024). Predistribution versus redistribution: Evidence from france and the united states. *American Economic Journal: Applied Economics*, 16(2):31–65.

Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, 36(S1):S13–S70.

Cederlöf, J. (2024). Reconsidering the cost of job loss: Evidence from redundancies and mass layoffs. Technical report, IFAU-Institute for Evaluation of Labour Market and Education Policy.

Davis, S. J. and von Wachter, T. (2011). Recessions and the costs of job loss. *Brookings Papers on Economic Activity*, 42(2):1–72.

Deaton, A. and Paxson, C. (1994). Intertemporal choice and inequality. *Journal of Political Economy*, 102(3):437–467.

Doniger, C. L. (2026). Education and the margins of cyclical adjustment in the labor market. *Review of Economic Studies*.

Engbom, N. (2022). Labor market fluidity and human capital accumulation. *NBER Working Paper 29698*.

Flinn, C. J. (2002). Labour market structure and inequality: A comparison of italy and the u.s. *The Review of Economic Studies*, 69(3):611–645.

Friedman, M. (1962). *Capitalism and Freedom*. University of Chicago Press.

Friedrich, B., Laun, L., and Meghir, C. (2022). Earnings dynamics of immigrants and natives in sweden 1985–2016. *Quantitative Economics*, 13(4):1803–1847.

Garbinti, B., García-Peñalosa, C., Pecheu, V., and Savignac, F. (2023). Trends and inequality in lifetime earnings in france. *SSRN Electronic Journal*.

Gregory, V., Menzio, G., and Wiczer, D. (2025). The alpha beta gamma of the labor market. *Journal of Monetary Economics*, 150:103695.

Groes, F., Kircher, P., and Manovskii, I. (2015). The u-shapes of occupational mobility. *The Review of Economic Studies*, 82(2):659–692.

Guvenen, F., Kaplan, G., Song, J., and Weidner, J. (2022). Lifetime earnings in the united states over six decades. *American Economic Journal: Applied Economics*, 14(4):446–479.

Guvenen, F., Karahan, F., Ozkan, S., and Song, J. (2017). Heterogeneous scarring effects of full-year nonemployment. *American Economic Review*, 107(5):369–73.

Guvenen, F., Pistaferri, L., and Price, D. J. (2024). Lifecycle origins of inequality. Presentation at the Society for Economic Dynamics Annual Meeting. Barcelona, June 27–29.

Haan, P., Kemptner, D., Prowse, V., and Schaller, M. (2025). Insurance, redistribution, and the inequality of lifetime income. *Quantitative Economics*, 16(2):565–613.

Haider, S. and Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *American Economic Review*, 96(4):1308–1320.

Halvorsen, E., Ozkan, S., and Salgado, S. (2022). Earnings dynamics and its intergenerational transmission: Evidence from norway. *Quantitative Economics*, 13(4):1707–1746.

Heathcote, J., Perri, F., and Violante, G. L. (2010). Unequal we stand: An empirical analysis of economic inequality in the united states, 1967–2006. *Review of Economic Dynamics*, 13(1):15–51.

Heathcote, J., Storesletten, K., and Violante, G. L. (2005). Two views of inequality over the life cycle. *Journal of the European Economic Association*, 3(2–3):765–775.

Hosseini, R., Kopecky, K., and Zhao, K. (2026). How important is health inequality for lifetime earnings inequality? *The Review of Economic Studies*, 93(1):556–599.

Huggett, M., Ventura, G., and Yaron, A. (2011). Sources of lifetime inequality. *American Economic Review*, 101(7):2923–2954.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *American Economic Review*, 83(4):685–709.

Jolivet, G., Postel-Vinay, F., and Robin, J. M. (2006). The empirical content of the job search model: Labor mobility and wage distributions in Europe and the US. *European Economic Review*, 50(4):877–907.

Kleven, H. J. and Schultz, E. A. (2014). Estimating taxable income responses using danish tax reforms. *American Economic Journal: Economic Policy*, 6(4):271–301.

Kreiner, C. T. and Svarer, M. (2022). Danish flexicurity: Rights and duties. *Journal of Economic Perspectives*, 36(4):81–102.

Krusell, P., Mukoyama, T., Rogerson, R., and Sahin, A. (2020). Gross worker flows and fluctuations in the aggregate labor market. *Review of Economic Dynamics*, 37:S205–S226.

Leth-Petersen, S. and Sæverud, J. (2022). Inequality and dynamics of earnings and disposable income in denmark 1987–2016. *Quantitative Economics*, 13(4):1493–1526.

Low, H., Meghir, C., and Pistaferri, L. (2010). Wage risk and employment risk over the life cycle. *American Economic Review*, 100(4):1432–1467.

Lund, C. G. and Vejlin, R. M. (2015). Documenting and improving the hourly wage measure in the danish ida database. Working Paper 2015-06, Institut for Økonomi, Aarhus Universitet.

Mogstad, M., Salvanes, K. G., and Torsvik, G. (2025). Income equality in the nordic countries: Myths, facts, and lessons. *Journal of Economic Literature*, 63(3):791–839.

Morchio, I. (2020). Work histories and lifetime unemployment. *International Economic Review*, 61(1):321–350.

Mueller, A. I. and Spinnewijn, J. (2025). The nature of long-term unemployment: Predictability, heterogeneity, and selection. *Journal of Political Economy*, 133(12):3846–3902.

OECD (2020). Recent trends in employment protection legislation. Technical report, OECD.

OECD (2026). *Taxing Wages 2026: The Progressivity of Labour Taxation in OECD Countries*. OECD Publishing, Paris.

Ozkan, S., Song, J., and Karahan, F. (2023). Anatomy of lifetime earnings inequality: Heterogeneity in job-ladder risk versus human capital. *Journal of Political Economy Macroeconomics*, 1(3):506–550.

Schmieder, J. F., von Wachter, T., and Heining, J. (2023). The costs of job displacement over the business cycle and its sources: Evidence from germany. *American Economic Review*, 113(5):1208–1254.

Song, J., Price, D. J., Guvenen, F., Bloom, N., and Von Wachter, T. (2019). Firming Up Inequality. *The Quarterly Journal of Economics*, 134(1):1–50.

A Sample Selection and Descriptives

A.1 Data Sources and Variable Definitions

Our analysis combines several administrative registers from Statistics Denmark, all linked at the individual level via personal identification numbers and covering the period 1980–2023. Table A.1 summarizes the main variables and their data sources. Below we provide further details on the construction of our employment-attachment measure.

Table A.1: Variable Names and Data Sources

Variable	DST variable	Data source	Notes
Earnings	`erhvervsindk_13`	IND	Wages, self-employment income, and certain fees. Pre-tax. Not top-coded.
Net Income	`dispon_13`	IND	After-tax income incl. transfers, plus residual income (interest income and realized gains/losses on securities, plus other miscellaneous income), net of deductible interest expenses. We remove imputed rent of owner-occupied housing.
Employment attachment	`pstill`, `p_soc_status_kode`, `expyear`	RAS, IDAP	Combines primary work position with annual hours estimated from mandatory pension (ATP) contributions. See text below for details.
Education	`hfaudd`	UDDA	Highest completed degree, measured at age 30.
Demographics	-	BEF	Age, gender, birth cohort

Note: DST denotes Statistics Denmark. The data sources are administrative registers at Statistics Denmark.

Measuring Employment Attachment Our employment measure combines two sources of information. The primary source is mandatory pension (ATP) contributions from all employers through the year, which are an increasing step function of contracted hours and thus allow us to estimate annual hours worked (for details, see Lund and Vejlin, 2015). We convert these into a full-time-equivalent (FTE) measure, H_{at}, such that $H_{at} = 1$ corresponds to full-time employment throughout year t and $H_{at} = 0$ to no employment. The resulting measure captures non-employment, part-time work, and partial-year employment, and is thus considerably more detailed than the binary or full-time/part-time classifications available in many other data sources. For individuals where pension contributions are not informative about hours worked—most importantly the self-employed—we instead rely on their primary work position (pstill, p_soc_status_kode) and classify them as employed full-time ($H_{at} = 1$) if their primary work position indicates employment.

A.2 Details on Employment Histories, Non-Employment States, and Shocks

This appendix describes how we construct the non-employment states used in Section 3.3. Models 1 and 2 are both based on the classification of non-employment states described below; the shock decomposition in Equation (10) instead relies on a separate set of event variables, described at the end of this appendix.

Voluntary and Involuntary Non-Employment We classify each year of non-employment as either involuntary or voluntary; this classification underlies both Model 1 and Model 2. A year is involuntary if the individual receives unemployment insurance (`arblhu`), social assistance (`kont_gl`, `kontanthj_13`, `khflygt`), or rehabilitation benefits (`reval`), is classified as sick (see Table A.2), or is classified as a disability pension recipient (`pstill` = 93 or `p_soc_status_kode` = 411). A year is voluntary if the individual works part-time, or has no earnings and receives no transfers—that is, self-financed non-employment—including years associated with childbirth, education, or retirement. Part-time work is always classified as voluntary, and any other year meeting an involuntary criterion is classified as involuntary. Each qualifying year contributes one year to the relevant history variable, regardless of the degree of part-time work or benefit receipt within that year. Table A.2 summarizes the states and data sources. Model 1 accumulates the years spent in the aggregate voluntary and involuntary categories; Model 2 instead accumulates the years spent in each of the underlying states listed in Table A.2 separately.

In Model 1, voluntary and involuntary non-employment events are mutually exclusive at the yearly level (to produce an upper bound of the importance of part-time non-employment we give this state priority over involuntary non-employment). Robustness checks where we do not require events to be mutually exclusive (and thus allow for individuals to have both involuntary and voluntary non-employment during a year) suggest that this choice is not important for our results.

In Model 2, we accumulate years spent in each of the underlying states separately. That is, an individual who is part-time employed for a part of the year while also experiencing unemployment is recorded with two events during that same year in Model 2. Similarly, an individual in both sickness and unemployment will be recorded with both events in Model 2 and as one involuntary event in Model 1. See an illustration in Table A.3.

Using these states, we classify 76 percent of the total deviation from full lifetime employment attachment. The residual consists mainly of years with high, but not complete, full-time employment (the 75th percentile of the employment measure among residual observations is 0.92), predominantly wage earners at basic and medium skill levels.

Table A.2: Non-Employment States and Definitions

State	Definition	Data source	Classification
Unemployment insurance	Receiving positive UI (`arblhu`)	IND	Involuntary
Social assistance	Receiving positive social assistance (`kont_gl`, `kontanthj_13`, `khflygt`)	IND	Involuntary
Rehabilitation	Receiving positive rehabilitation benefits (`reval`)	IND	Involuntary
Sickness year	Classified as sick in a given year, if the individual is classified as such (`pstill`= 43 or `p_soc_status_kode` = 317) AND is receiving sickness benefits (`syg_barsel_13`) of more than 25,000 DKK in the given year.	IDAP, IND	Involuntary
Disability	If an individual has ever been classified as a pension recipient (førtidspensionist) in a given year (`pstill`= 93 or `p_soc_status_kode` = 411)	IDAP	Involuntary
Part-time work	Defined as part-time by `heltid_deltid_kode` (referencetidspunkt: ultimo november)	RAS	Voluntary
Education	No earnings and no other transfers + classified as under education (`pstill` = 91 or `p_soc_status_kode` = 511, 517)	IDAP, IND	Voluntary
Retirement	No earnings and no other transfers + classified as retired (`pstill` = 92, 94 or `p_soc_status_kode` = 414, 415)	IDAP, IND	Voluntary
Childbirth	Increase in the number of children (`antboernf`)	BEF, IND	Voluntary
Other self-financed non-employment	No earnings, no transfers, and no involuntary state	IND	Voluntary

Note: Part-time work is always classified as voluntary. Any other year meeting an involuntary criterion is classified as involuntary, also if a voluntary criterion is met.

Table A.3: Examples of Coding Non-Employment Histories

Status during year	Model 1	Model 2
Full-time employed	None	None
Unemployment insurance only	Involuntary	UI
Sickness only	Involuntary	Sickness
Part-time only	Voluntary	Part-time
Education, no earnings/transfers	Voluntary	Education
Part-time + sickness	Voluntary	Part-time + sickness
Part-time + unemployment insurance	Voluntary	Part-time + UI

Note: Illustration of how years with non-employment are coded. In Model 1, each year is classified as either voluntary or involuntary, and part-time work takes priority over involuntary non-employment. In Model 2, each underlying state is recorded separately. UI denotes unemployment insurance.

Timing of Measurement Status-based classifications (`pstill`, `p_soc_status_kode`, `heltid_deltid_kode`) refer to the individual's primary position at the end of November, whereas benefit amounts (unemployment insurance, social assistance, sickness benefits) are annual totals. History variables based on November status thus count the number of years in which a given state was the primary status, rather than total time spent in the state. This has two limitations. First, spells that do not cover November are missed entirely, so the status-based components of the classification in Table A.2 (part-time work, education, retirement, and disability) should be interpreted as lower bounds on actual exposure. Second, the part-time classification refers to contracted hours in the November job and therefore does not capture within-year variation in hours. Each qualifying year is counted equally, irrespective of the extent of the reduction in hours. These limitations are one reason the main employment-attachment measure is instead based on pension contributions, which reflect hours across all jobs during the year (see Appendix A.1).

Employment Shocks The shock decomposition in Equation (10) uses the following event variables:

- Mass layoff: The number of displacement events experienced, following Bertheau et al. (2023): a displacement event requires that (i) the individual separates from their establishment between year t−1 and t, after having been employed there for at least three consecutive years; (ii) the establishment had at least 50 employees in year t−1 and reduces its workforce by at least 30 percent between t−1 and t; (iii) the individual is not recalled to the same establishment within five years; (iv) the individual does not move jointly with former coworkers to a firm that absorbs more than 20 percent of the old establishment's workforce; and (v) the individual is not in public administration (NACE 84).

- Sickness shock: The number of times an individual experiences a health shock, in which the individual is classified as sick (`pstill` $= 43$ or `p_soc_status_kode` $= 317$), receives sickness benefits (`syg_barsel_13`) above 25,000 DKK, and experiences an income drop of at least 70 percent relative to the previous year.

- Disability: An indicator for ever being classified as a disability pension recipient. We use an indicator rather than a count because disability pension is typically an absorbing state: once classified, individuals rarely return to employment.

- Recession exposure by industry: The number of recession years (1986, 1992, 1993, 2008, 2009, 2020) interacted with the individual's lifetime industry (the 1-digit NACE industry in which they worked most years).

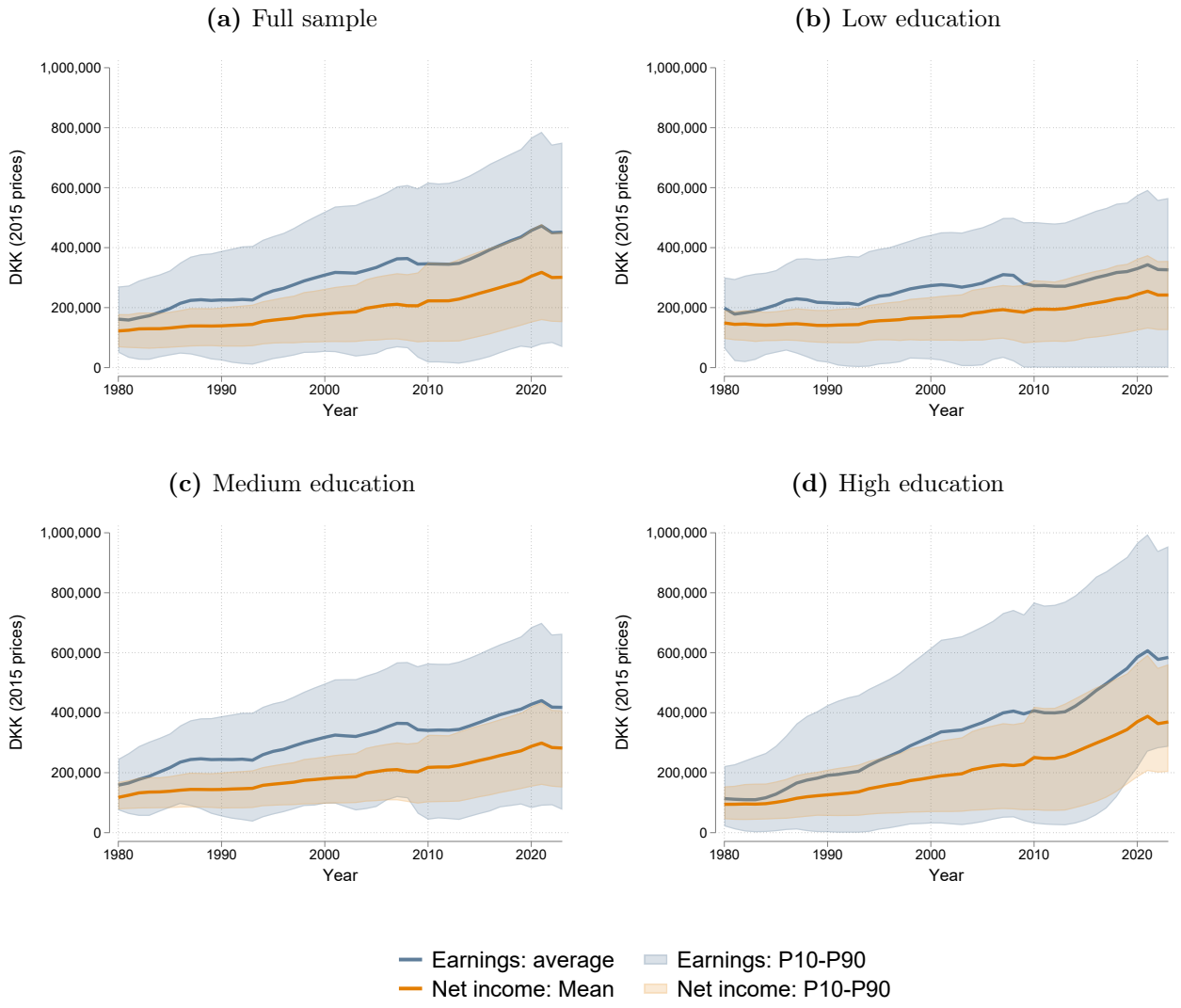
- Children: The number of increases in the number of children in the individual's family (`antboernf`).

A.3 Descriptive Statistics

This section presents descriptive evidence on the development of earnings and net income, the composition of our sample, and the distribution of lifetime employment attachment.

Figure A.1 shows the development of average earnings and net income over time for the full sample.

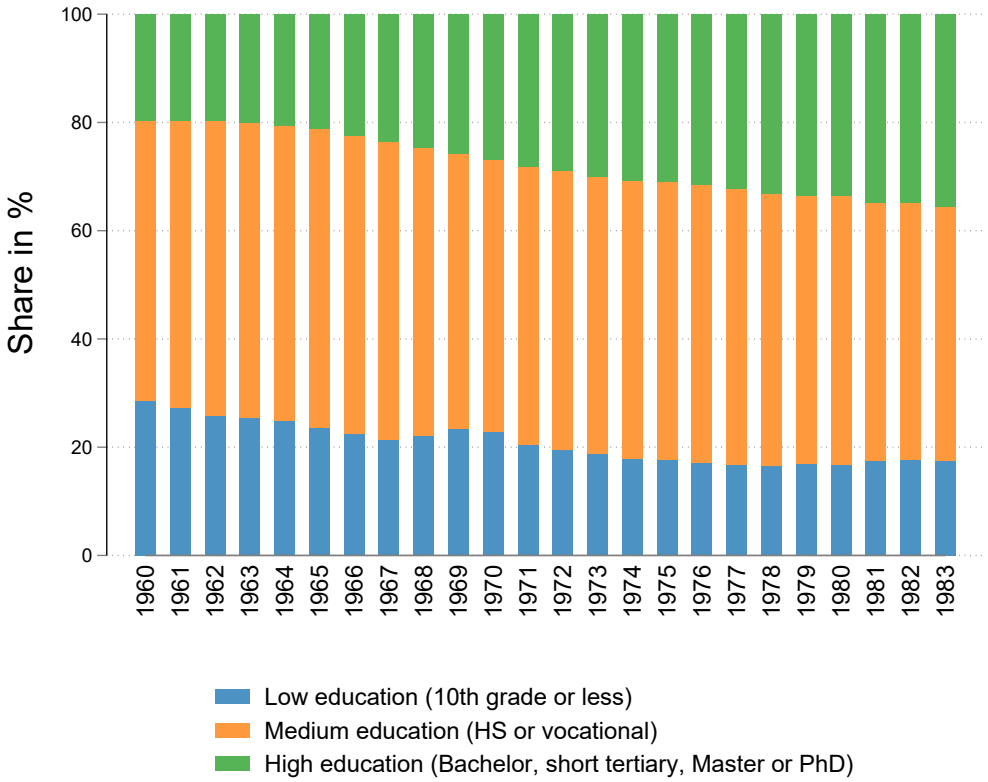
Figure A.1: Earnings and Net Income over Time



Note: Panels (a)-(d) plot mean annual earnings and net income as well as P10-P90 in the sample from 1980 to 2023, in 2015 DKK.

Figure A.2 shows the educational composition by birth cohort. The share of individuals with only primary education declines steadily across cohorts, while the share with university education rises. This compositional shift motivates presenting all results both for the full sample and separately by education group, since changes in aggregate lifetime inequality may otherwise conflate changes within groups with changes in the relative size of groups.

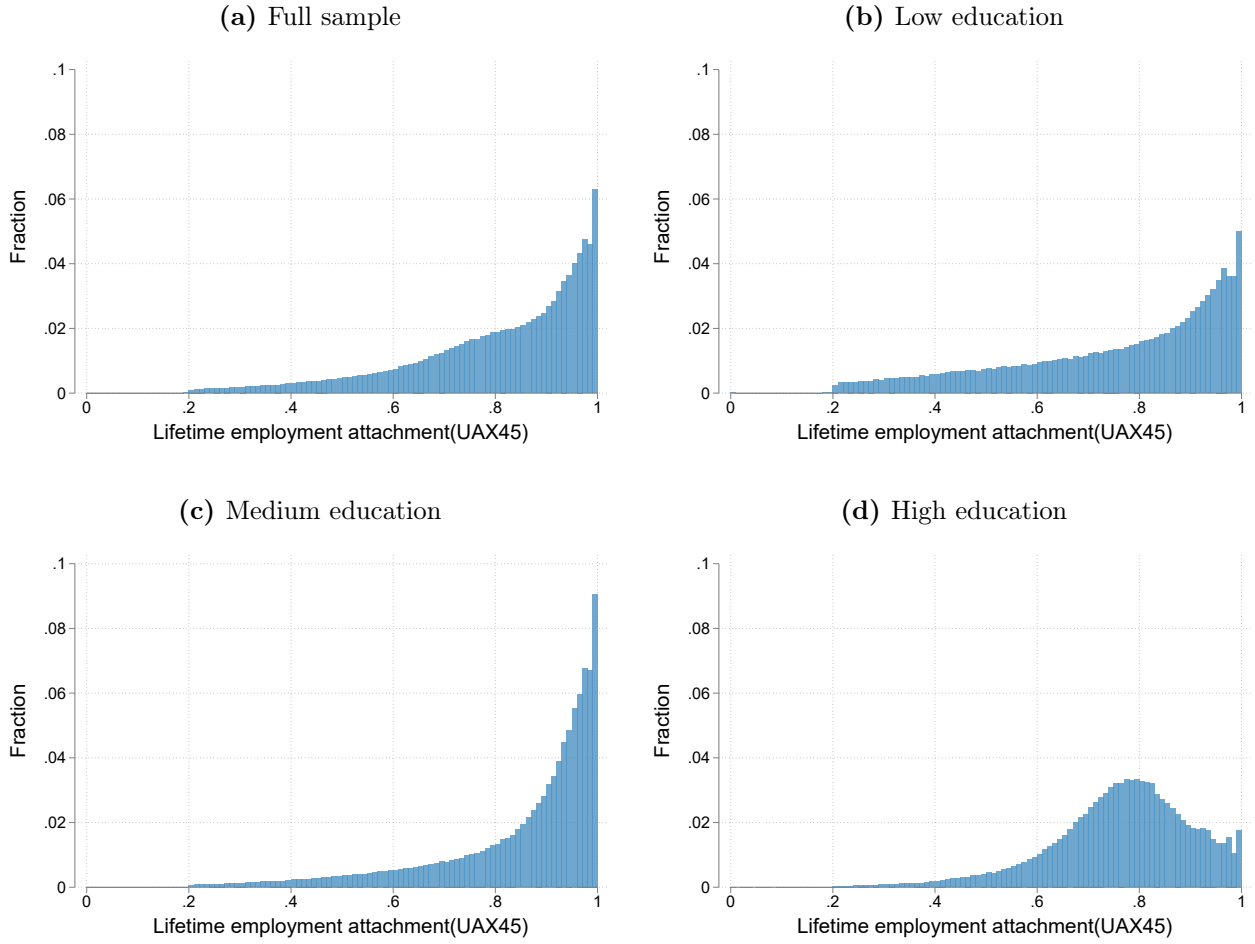
Figure A.2: Educational Composition by Birth Cohort



Note: The figure plots shares of individuals with low, medium, and high education by birth cohort (1960-1983). Education is measured at age 30.

Figure A.3 shows the distribution of lifetime employment attachment up to age 45 (as defined in Equation (2)), for the full sample and by education group. While most individuals accumulate close to full-time employment, a substantial share fall well below, and this lower tail is considerably more pronounced among low-educated workers. This part of the distribution would largely be excluded under the earnings- or hours-based sample restrictions common in the literature (see Appendix A.4), and retaining it is central to our analysis of the role of employment attachment.

Figure A.3: Distribution of Lifetime Employment Attachment



Note: The figure shows the distribution of lifetime employment attachment up to age 45 (defined in Equation (2)) for all cohorts for which UAX45 is available, for the full sample and by education group. A value of 1 corresponds to full-time employment in all years from age 20 to 45.

In addition to Figure A.3, Table A.4 reports summary statistics for lifetime employment attachment up to age 45, for the full sample and by education group. The spread differs markedly across groups: the interquartile range is 0.317 among individuals with low education, compared to 0.178 among those with a medium education — nearly twice as wide. The standard deviation shows the same pattern (0.210 versus 0.164). This confirms that limited educational attainment is associated not only with lower average employment attachment, but also with substantially more heterogeneous employment histories. The high education group is an exception to this ranking, with both a lower mean and a narrower IQR than the medium education group, likely reflecting later labor market entry during the UAX45 window rather than weaker attachment.

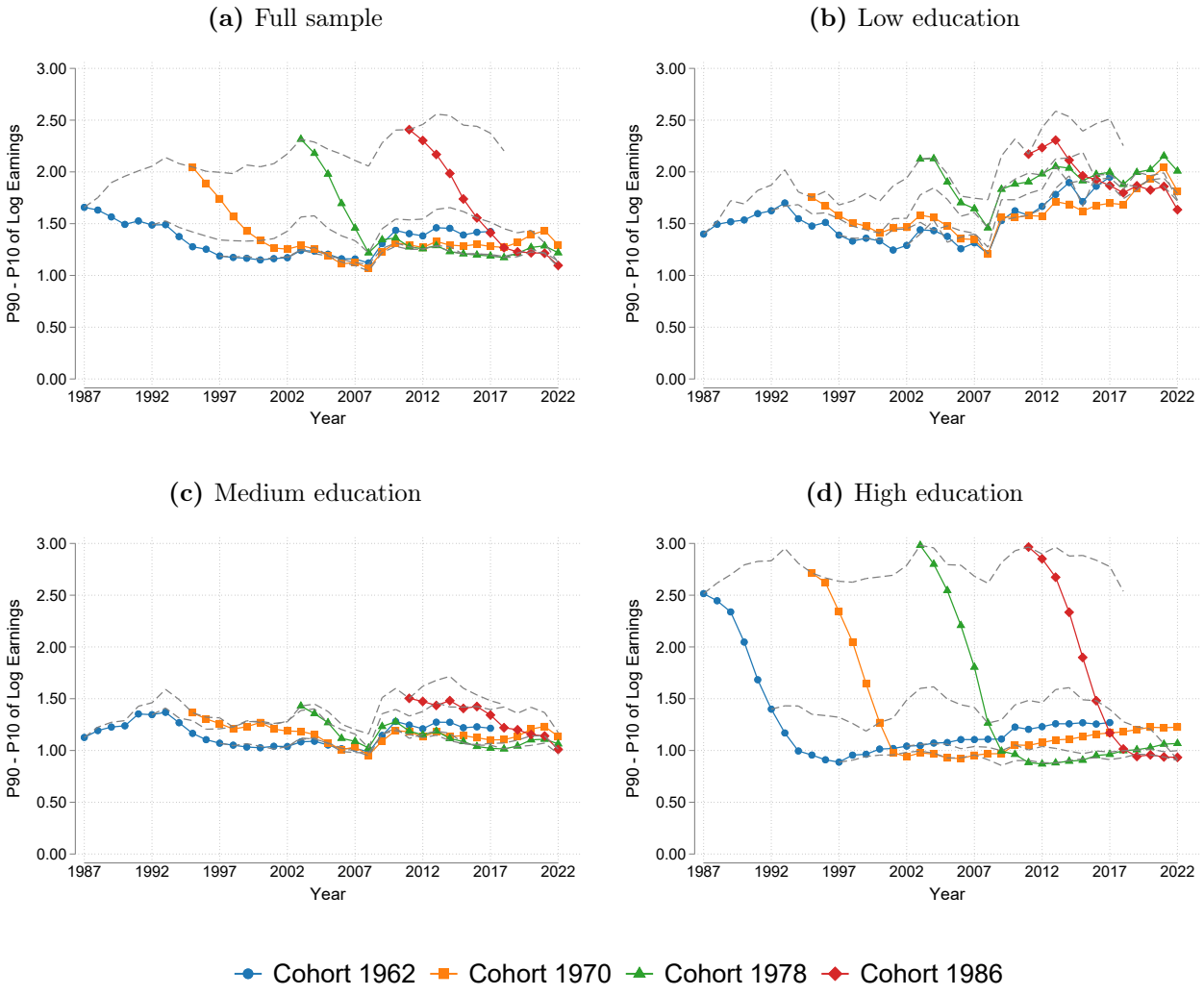
Table A.4: Summary Statistics for Lifetime Employment Attachment up to Age 45

Group	Mean	SD	P25	Median	P75	IQR
Full sample	0.806	0.175	0.714	0.855	0.947	0.233
Low education	0.755	0.210	0.616	0.816	0.933	0.317
Medium education	0.849	0.164	0.788	0.912	0.966	0.178
High education	0.763	0.137	0.689	0.777	0.858	0.169

Note: The table reports summary statistics for lifetime employment attachment up to age 45 (defined in Equation (2)), for the full sample and by education group. A value of 1 corresponds to full-time employment in all years from age 20 to 45. P25 and P75 denote the 25th and 75th percentiles, and IQR is the interquartile range (P75 - P25). Education is measured at age 30.

Figure A.4 replicates the life-cycle inequality patterns documented in Leth-Petersen and Sæverud (2022) in our sample: within cohorts, cross-sectional earnings dispersion declines with age, as early-career volatility fades and earnings profiles stabilize. The decline is particularly steep among the highly educated, whose dispersion is very high at early ages when many are still completing their education. The figure serves two purposes. First, it validates our sample construction by reproducing a central finding from the Danish literature, despite our sample being considerably less restrictive in terms of earnings requirements (see Appendix A.4). Second, it underscores the motivation for the lifetime approach taken in this paper: while cross-sectional dispersion narrows at young ages (and later on increase) this need not imply that lifetime inequality narrows with age (Figure 1), see the discussion in Section 3.1). Differences arise when income differences persist and accumulate over the life cycle, and it is precisely this accumulated component that our lifetime measures capture. Appendix B.7 provides a direct comparison of cross-sectional and lifetime inequality in our sample.

Figure A.4: Life-Cycle Patterns for Selected Cohorts



Note: P90-P10 log earnings differential across ages and cohorts. The figure replicates life-cycle inequality patterns documented in Leth-Petersen and Sæverud (2022) (Figure 5), showing how cross-sectional earnings dispersion narrows with age.

A.4 Details on Sample Relative to Previous Work

Table A.5 provides an overview of the sample restrictions imposed in a selection of related papers alongside our own. The papers vary considerably in their age spans, earnings thresholds, and attachment requirements, reflecting both differences in data availability and research focus. Several papers — including Haider and Solon (2006) and Böhlmark and Lindquist (2006) — study the association between current and lifetime income rather than lifetime earnings inequality directly, and their restrictions are accordingly less demanding. Others, such as Guvenen et al. (2022) and Bönke et al. (2015), impose stricter lifetime attachment requirements to ensure complete earnings biographies. Our own restrictions are relatively permissive: we require only that individuals are observed for at least 75 percent of possible years and have some labor market attachment, and we include self-employed individuals, a group often excluded in the literature.

A key difference between our approach and much of the prior literature concerns the treatment of incomplete earnings histories. Most existing studies either require complete earnings biographies by construction — for instance, Guvenen et al. (2022) divide by a fixed denominator of 31 years and restrict the sample to individuals with valid biographies up to the relevant age — or impute missing earnings years, as in Bick et al. (2024). By contrast, our UAX measure uses an at-risk correction, dividing cumulative earnings by the number of years an individual is actually observed rather than a fixed number of possible years. This allows us to retain individuals with incomplete careers in the sample without requiring imputation or exclusion.

[26]This high sample share is due to the nature of their data sources, which cannot be replicated on Danish data. Haider and Solon (2006) drop only 33 individuals due to sample criteria and end up with a sample of 821 individuals.

[27]The replication of sample restrictions of Bönke et al. (2015) omits their East/West Germany, repatriate, and pension-system rejoiner restrictions, as these categories have no meaningful equivalent in the Danish setting and data. Our replication sample is therefore significantly less restrictive along these dimensions than the original.

[28]The full-attachment requirement in Bick et al. (2024) is only satisfiable for cohorts old enough to have completed the relevant age range in the data window, which mechanically drops the number of observations significantly when applied to a broader set of cohorts in the Danish data.

Table A.5: Sample Restrictions in Related Papers

Paper	Age span	Requirement to enter sample	Yearly threshold value	Other	*N* (DK)	Sample share after restrictions
This paper	20-60	Observed $\geq$ 75% of possible years. 25% employment up to age 40.		Self-employed included. Men only.	30,016,777	92.5%
Deaton and Paxson (1994)	20-75 (Taiwan) 23-78 (US) 22-77 (UK)	Age of household head.		Repeated cross-sections. Household-level data. Urban households only (US).	-	-
Haider and Solon (2006)	19-59	At least 10 years of positive earnings		Men only. Zero earnings and $<$ \$50 both left-censored at \$50.	30,560,556	96.1%[26]
Huggett et al. (2011)	23-60	Yearly requirement	Age $>$ 30: $>$ \$1500 (1968) + $>$ 520 hours Age $\leq$ 30: $>$ \$1000 (1968) + $>$ 260 hours	Male household heads only. PSID survey data.	21,409,858	Not reported
Guvenen et al. (2022)	25-55	At least 15 years above threshold. Total lifetime earnings (ages 25–55) $\geq$ 31 $\times$ cohort-specific average annual threshold.	$>$ 520 hours $\times$ 0.5 yearly minimum wage	Workers in "commerce and industry". Remove income from self-employment.	7,996,928	Not reported
Leth-Petersen and Sæverud (2022)	25-55	Earnings and disposable income both at least the yearly threshold value	28,500 DKK (2018 prices)	Both men and women.	21,979,057	Not reported
Böhlmark and Lindquist (2006)	(first) 20-60 (second) 19-53	At least 10 years of positive earnings		Men only. Immigrants after age 16 excluded. Individuals must not leave sample due to death or emigration.	28,978,392	Not reported
Bönke et al. (2015)	17-60	Allow for an average of 1 month missing per year (i.e. without social security info) after the age of 30		West German men only. Exclude self-employed, civil servants, and emigrants.	26,547,493[27]	26.4% (Appendix I.4)
Bick et al. (2024)	25-55	Men with $\geq$520 hours in all 31 years.	$>$520 hours every year	NLSY79 survey data. Hourly wages $<$ half the minimum wage censored; hours set to missing for top 0.1% of the hourly wage distribution.	3,250,753[28]	22.4%
Ozkan et al. (2023)	25-55	Earnings above the threshold in at least three quarters of years and no two consecutive years below it.	25 percent of full-year, full-time pay at half the minimum wage	men only, self-employed excluded	-	45.5%

Note: After restricting attention to men born between 1960 and 1983 who are alive and residing in Denmark for at least 75 percent of the possible years, but before enforcing the employment-attachment requirement, the sample consists of 32,446,727 observations. All number of observations in the column "N (DK)" should be seen relative to this. The column "Sample share after restrictions" indicates the share of each paper's own sample that remains for analysis after their respective sample restrictions.

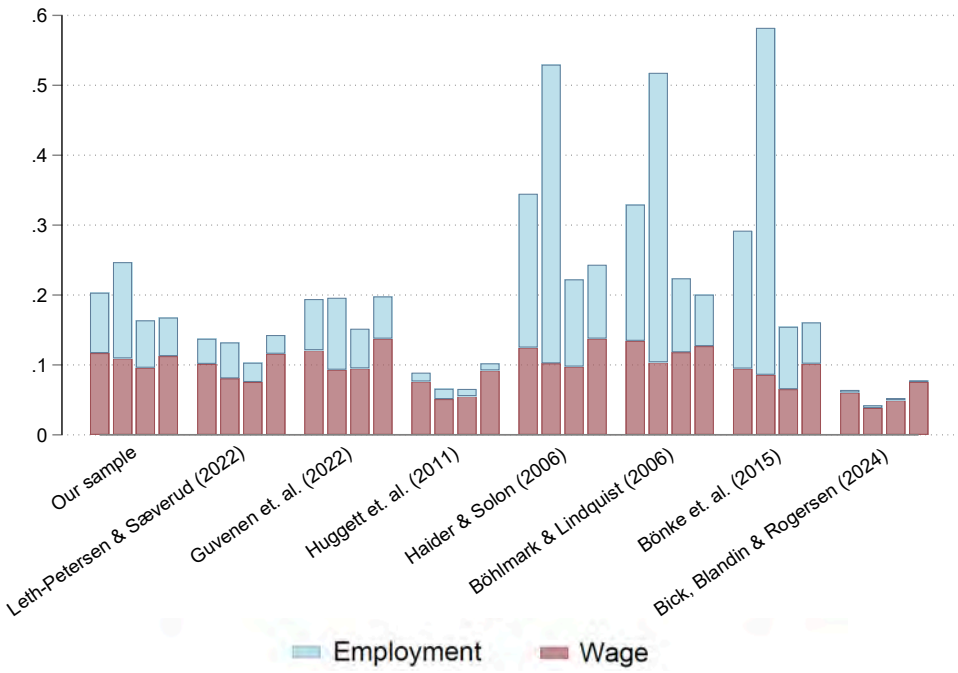
To assess how sensitive our main results are to the choice of sample restrictions, Figure A.5 replicates the ensemble decomposition of inequality up to age 45 from Figure 2 under each of the alternative restrictions used in related papers described in Table A.5.

We implement each restriction by applying it to our own unrestricted sample and then constructing lifetime earnings exactly as in our baseline, using the at-risk correction (see Table A.5 for the exact thresholds, age spans, and group exclusions). This isolates the effect of the sample restriction itself, holding the data source, the lifetime earnings measure, and the decomposition method fixed. We approximate each restriction as follows. For the annual-earnings thresholds (Huggett et al., 2011; Leth-Petersen and Sæverud, 2022), we retain only person-years in which real earnings exceed the relevant threshold, applied observation by observation. For the biography requirements (Guvenen et al., 2022; Bick et al., 2024; Bönke et al., 2015), we require individuals to be observed with sufficient earnings for a minimum number of years: following Guvenen et al. (2022), we require earnings above a cohort-specific threshold in at least 15 years and total earnings of at least 31 times the annual threshold, and following Bönke et al. (2015) and Bick et al. (2024), we require near-complete earnings biographies from age 30 onward. For the positive-earnings requirements (Haider and Solon, 2006; Böhlmark and Lindquist, 2006), we require at least ten years of positive earnings. Because the underlying data are the same across all bars, remaining differences reflect the restrictions themselves rather than differences in data or country.

Two findings stand out. First, the level of measured inequality varies enormously across restrictions. Restrictions based on strict annual earnings thresholds (e.g. Leth-Petersen and Sæverud, 2022; Huggett et al., 2011) yield lower inequality than our baseline, as they remove the weakly attached part of the distribution. At the very extreme, requiring practically full employment biographies as in Bick et al. (2024) fully removes the employment-attachment component of inequality. Conversely, restrictions requiring little more than positive annual earnings (e.g. Haider and Solon, 2006; Böhlmark and Lindquist, 2006) yield substantially higher inequality than our baseline: without a meaningful attachment requirement, individuals with essentially no labor market connection enter with near-zero lifetime earnings and inflate the variance of logs. Our sample lies between these extremes, which reflects the design of our restriction: a modest requirement on lifetime attachment removes individuals with essentially no connection to the labor market, while retaining the weakly attached individuals who are central to our analysis. Notably, the composition of inequality also shifts: under the more restrictive annual-earnings thresholds, the employment-attachment component accounts for a smaller share of total inequality than in our baseline. This is precisely because these restrictions remove individuals with weak attachment, mechanically suppressing the very margin we identify as a key driver. Studies imposing such restrictions may therefore understate the role of employment attachment in lifetime inequality. Second, this illustrates an advantage of conditioning on a lifetime measure rather than an annual one: annual thresholds select on the outcome year by year and mechanically truncate the earnings distribution, whereas our mild lifetime criterion (employment in at least 25 percent of possible

years up to age 40) only screens out non-participants, imposes no earnings floor on those with some attachment, and leaves individual earnings histories intact.

Figure A.5: Ensemble Decomposition under Alternative Sample Restrictions



Note: The figure shows the results from Figure 2 for approximations of different sample restrictions from the literature (see Table A.5). For each set of sample restrictions, the first bar to the left shows the decomposition for the full sample, the second bar for low educated, the third bar for medium educated, and the fourth bar for the high educated.

Table A.6 reports, for the full sample and separately by education group, the share of individuals excluded by the up-to-age-40 25 percent employment requirement. For the full sample, the exclusion rate is fairly stable at around 6 percent for cohorts born before the mid-1970s, but rises gradually thereafter, reaching 9.0 percent for the 1982 and 1983 cohorts. This upward trend is driven almost entirely by low-educated individuals: their exclusion rate roughly doubles, from 14–17 percent among cohorts born in the 1960s to over 25 percent among cohorts born from the late 1970s onward. Exclusion rates for medium- and high-educated individuals remain comparatively stable throughout, at 2–4 percent.

A descriptive analysis of the excluded individuals shows that they are disproportionately unemployed, on disability pension, or on social assistance. Their average employment is typically far below the 25 percent threshold rather than marginally below it, suggesting that the restriction does not primarily exclude borderline cases sensitive to the exact cutoff, but rather isolates a group with persistently weak labor market attachment.

Table A.6: Number of Individuals Dropped by Cohort

Birth cohort	**Full sample**		**Low education**		**Medium education**		**High education**	
	% dropped	Initial N	% dropped	Initial N	% dropped	Initial N	% dropped	Initial N
1960	6.6	36,099	14.5	11,641	2.8	17,750	2.9	6,708
1961	6.1	35,972	13.5	11,001	3.0	18,189	2.8	6,782
1962	6.2	37,070	14.3	10,814	3.1	19,301	2.9	6,955
1963	6.1	39,386	14.3	11,353	2.6	20,529	2.9	7,504
1964	6.2	40,601	14.7	11,550	2.6	21,123	2.9	7,928
1965	5.9	41,155	15.1	11,196	2.5	21,629	2.4	8,330
1966	6.0	42,743	15.7	11,137	2.4	22,462	2.7	9,144
1967	6.1	39,767	16.3	9,912	2.7	20,920	2.8	8,935
1968	6.3	37,297	15.7	9,617	2.5	18,932	3.2	8,748
1969	6.1	35,526	15.2	9,533	2.3	17,279	3.1	8,714
1970	6.0	35,542	15.2	9,316	2.4	17,106	3.0	9,120
1971	6.1	37,495	17.0	9,147	1.9	18,344	2.9	10,004
1972	6.1	37,558	17.7	8,768	2.1	18,499	2.8	10,291
1973	6.3	35,638	19.2	8,169	2.0	17,371	2.8	10,098
1974	6.5	35,652	20.6	7,919	2.0	17,428	2.8	10,305
1975	6.5	36,113	20.7	8,012	2.0	17,586	2.8	10,515
1976	6.8	33,527	21.8	7,360	2.2	16,258	2.8	9,909
1977	7.2	31,472	23.6	6,756	2.4	15,171	3.0	9,545
1978	7.6	31,660	25.1	6,861	2.1	15,005	3.2	9,794
1979	8.0	30,455	25.4	6,731	2.4	14,203	3.6	9,521
1980	8.1	29,647	25.6	6,465	2.6	13,870	3.6	9,312
1981	8.3	27,482	26.0	6,249	2.3	12,317	3.6	8,916
1982	9.0	27,919	27.3	6,457	2.6	12,481	4.1	8,981
1983	9.0	27,224	28.1	6,302	2.6	11,971	3.9	8,951

Note: Table A.6 shows, for the full sample as well as each of the three education groups, the number of individuals by cohort before applying the up-to-age-40 25 percent employment requirement and the percentage dropped by this sample restriction for each cohort.

B Additional Results: Part 1

B.1 Inequality within Education Groups

This section documents the within–between variance decomposition (Equation (5)) underlying the focus on within-group inequality in Section 3.2. Table B.1 reports the decomposition of the variance of log lifetime earnings into within- and between-education-group components at different ages. The within-group component is by far the dominant source of inequality at all ages, accounting for 96 percent of total variance at age 30 and 90 percent at age 50. The between-group share grows modestly from age 35 onwards, reflecting that educational earnings differences accumulate over the life cycle, but remains small throughout.

Table B.1: Within- and Between-Group Variance

Age	Within variation	Between variation	Total variance
30	.3031	.0109	.3140
35	.2216	.0057	.2274
40	.1795	.0103	.1898
45	.1871	.0165	.2036
50	.2070	.0235	.2305
55	.2273	.0296	.2569
60	.2411	.0324	.2735

Note: Decomposition of the variance of log lifetime earnings, $Var(\ln LI_{UAX})$, into within- and between-education-group components at different ages following Equation (5) for the lifetime sample.

B.2 Income Mobility and Rank-Rank Correlations

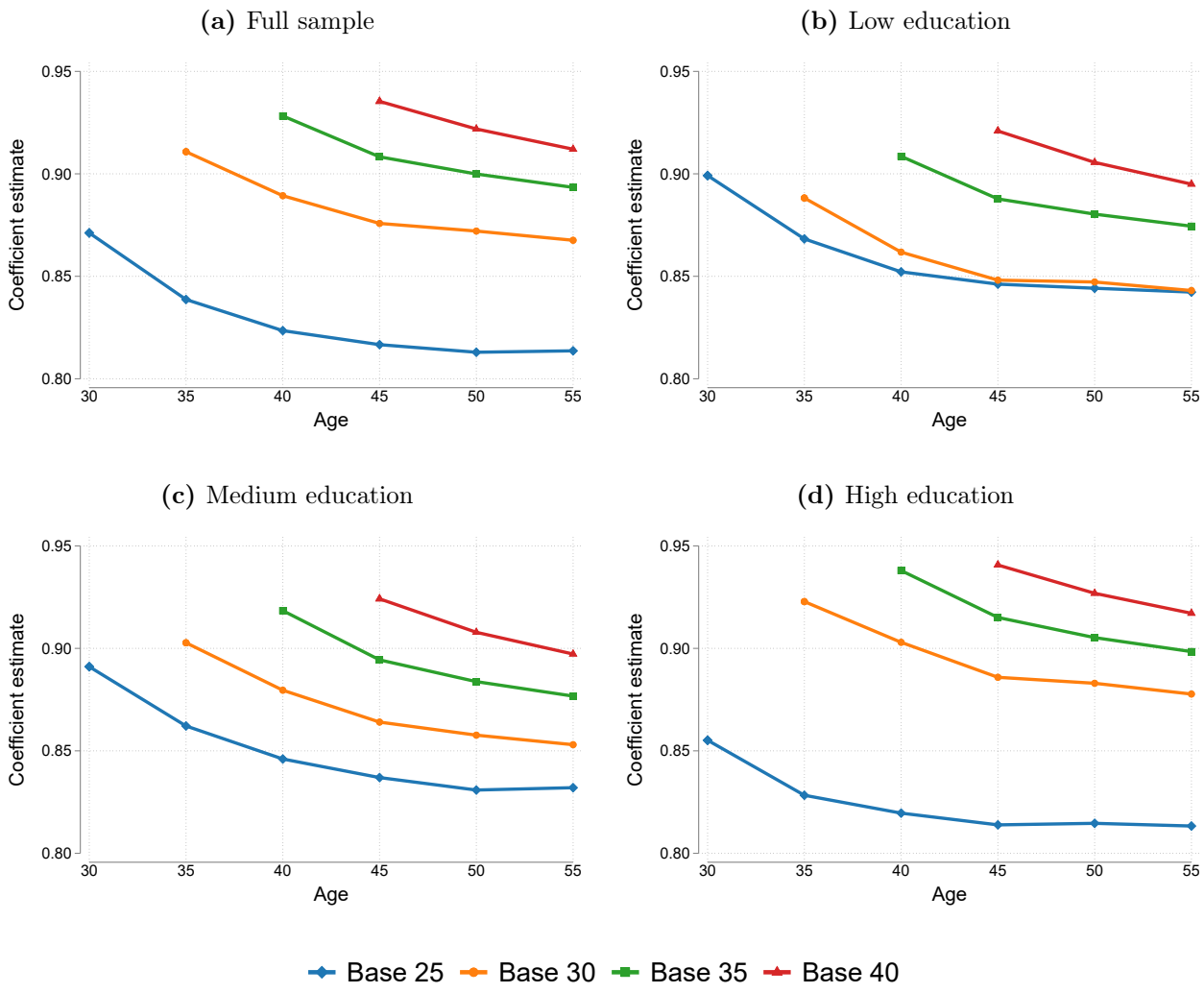
A key workhorse, inspired by the intergenerational mobility literature, is a set of rank-rank regressions of the form:

$$Y_{a,i} = \alpha^{a_0,a} Y_{a_0,i} + \epsilon_{a,i} \tag{11}$$

where $Y_{a,i}$ is individual i's rank in the distribution of annual earnings at age a, and α measures the dependence of current income rank at age a on previous periods income rank (as determined by age a_0). We work with income in ranks to ease interpretability and since this is a flexible way to incorporate periods with zero earnings due to non-employment in a given year (they will simply be assigned the lowest rank). The smaller the estimate of $\alpha^{a_0,a}$ the higher the income mobility meaning that income differences at age a are to a lower extent explained by income differences earlier in the life cycle.

In Figure B.1, we plot estimates of α (so-called mobility curves) in our sample for different a_0 benchmarks, estimated on the lifetime sample. Across sub-samples, we see that α is generally higher, the higher the initial base (a_0). This implies that mobility is generally lower the later in the life cycle we measure mobility from (set base year a_0). In addition, mobility curves are declining in a suggesting that the longer the time span from a_0 to a the weaker the predictor is a_0 for income at a. The persistence estimates are nevertheless high throughout: for base age 40, coefficients range from roughly 0.85 to 0.95 across samples, and within a given sample the slope of the mobility curve is quite similar across different curves (i.e. different a_0 measures). Overall, these curves suggest that rankings based on earnings in a given age become more and more stable with age consistent with our previous findings that a larger portion of lifetime inequality materializes earlier in the life cycle compared to later in the life cycle.

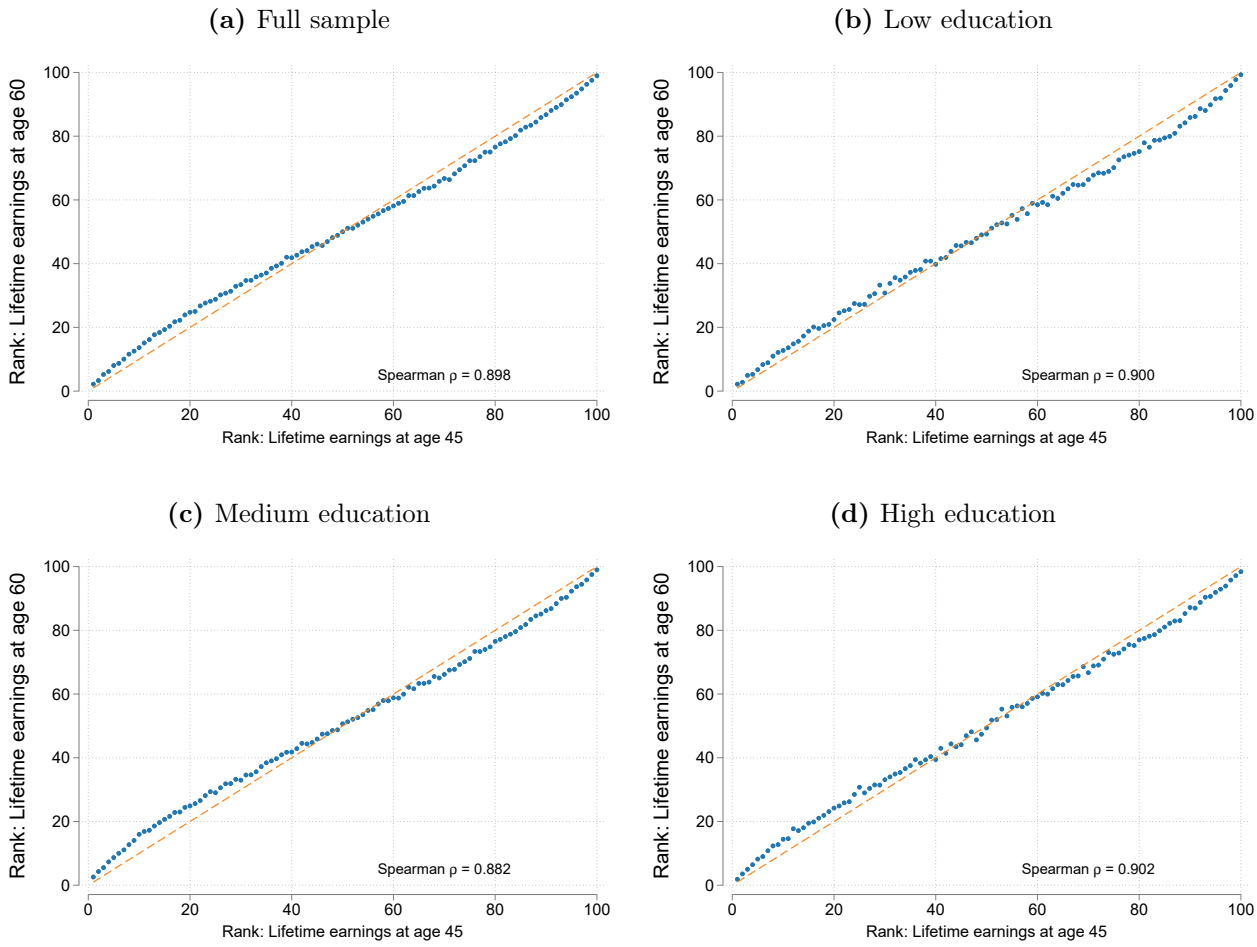
Figure B.1: Mobility over the Life Cycle



Note: Income-rank persistence over the life course from rank-rank regressions that relate an individual's income rank at age a to their rank at an earlier "base" age, following Equation (11). The vertical axis shows the estimated persistence (higher values = lower mobility). Lines decline as the distance from the base age increases, indicating that earlier ranks predict later ranks less over longer horizons. Coefficients are higher when the base age is later (e.g. Base 40), consistent with more stable rank positions at older ages.

While the mobility curves in Figure B.1 are based on annual income ranks, Figure B.2 turns to the stability of the lifetime measures themselves. It plots the mean rank of lifetime earnings accumulated to age 60 (UAX60) within each percentile bin of lifetime earnings at age 45 (UAX45), for the lifetime sample. Ranks are percentile ranks (100 quantile bins) of lifetime earnings at ages 45 and 60, computed in the pooled sample; in panels (b)–(d), ranks are computed within each education group. Each dot shows the mean age-60 rank among individuals in a given age-45 percentile bin, for individuals with both measures available, and the reported Spearman correlations are computed on the underlying, unbinned lifetime earnings. The dots lie very close to the 45-degree line, and the Spearman rank correlation is 0.90 in the full sample. Thus, although earnings continue to accumulate for another 15 years, individuals' positions in the lifetime earnings distribution are essentially settled by age 45. This supports the use of up-to-age-45 measures in the cohort analysis in Section 4.

Figure B.2: Rank Stability of Lifetime Earnings



Note: This figure shows the rank-rank correlation between lifetime earnings measured at age 45 (UAX45) and age 60 (UAX60) for the lifetime sample. Lifetime earnings are defined in Equation (1) as cumulative earnings up to age X. Each dot represents the mean rank of UAX60 within a UAX45 percentile bin. The dashed line indicates perfect rank preservation. Spearman rank correlations are shown in each panel.

B.3 Lifetime Wage-Employment Decomposition

This section presents the classical wage-hours variance decomposition as a complement to the ensemble decomposition (Equation (7)) used in the main text. While the ensemble method has the advantage that the components sum to total inequality, the classical decomposition makes the role of the covariance between employment and wages explicit. Using the definition of LW^i_{UAX}, we decompose:

$$\begin{aligned} Var(\ln LI^i_{UAX}) &= Var\left(\ln LH^i_{UAX} + \ln LW^i_{UAX}\right) \\ &= Var\left(\ln LH^i_{UAX}\right) + Var\left(\ln LW^i_{UAX}\right) + 2Cov(\ln LH^i_{UAX}, \ln LW^i_{UAX}) \end{aligned} \tag{12}$$

The first term in this decomposition, $Var\left(\ln LH^i_{UAX}\right)$, quantifies the role of dispersion in lifetime employment attachment as a driver of dispersion in lifetime earnings across individuals. Dispersion in employment attachment across individuals may arise from differences in non-employment occurrence (and/or length) over the life cycle such as e.g. unemployment, part-time work, sickness period(s), leave, educational enrollment, etc.

The second term, $Var\left(\ln LW^i_{UAX}\right)$, quantifies the role of dispersion in lifetime wages. As discussed above, LW^i_{UAX} is to some extent an accounting/residual measure which may be shaped by many factors including differences in e.g. the life-cycle profile of wages as well as potentially interactions between the timing of employment and wages. For this reason, we also think of the second term as representing the role of factors not directly accounted for by (accumulated) employment attachment.

The last term in the decomposition, $2Cov(\ln LH^i_{UAX}, \ln LW^i_{UAX})$, describes the dependence between lifetime employment and lifetime wages in the data. A positive covariance means that in the data individuals with higher employment attachment also command higher lifetime wages on average. This would therefore describe a situation where fluctuations in employment attachment across individuals lead to increasing inequality both via the immediate earnings gain from periods with above average employment attachment but also due to e.g. additional favorable wage dynamics for these individuals over time. Note that measurement error in employment attachment (that is actual error in hours or unaccounted for periods of non-employment) would tend to drive lifetime wages in the opposite direction as employment and therefore bias the results towards a negative covariance. Alternatively, a negative covariance would describe a situation where individuals with lower lifetime wages would also tend to work more over the life cycle. Learning-by-doing human capital theory on the other hand would suggest a positive covariance, since those who work a lot also command high wages due to higher levels of human capital.

In Figure B.3, we report each of the components in our variance decomposition of Equation

(12) across our 4 samples.[29]

The results align closely with the ensemble decomposition in Figure 2: variation in employment attachment is an important driver of lifetime earnings inequality, most so for the low educated, while wage dispersion dominates for the medium and high educated. The levels attributed to each component differ only slightly from Figure 2 (e.g. 0.08 versus 0.10 log points for the employment component at age 50 in the full sample) because the ensemble method allocates the covariation between employment and wages to the two components, whereas it is reported separately here.

The main additional insight from the classical decomposition is therefore the covariance term itself. At age 30, the covariance is negative in all samples, and most pronounced among the highly educated, consistent with the measurement and timing effects discussed above. From around age 45 it turns modestly positive, implying that individuals with higher lifetime employment attachment also command somewhat higher lifetime wages, in line with, for example, human capital accumulation through experience. The covariance component remains small relative to the two variance terms throughout, so the relative roles of employment and wages are robust to how the covariation is allocated.

[29]Note that the education-specific groupings now focus on decomposing "the within-education group variance" and therefore they do not add up to the numbers reported in Figure 1.

Figure B.3: Classical Variance Decomposition



Note: Decomposition of lifetime earnings inequality using Equation (12) into three components: employment attachment (orange), wages (blue), and their covariance (red). Each part of the bar represents the part of total lifetime earnings inequality explained by these components at a given accumulation age.

B.4 Decomposition of Employment Attachment

Table B.2 complements Table 1 by reporting the full set of variance shares for all variables in Model 2 in Section 3.3.1.

Table B.2: Decomposing Earnings and Employment Differences: Full Model 2

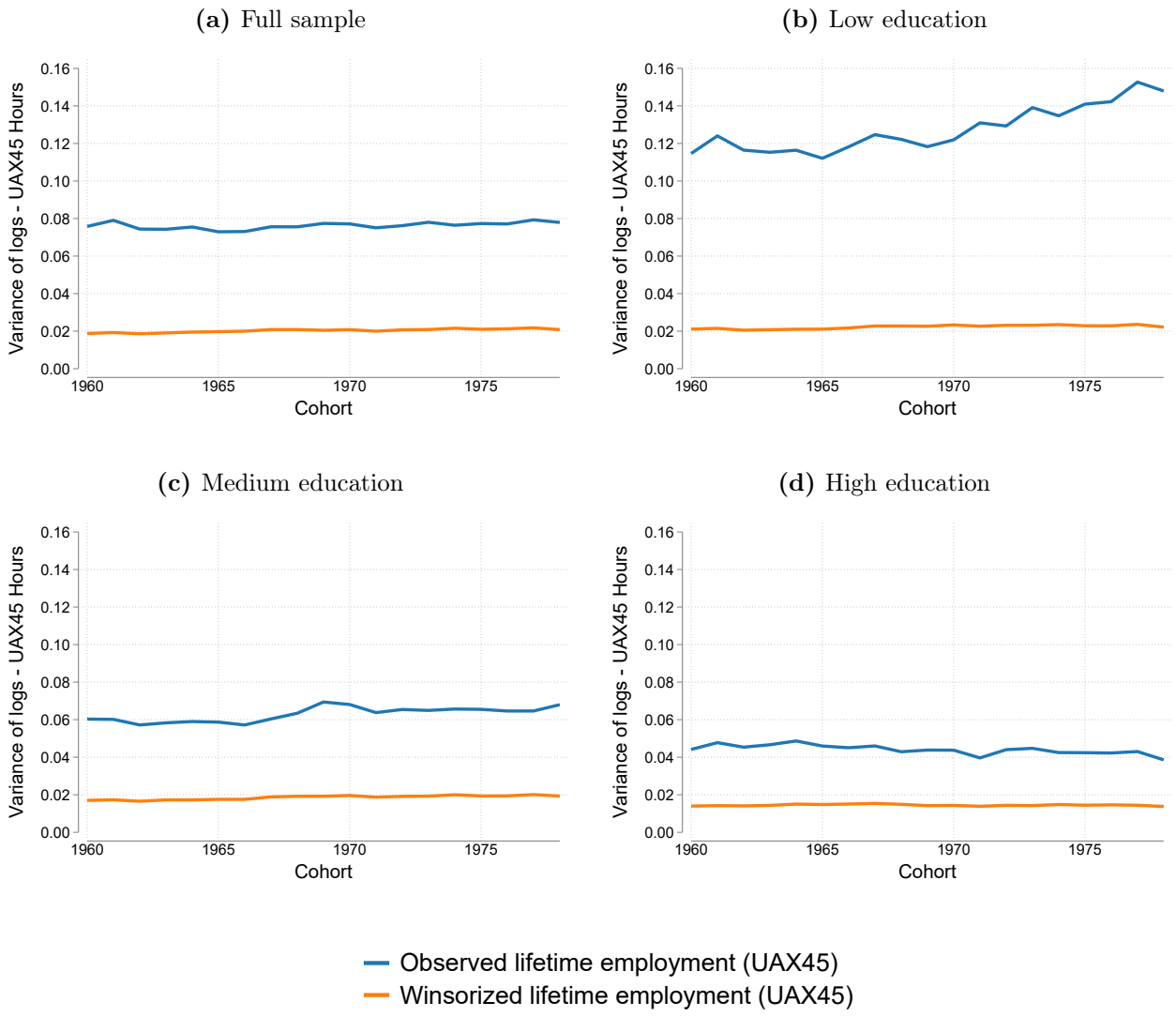
		Model 2									
	Total	Part-time	Children	Education	Retirement	Sickness	Disability	UI	Soc. assist.	Rehab.	Residual
Earnings											
Full Sample	.2036	.0067	.0032	.0001	.0000	.0102	.0127	.0272	.0401	.0000	.1034
	[100]	[3.31]	[1.59]	[0.03]	[0.01]	[4.99]	[6.25]	[13.38]	[19.72]	[0.00]	[50.72]
Low Education	.2473	.0181	.0018	.0001	.0000	.0097	.0247	.0228	.0600	.0000	.1101
	[100]	[7.32]	[0.72]	[0.02]	[0.01]	[3.94]	[9.99]	[9.22]	[24.26]	[0.00]	[44.52]
Medium Education	.1638	.0097	.0042	.0005	.0000	.0083	.0078	.0185	.0241	.0000	.0907
	[100]	[5.89]	[2.59]	[0.32]	[0.00]	[5.05]	[4.77]	[11.30]	[14.73]	[0.00]	[55.35]
High Education	.1686	.0013	.0019	.0004	.0000	.0077	.0033	.0366	.0234	.0001	.0939
	[100]	[0.75]	[1.16]	[0.23]	[0.01]	[4.54]	[1.97]	[21.68]	[13.92]	[0.05]	[55.69]
Employment											
Full Sample	.0753	.0080	.0000	.0007	.0000	.0028	.0063	.0106	.0221	.0000	.0248
	[100]	[10.64]	[0.05]	[0.97]	[0.02]	[3.68]	[8.42]	[14.48]	[29.34]	[0.01]	[32.39]
Low Education	.1165	.0088	.0002	.0004	.0000	.0056	.0133	.0147	.0421	.0000	.0314
	[100]	[7.57]	[0.18]	[0.35]	[0.01]	[4.84]	[11.41]	[12.65]	[36.11]	[0.01]	[26.87]
Medium Education	.0589	.0068	.0000	.0007	.0000	.0023	.0047	.0095	.0164	.0000	.0185
	[100]	[11.50]	[0.01]	[1.22]	[0.01]	[3.97]	[8.00]	[16.12]	[27.77]	[0.00]	[31.40]
High Education	.0465	.0051	.0001	.0007	.0000	.0012	.0012	.0104	.0073	.0000	.0205
	[100]	[11.05]	[0.14]	[1.58]	[0.05]	[2.61]	[2.56]	[22.32]	[15.71]	[0.00]	[43.98]

Note: Table B.2 reports the full set of Model 2 components from the ensemble decomposition in Equation (9) of lifetime earnings inequality (up to age 45); Table 1 shows the condensed version. The regressors are part-time work, childbirth-related absences, education, retirement, sickness, disability, unemployment insurance, social assistance, and rehabilitation benefits, plus a residual (see Appendix A.2 for definitions). For each predictor, the first row (Earnings) reports the covariance contribution to total lifetime earnings inequality, with the share of total inequality given in square brackets. The second row (Employment) reports the corresponding contribution to inequality in lifetime employment attachment, with the share of employment-attachment inequality given in square brackets. Results are reported for the full sample and for each education group.

B.5 Lower Tail of the Employment-Attachment Distribution

This section examines how much of the dispersion in lifetime employment attachment is driven by the lower tail of the distribution. Figure B.4 plots the variance of log lifetime employment up to age 45 by birth cohort, together with a counterfactual in which the distribution is winsorized at the 20th percentile within each cohort, that is, individuals below the 20th percentile are assigned the value at the 20th percentile. Comparing the two series shows that the bottom 20 percent of the attachment distribution accounts for around 75 percent of the variance in lifetime employment in the full sample, and even more among the low educated. Moreover, the winsorized series is essentially flat across cohorts in all samples, so the rise in employment-attachment inequality across cohorts among the low educated (panel (b)) is driven almost entirely by the bottom of the distribution. This motivates the Bottom20 analysis in Section 3.3.2 and foreshadows the cohort results in Section 4. Table B.3 reports the R-squared across different specifications of the bottom 20 regressions in Section 3.3.2. The results are discussed in Section 3.3.2.

Figure B.4: Inequality in Lifetime Employment



Note: Figure B.4 shows the variance of log lifetime employment attachment up to age 45 by birth cohort (blue), and the corresponding variance when the attachment distribution is winsorized at the 20th percentile within each cohort (orange).

Table B.3: Bottom 20: Employment Shocks

	R^2					
	Full model	Excl. mass layoffs	Excl. sickness	Excl. disability	Excl. children	Excl. recessions
Full sample	0.1690	0.1667	0.1392	0.1446	0.1635	0.1065
Low education	0.2133	0.2078	0.1754	0.1853	0.2110	0.1371
Medium education	0.1782	0.1761	0.1500	0.1466	0.1716	0.1140
High education	0.0941	0.0929	0.0808	0.0891	0.0834	0.0448

Note: Table B.3 reports the R-squared from estimating Equation (10), which shows which employment shocks best predict if an individual is in the bottom 20 percent of the employment-attachment distribution (up to age 45). That is, each "Excl." column reports the R-squared when a specific employment shock is excluded from the full specification, to illustrate the relative contribution to the model's explanatory power.

B.6 Lifetime Transfers and Lifetime Employment Attachment

This section examines the relationship between lifetime employment attachment and lifetime transfers in more detail.

Figure B.5 shows a concentration curve (ranking individuals by lifetime employment attachment and cumulating their share of aggregate lifetime transfers). Across all four panels, the concentration curve lies well above the line of equality, indicating that this relationship is concentrated among individuals with the weakest employment histories.

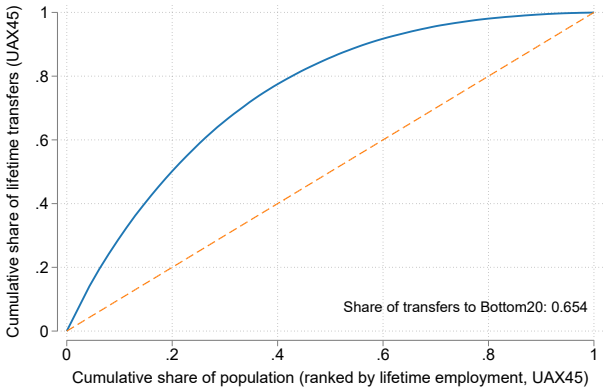
Figure B.6 plots average lifetime transfers within each decile of the lifetime employment-attachment distribution, for the full sample and by education group. In all four panels, average transfers decline sharply with employment attachment, from around 50,000–80,000 DKK in the lowest deciles to close to zero among the most attached individuals. The Spearman rank correlation between the two measures is strong throughout, ranging from $\rho = -0.738$ among high-educated workers to $\rho = -0.879$ among low-educated workers. This decile-level view complements the concentration curve in Figure B.5 (see also Section 3.4).

Figure B.5: Concentration Curve of Lifetime Transfers by Lifetime Employment Attachment

(a) Full sample



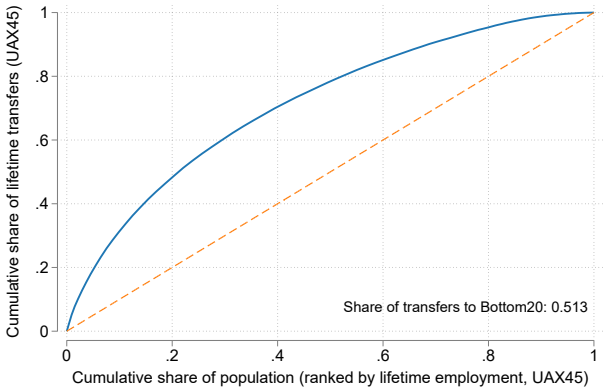
(b) Low education



(c) Medium education

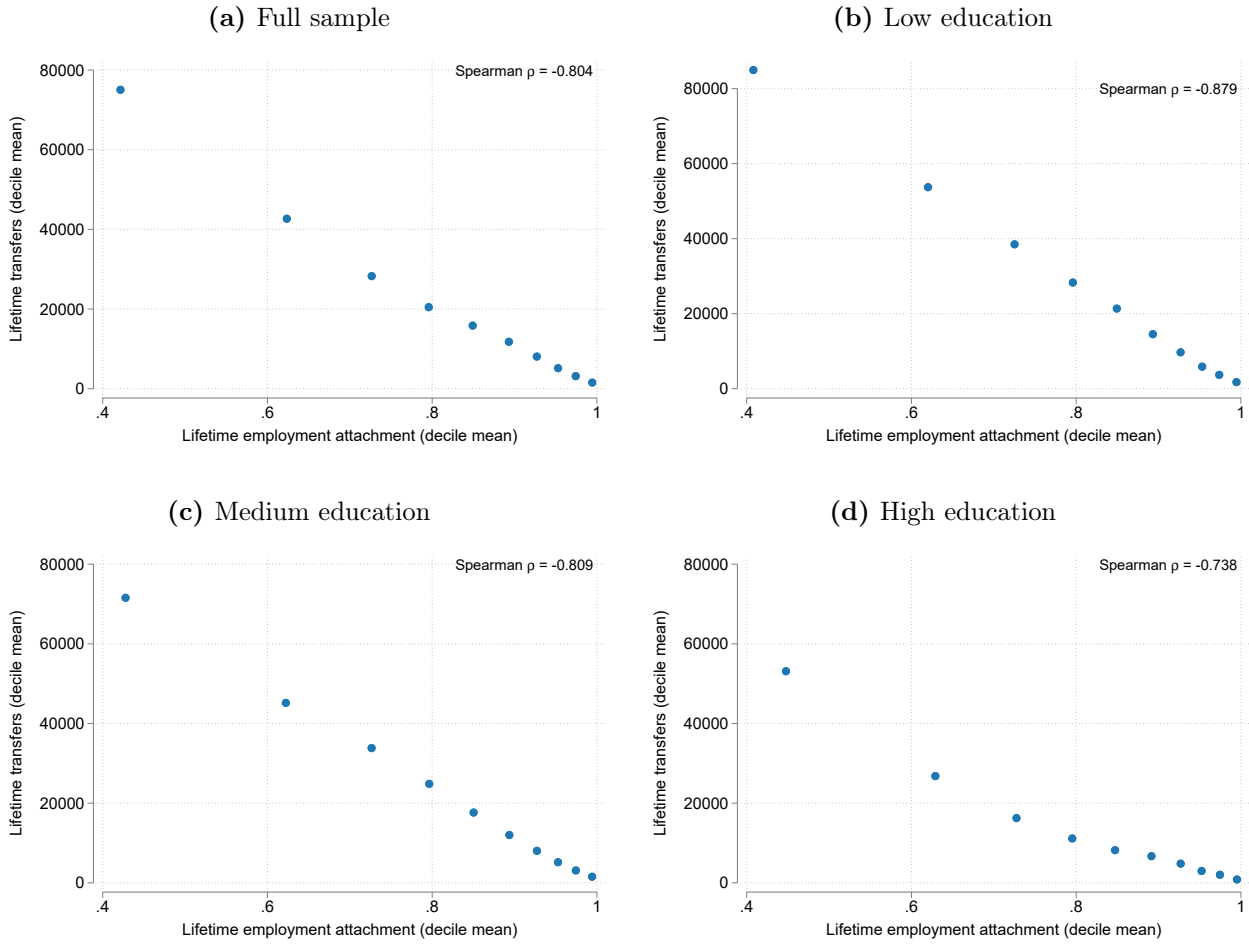


(d) High education



Note: The figure shows a concentration curve of lifetime transfers with respect to lifetime employment attachment. Individuals are ranked by lifetime employment attachment up to age 45 (defined in Equation (2)); the horizontal axis shows the cumulative share of the population and the vertical axis the corresponding cumulative share of aggregate lifetime transfers. The dashed line indicates the line of equality, corresponding to transfers being distributed evenly across the employment-attachment distribution. The annotated share reports the fraction of that panel's aggregate lifetime transfers received by the bottom quintile of the employment-attachment distribution within the corresponding sample (as defined in Section 3.3.2)

Figure B.6: Lifetime Transfers by Decile of Lifetime Employment Attachment

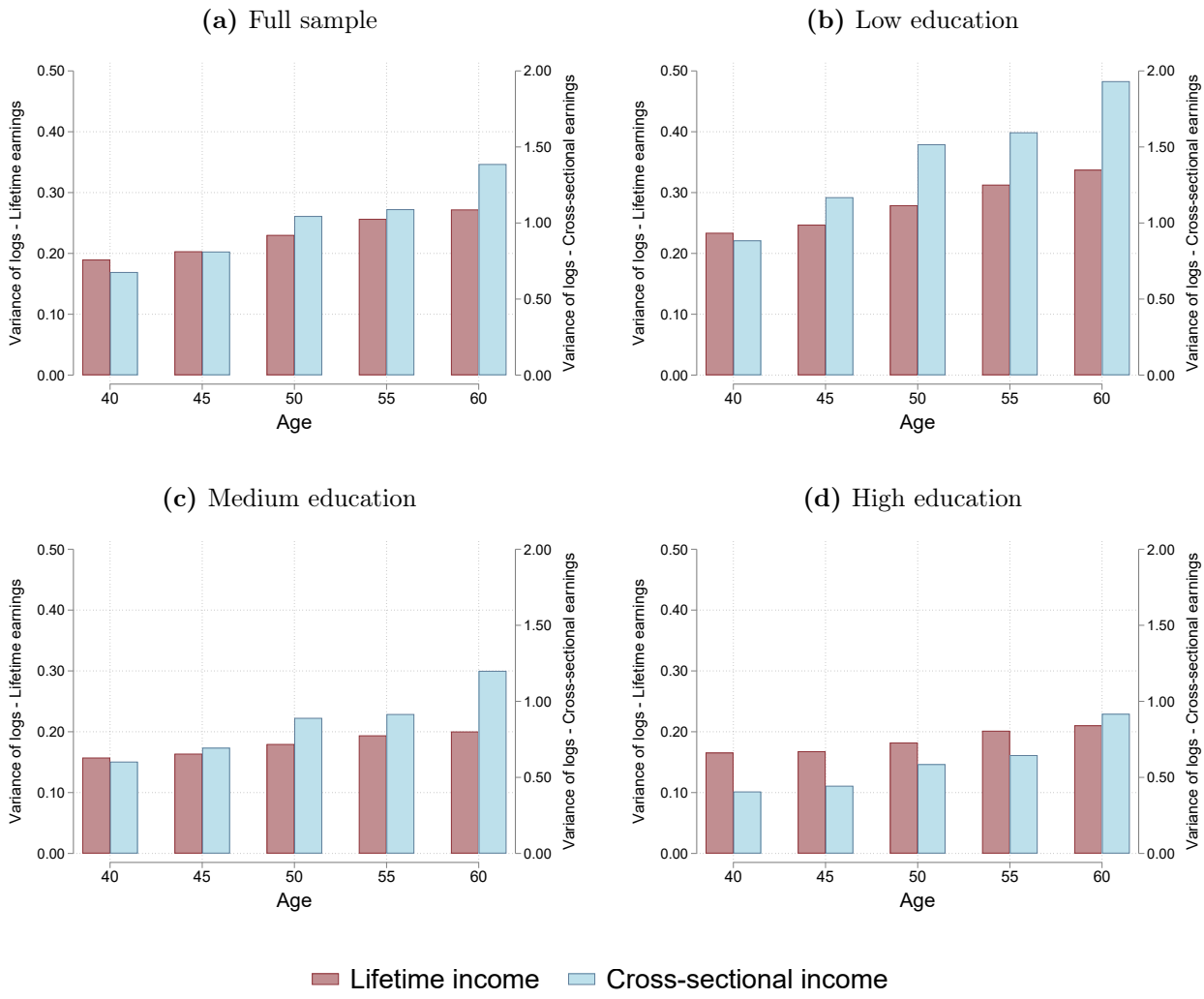


Note: Figure B.6 plots average lifetime transfers within each decile of the lifetime employment-attachment distribution, for the full sample and by education group. Individuals are ranked by lifetime employment attachment up to age 45 (defined in Equation (2)); deciles are computed cohort-specifically, using the same ranking as Bottom20 in Section 3.3.2. The annotated statistic reports the Spearman rank correlation between lifetime employment attachment and lifetime transfers at the individual level, within the corresponding sample.

B.7 Lifetime vs. Cross-Sectional Inequality

In Figure B.7, we compare lifetime inequality with cross-sectional inequality at different points in the life cycle. Note that the two series are plotted on separate axes. A clear pattern emerges: at every age, cross-sectional inequality is substantially higher than lifetime inequality. This difference reflects the fact that lifetime measures smooth over temporary shocks and transitory fluctuations, whereas cross-sectional snapshots capture short-run volatility and non-employment spells more directly. Put differently, lifetime inequality reflects more persistent differences, while cross-sectional measures are inflated by short-run variation that washes out when accumulated over time. The gap is considerably larger than in the comparisons with Leth-Petersen and Sæverud (2022) and Huggett et al. (2011) in Section 3.1, because those studies impose minimum earnings requirements, whereas our sample does not: without an earnings floor, cross-sectional inequality is inflated by years with very low or zero earnings.

Figure B.7: Lifetime vs. Cross-Sectional Inequality over the Life Cycle



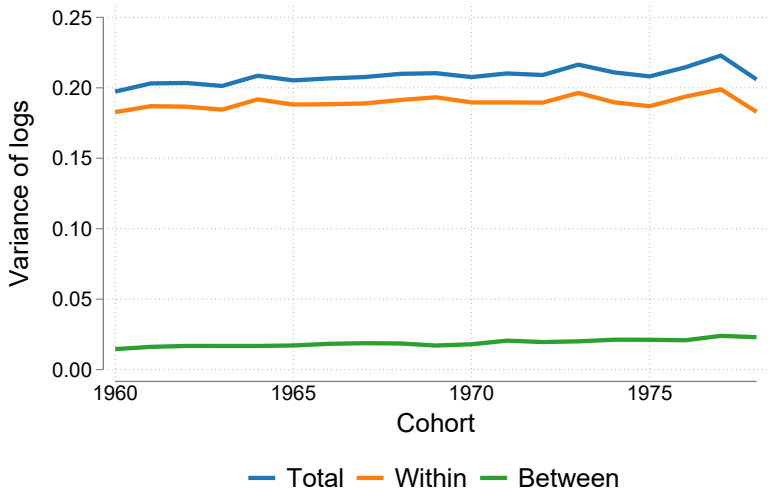
Note: Comparison of cross-sectional and lifetime earnings inequality across ages. Lifetime earnings inequality (red bar) is measured as $Var(\ln LI_{UAX})$, where LI_{UAX} is defined as in Equation (1). Cross-sectional inequality (blue bar) is measured as the variance of log annual earnings (right axis). At all ages, cross-sectional inequality exceeds lifetime inequality, reflecting the influence of transitory shocks and short-run volatility on annual earnings measures.

C Additional Results: Part 2

C.1 Variance Decomposition across Cohorts

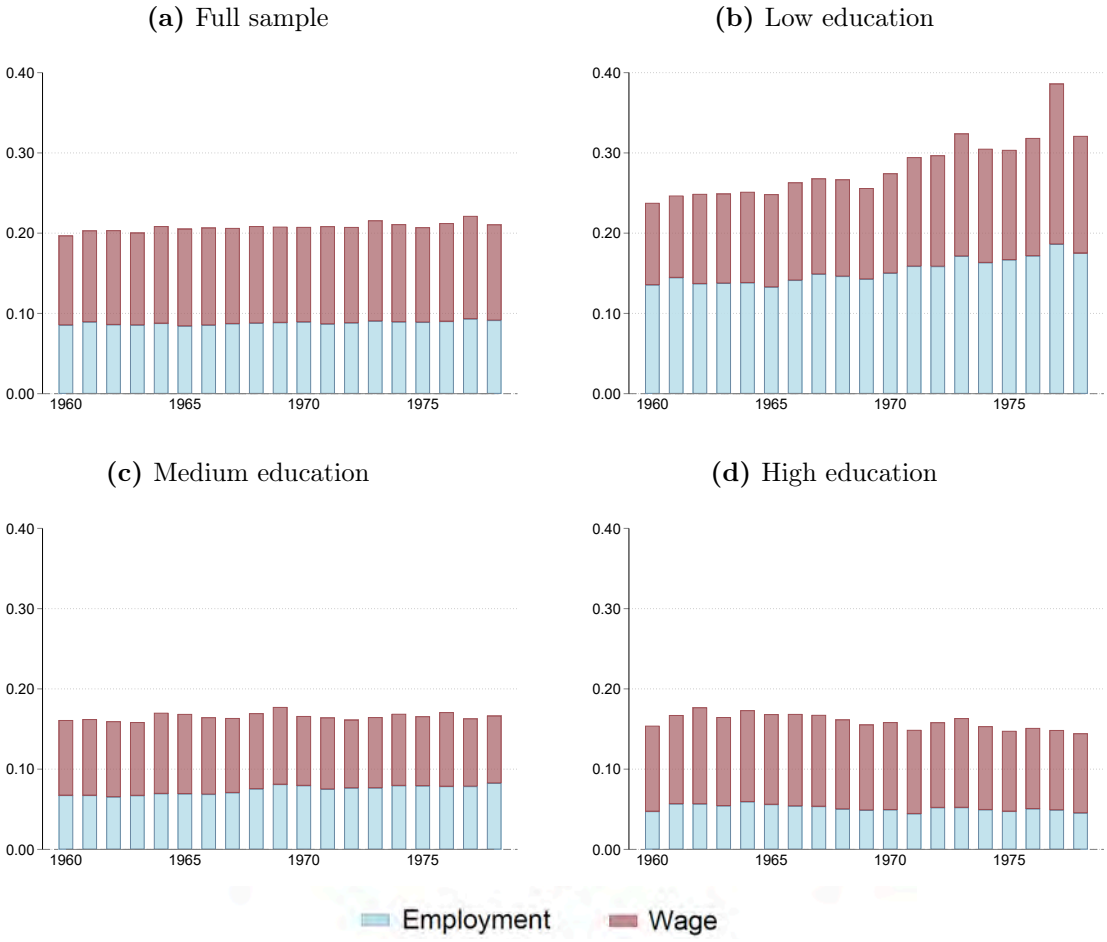
This section documents the variance decompositions underlying the cohort analysis in Section 4.2. Figure C.1 decomposes the variance of log lifetime earnings up to age 45 into within- and between-education-group components for each birth cohort. As in the lifetime sample (Table B.1), the within-group component dominates, accounting for around 90 percent of total variance across all cohorts, which motivates the focus on within-group inequality in the main text.

Figure C.1: Within-Between Decomposition



Note: Lifetime earnings inequality (UAX45) decomposed into within- and between-group components across birth cohorts (horizontal axis). The within component captures dispersion among individuals inside education groups, while the between component captures differences in mean log lifetime earnings across education groups (see Section 2.4 for definitions). The within component dominates, indicating that most inequality arises within rather than between education groups.

Figure C.2: Wage and Employment Decomposition

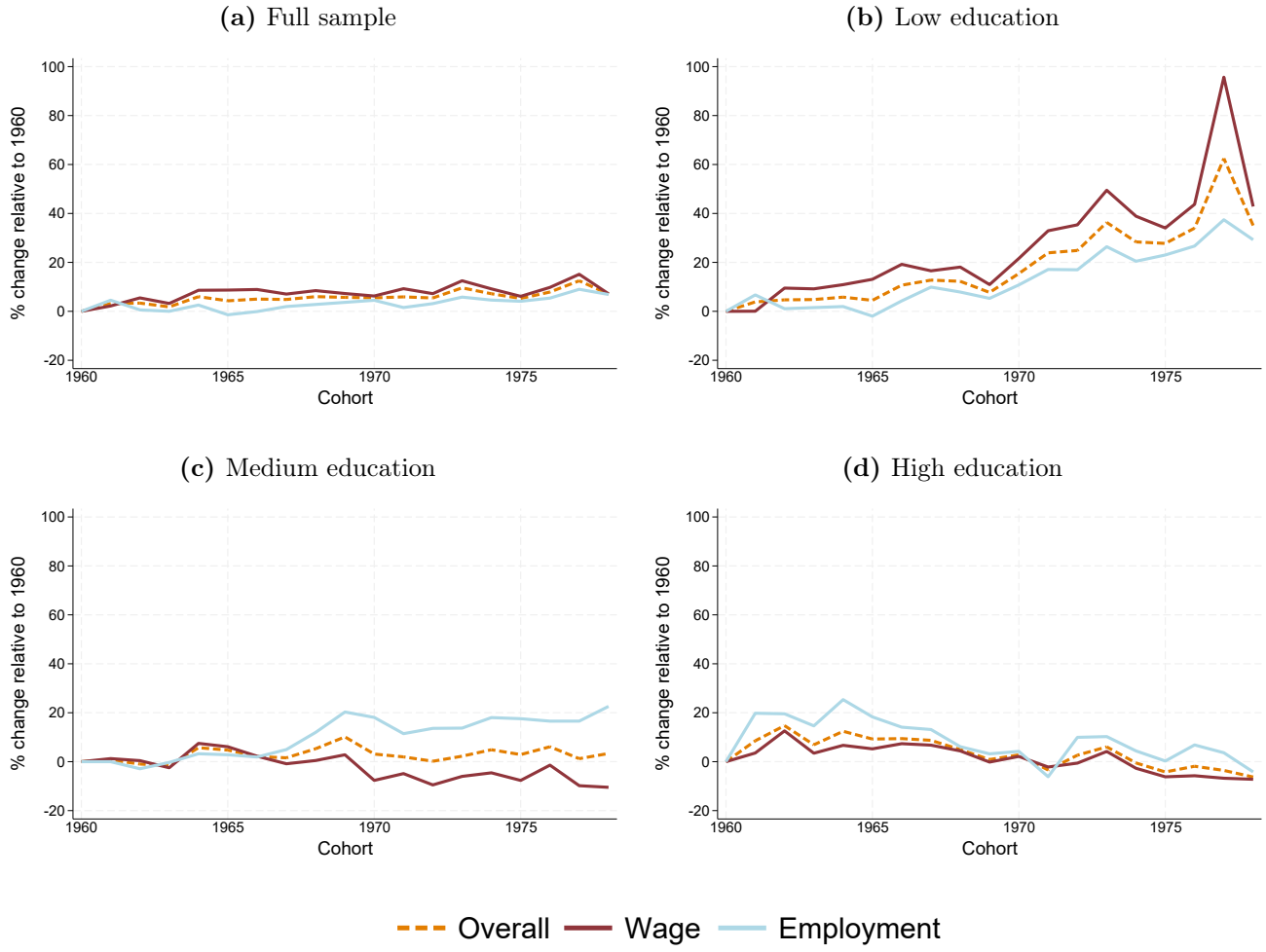


Note: Decomposition of lifetime earnings inequality using Equation (7) into two components: employment attachment (blue) and wages (red).

Figure C.2 then decomposes lifetime earnings inequality into the contributions of employment attachment and wages for each birth cohort (Equation (7)). Across cohorts, the employment-attachment component is broadly stable in the full sample but rises markedly among the low educated, accounting for a large part of the increase in their lifetime earnings inequality; the spike for the youngest cohorts reflects the COVID-19 period (see footnote 22).

Figure C.3 expresses the same changes relative to the 1960 cohort. For the low educated, the employment-attachment component rises by around 30–40 percent across cohorts, while the full sample shows virtually no change. This quantifies the conclusion in Section 4.2 that rising dispersion in employment attachment among the low (and to some extent medium) educated is a key driver of the upward trend in lifetime inequality.

Figure C.3: Change in Variance Components over Time

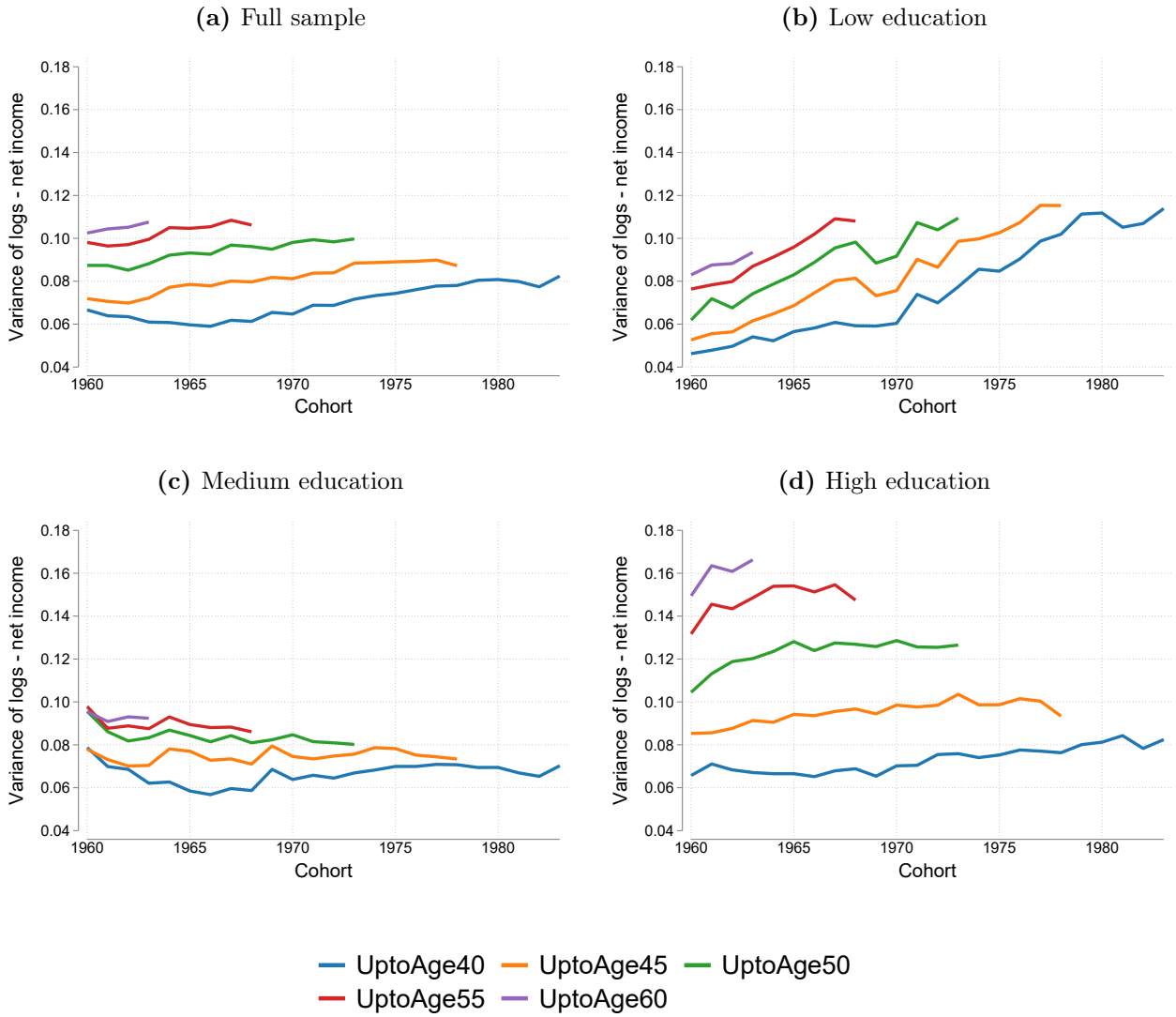


Note: Figure C.3 shows the percentage change in the overall, wage, and employment-attachment components of within-group variance relative to the 1960 cohort, based on the levels in Figure C.2.

C.2 Inequality in Net Income

This section reports the net income counterpart to the earnings results in Figure 4. Figure C.4 plots lifetime net income inequality across birth cohorts for each accumulation age, for the full sample and by education group. Two features stand out. First, inequality levels are substantially lower than for earnings at all ages and for all cohorts, reflecting the redistributive role of taxes and transfers. Second, the cohort patterns differ from those for earnings: net income inequality rises across cohorts among the low educated and, in contrast to earnings, also among the high educated, while it is broadly stable among the medium educated. In the full sample, it increases modestly. Figure C.5 compares earnings and net income inequality directly for accumulation ages 45 and 50.

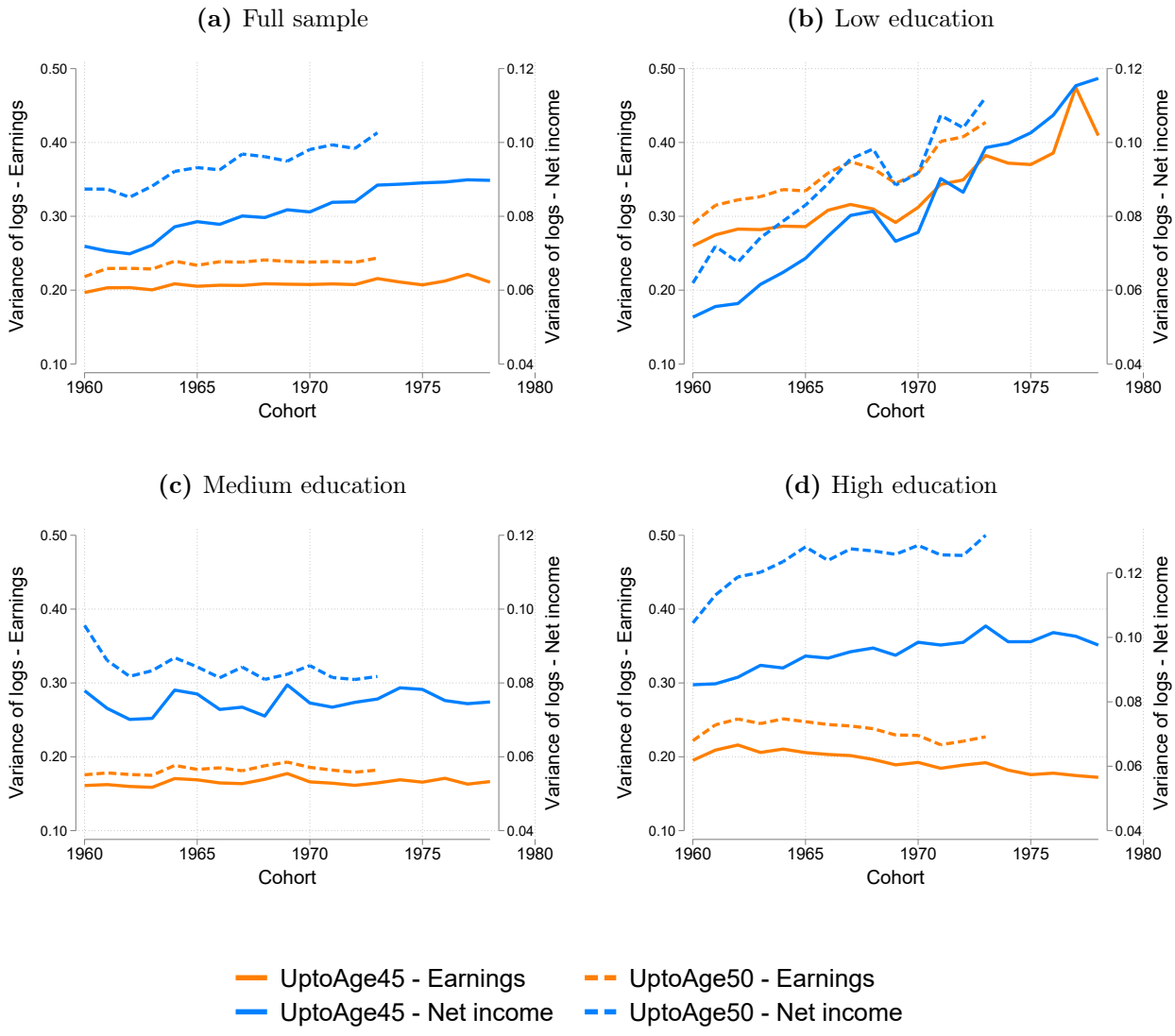
Figure C.4: Lifetime Inequality in Net Income



Note: Lifetime net income inequality across birth cohorts (horizontal axis) and accumulation age (lines). Net income is defined as after-tax income including transfers (see Section 2.2). Inequality levels are lower than for earnings (Figure 4). Net income inequality rises across cohorts among the low- and high-educated groups and is stable among the medium educated.

Figure C.5 shows that the patterns documented in Section 4.3 (Figure 5) are not specific to age 45. Note that the two measures are shown on different axes (earnings on the left, net income on the right). For both accumulation ages, net income inequality is lower than earnings inequality in all cohorts and education groups, but it increases more across cohorts in relative terms. This is most pronounced among the low educated. Among the high educated, net income inequality rises although earnings inequality declines slightly.

Figure C.5: Earnings vs. Net Income across Cohorts



Note: Figure C.5 compares lifetime earnings (orange, left axis) and net income (blue, right axis) inequality across birth cohorts. Solid lines show inequality up to age 45 and dashed lines up to age 50. Net income inequality is lower than earnings inequality, but increases more across cohorts in relative terms, indicating that the equalizing capacity of the tax-and-transfer system has somewhat weakened over time.

C.3 Employment-Attachment Decomposition

A key finding in the main text is that dispersion in employment attachment is a major contributor to inequality in earnings and that equalization occurs mainly through transfers. To further examine how the Danish tax-and-transfer system interacts with differences in individuals' labor market attachment, we divide individuals into deciles based on their lifetime employment attachment up to age 45. The first decile therefore contains individuals with the weakest connection to the labor market over this period, while the tenth decile contains those with the strongest and most continuous employment.

For lifetime earnings and lifetime net income we now calculate how much of the total inequality in log lifetime income is explained by differences between these ten groups rather than within them.[30]

The share of total variance which is captured by the between-group variance is a measure of how dispersion in employment attachment leads to differences in lifetime income. The between-group share is a natural object in this context: income transfers are targeted precisely at spells of non-employment, so inequality between attachment groups is the margin that the tax-and-transfer system is designed to compress. A higher share means that lifetime inequality mainly reflects persistent income gaps between individuals with strong and weak labor market attachment, whereas a lower share means that most inequality arises among individuals with similar attachment levels. Similarly, the difference in the between-group variance share for earnings and net income is a measure of the extent to which the tax-and-transfer system offsets or compresses inequalities coming from dispersion in employment attachment. If the tax-and-transfer system is highly redistributive, the between-group share should be markedly smaller for net income than for earnings.

Figure C.6 plots the between-group share across cohorts. The blue line shows the share for earnings, and the orange line shows the share for net income. The shaded area between the two lines represents the degree to which redistribution reduces income differences between attachment groups—that is, the redistributive compression of attachment-driven inequality. The within-group shares equal one minus the between-group shares by construction.

The figure demonstrates three key points. First, for all cohorts, a large part of lifetime income inequality originates from differences between individuals who have been more or less continuously

[30]Specifically, we compute the variance of the mean log income of each attachment decile (given by average lifetime employment up to age 45) within a cohort—this captures the between-group component—and divide it by the total variance of log lifetime income for the same cohort.

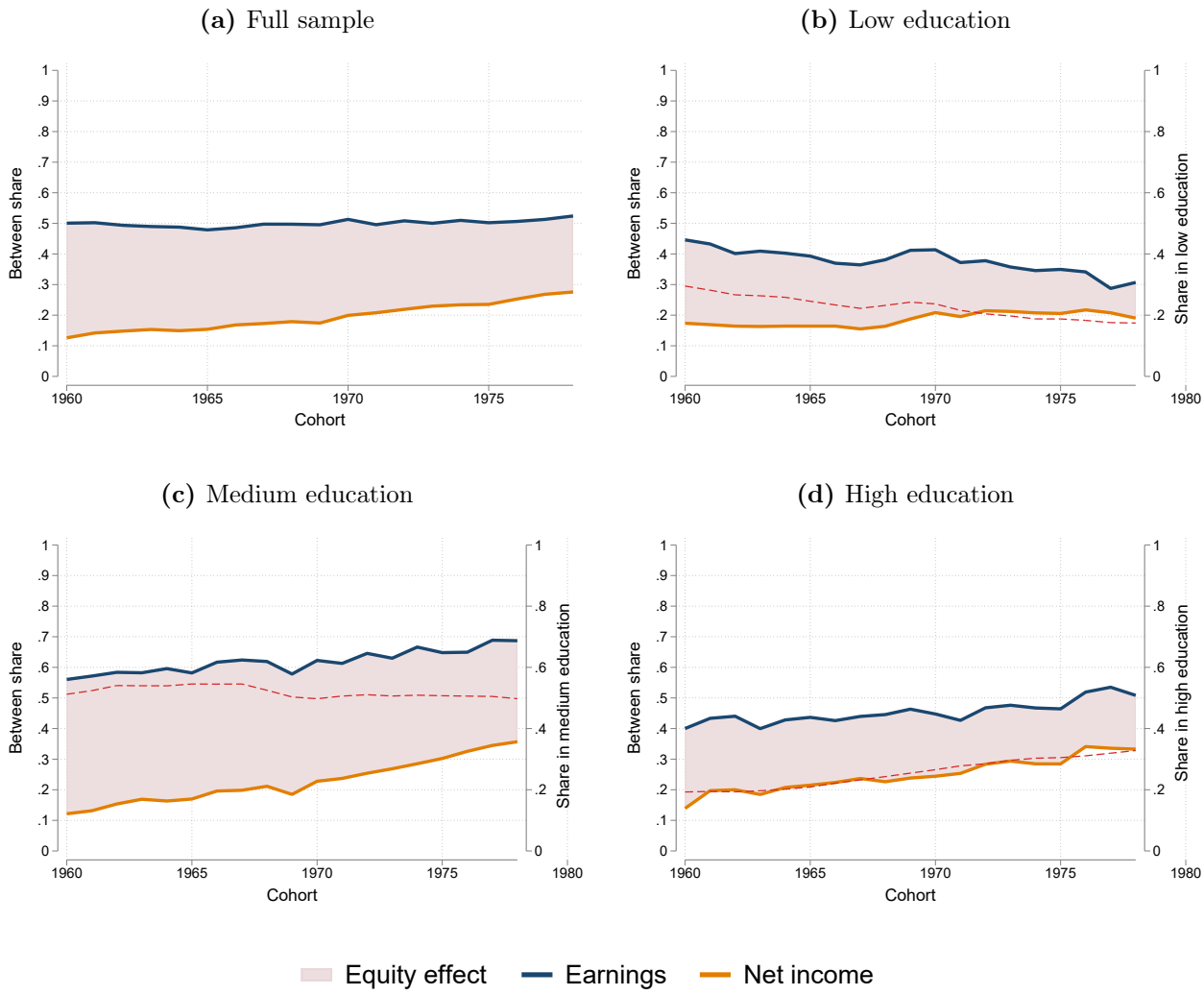
$$\begin{aligned} Var(\ln LI^i_{UAX}) &= Var^{between}_{UAX} + Var^{within}_{UAX} \\ &= Var(\overline{\ln LI_{UAX,g}}) + E[Var(\ln LI_{UAX,i}|g)] \end{aligned}$$

where g indexes the decile of lifetime employment. The between-group share is then defined as

$$s_{UAX} = \frac{Var^{between}_{UAX}}{Var(\ln LI^i_{UAX})}$$

attached to the labor market: with ten attachment groups, the between- and within-group shares of earnings inequality are roughly comparable. Second, redistribution compresses precisely this margin, as the between-group share is substantially lower for net income than for earnings. Third, the shaded area becomes narrower for later cohorts. Since equalization occurs mainly through transfers (Sections 3.4 and 4.3) and the effect of taxes is relatively stable across cohorts (Figure 5), this suggests that transfers have become less effective at compressing differences between individuals with strong and weak lifetime labor market attachment. Note that these are relative measures, so they speak to the relative rather than the absolute size of the compression. In other words, while the tax-and-transfer system continues to equalize lifetime incomes, its ability to offset inequality stemming from employment differences has weakened somewhat for more recent cohorts.

Figure C.6: Between-Employment-Group Variance Shares

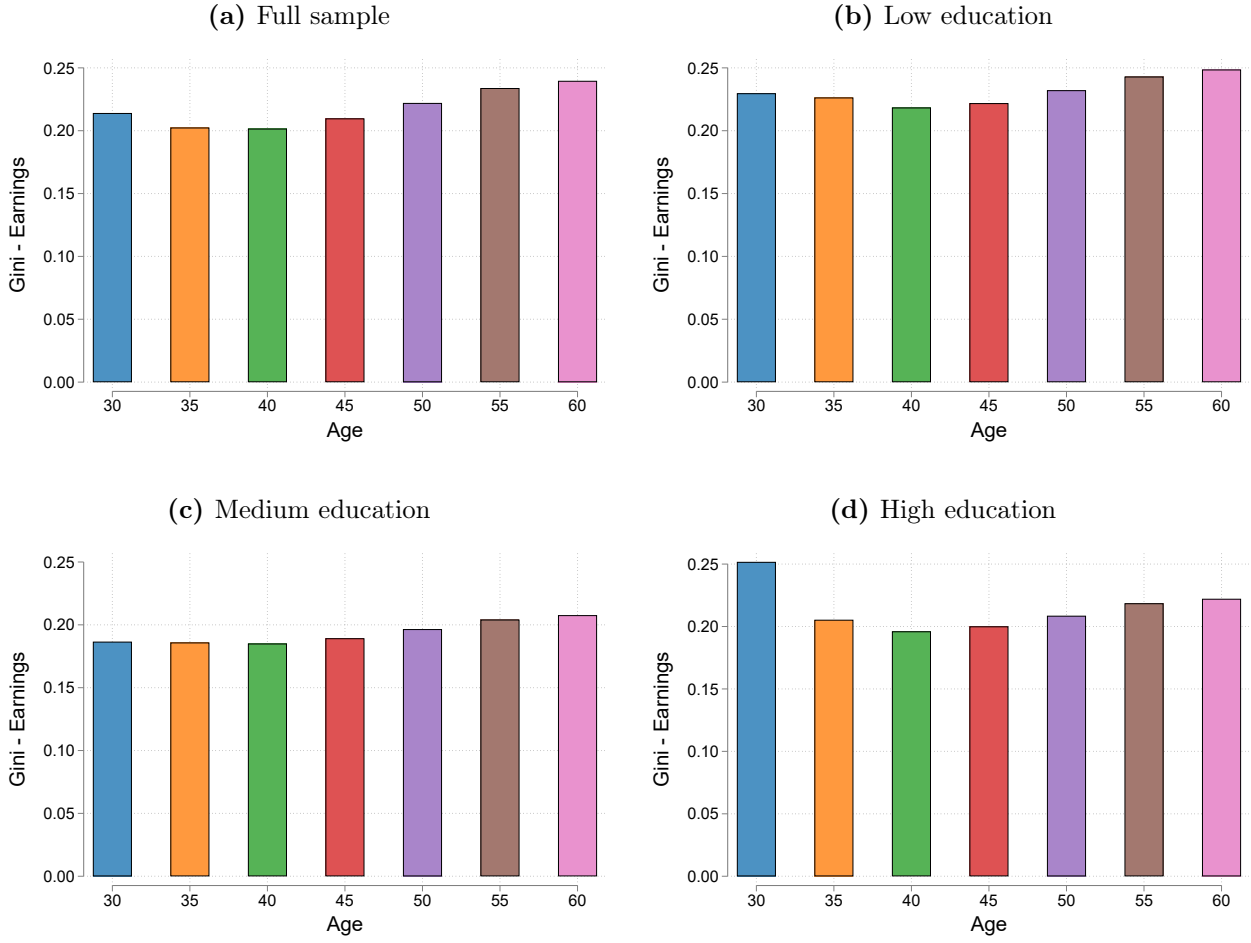


Note: Between-group shares of lifetime income inequality at UAX45, where groups are defined by lifetime employment attachment. The vertical axis shows the share of total variance explained by differences between groups. Separate lines are shown for earnings and net income, and the gap between earnings and net income reflects the redistributive compression of attachment-driven inequality. The narrowing gap over time suggests that the equalizing effect of redistribution has weakened somewhat.

D Robustness Checks

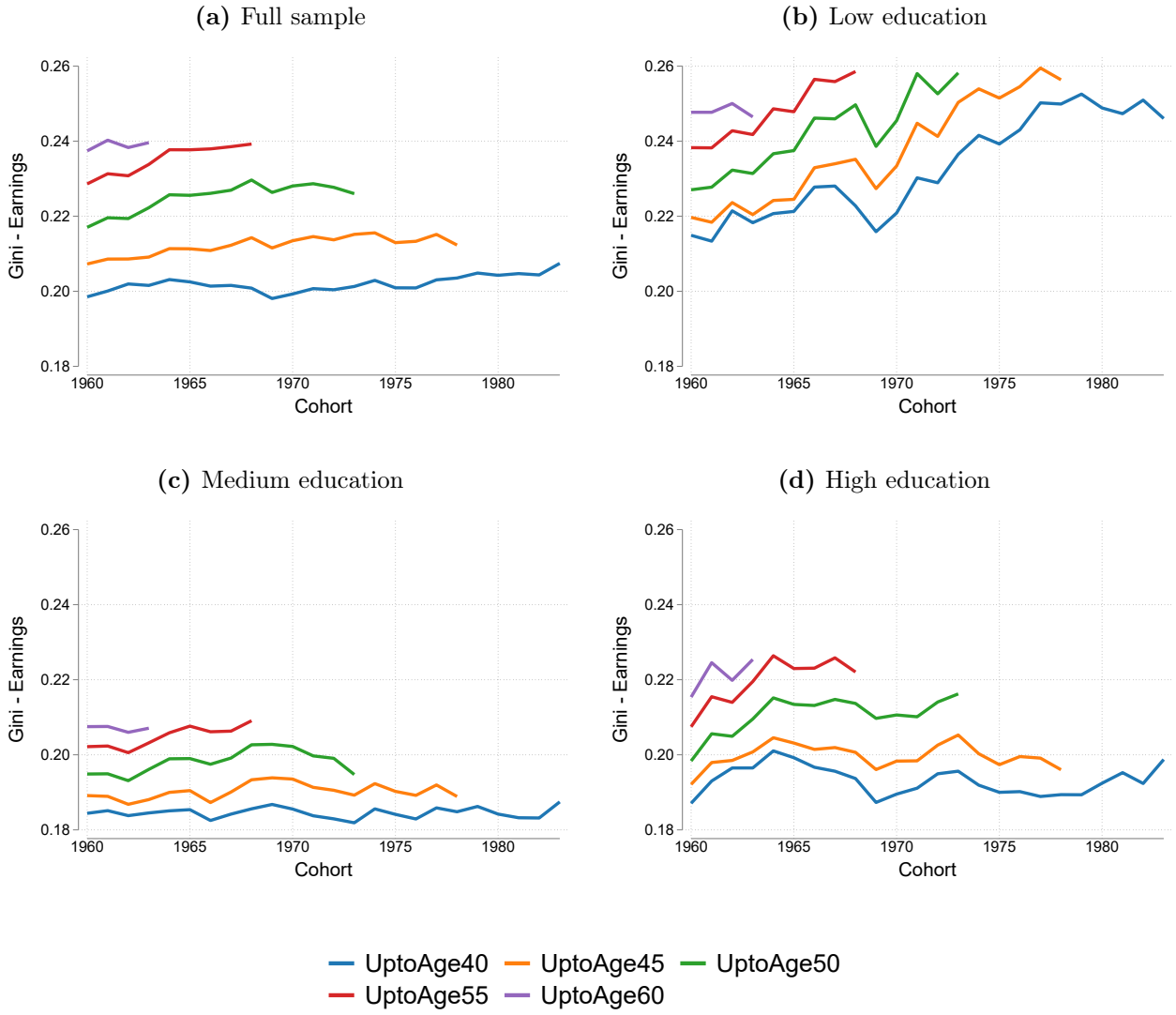
This appendix contains the figures underlying the robustness checks discussed in Section 5. Figure D.1 replicates Figure 1, while Figures D.2 and D.3 replicate the cohort analysis in Figure 4, for earnings and net income, respectively, using the Gini coefficient instead of the variance of logs. Figure D.4 replicates Figure B.4 using the Gini coefficient, revisiting the importance of the bottom 20 percent of the employment-attachment distribution. Figures D.5, D.6 and D.7 instead tighten the employment-attachment requirement from 25 to 50 percent of potential working years up to age 40. Finally, Figures D.8, D.9 and D.10 winsorize annual income at the 5th and 95th percentiles rather than the baseline 1st and 99th. In all cases, the age- and cohort patterns and education gradients from the main analysis remain intact.

Figure D.1: Gini: Earnings



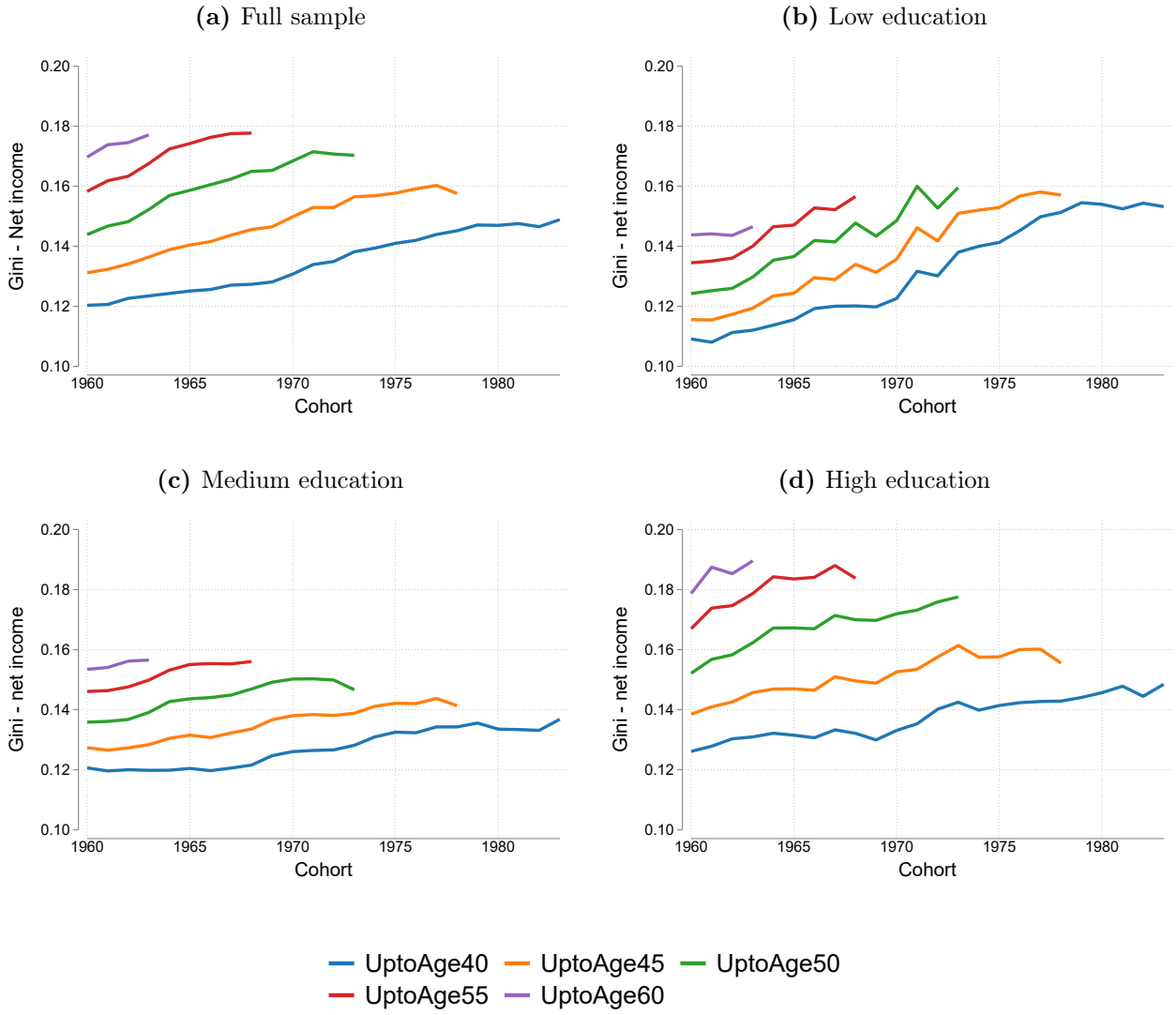
Note: Gini coefficient of lifetime earnings by age, as an alternative to the variance of logs in Figure 1. The Gini follows the same patterns as in Figure 1 as inequality decreasing until age 40 after which it steadily increases.

Figure D.2: Gini: Earnings



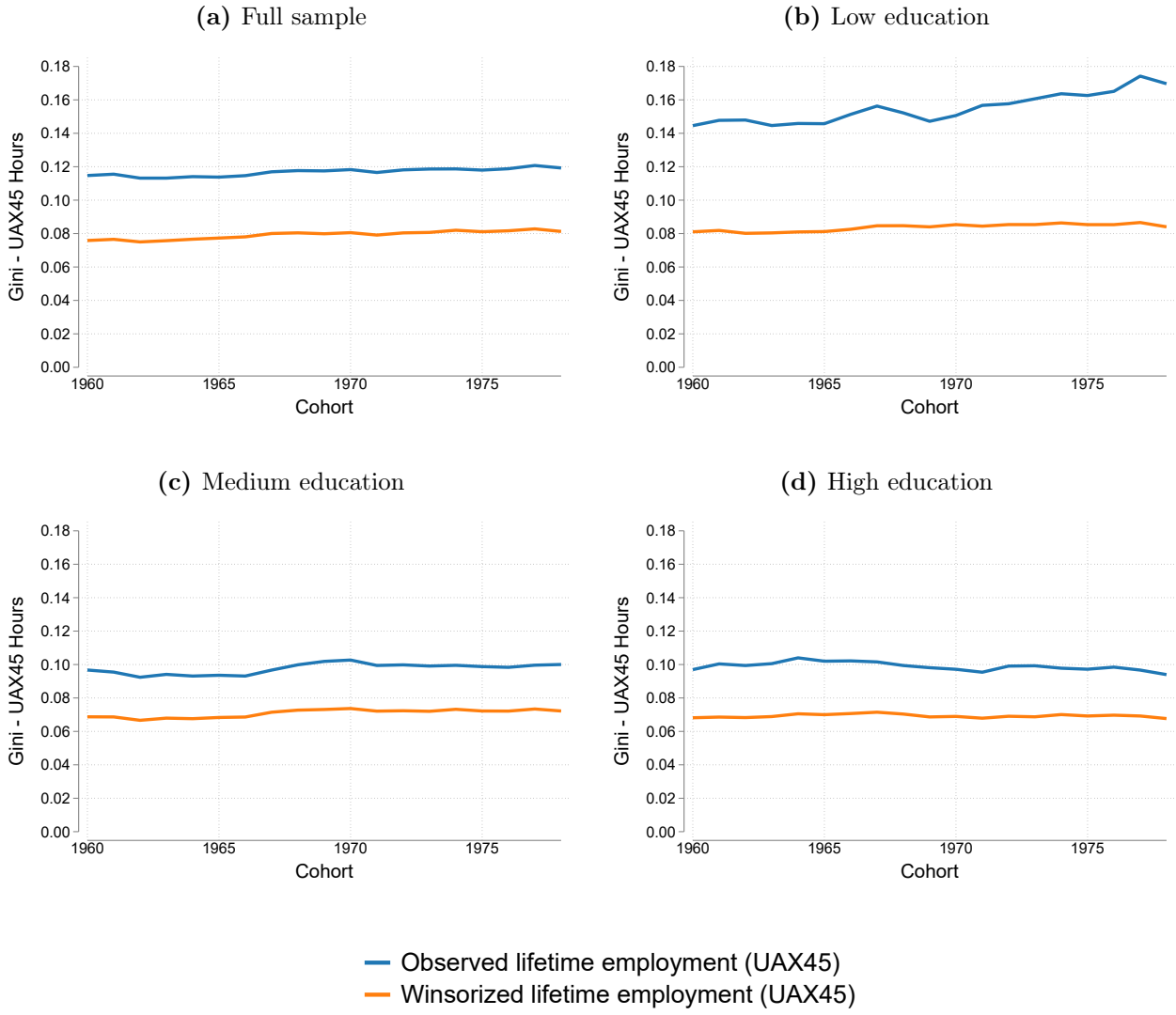
Note: Gini coefficient of lifetime earnings by birth cohort, as an alternative to the variance of logs in Figure 4. The Gini is broadly stable across cohorts in the full sample, and the increase is concentrated among the low educated.

Figure D.3: Gini: Net Income



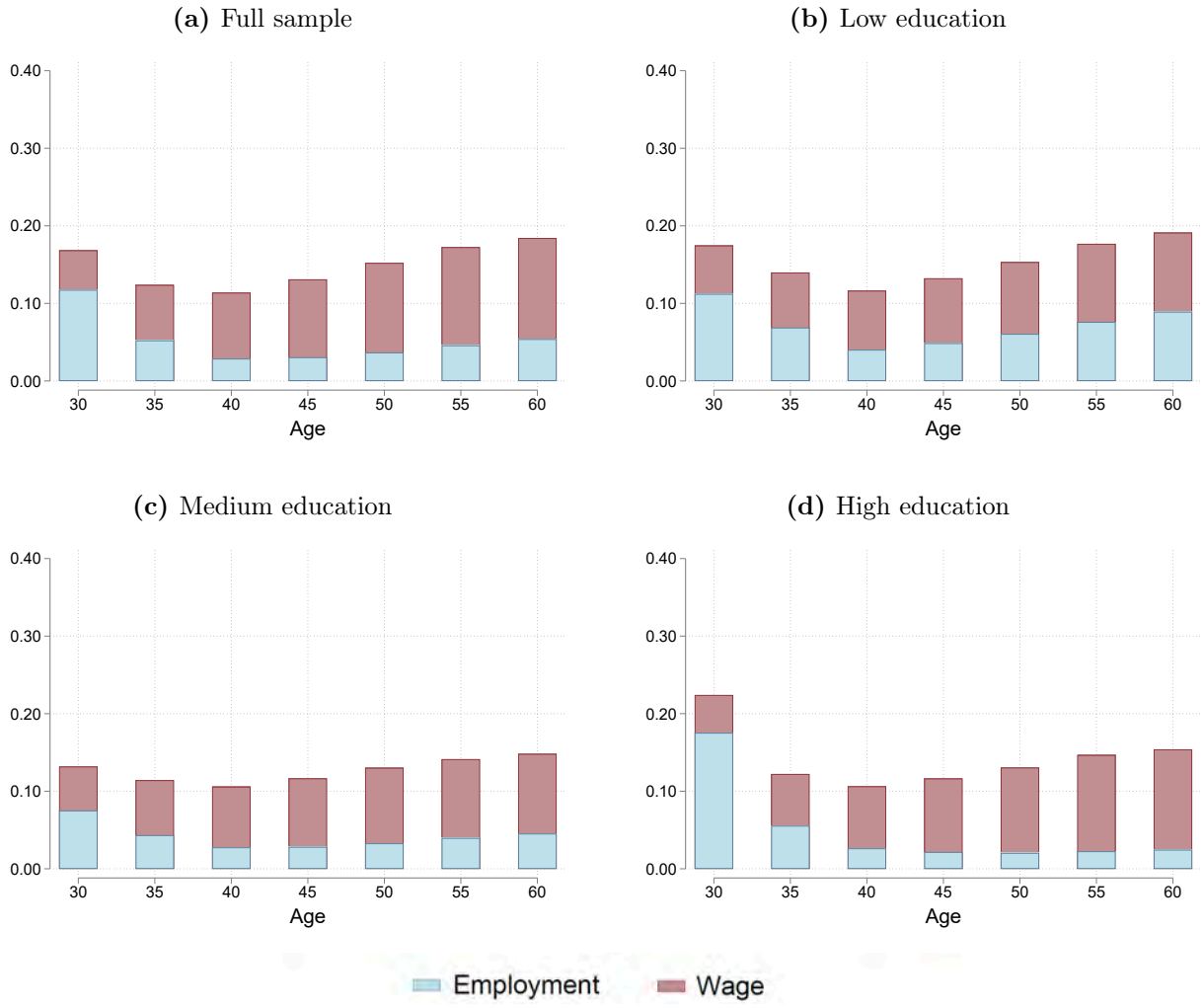
Note: Lifetime net income inequality re-estimated using the Gini coefficient as an alternative metric to the variance of logs (Figure C.4). In contrast to earnings, the Gini for net income rises across cohorts in all education groups.

Figure D.4: Gini: Inequality in Lifetime Employment



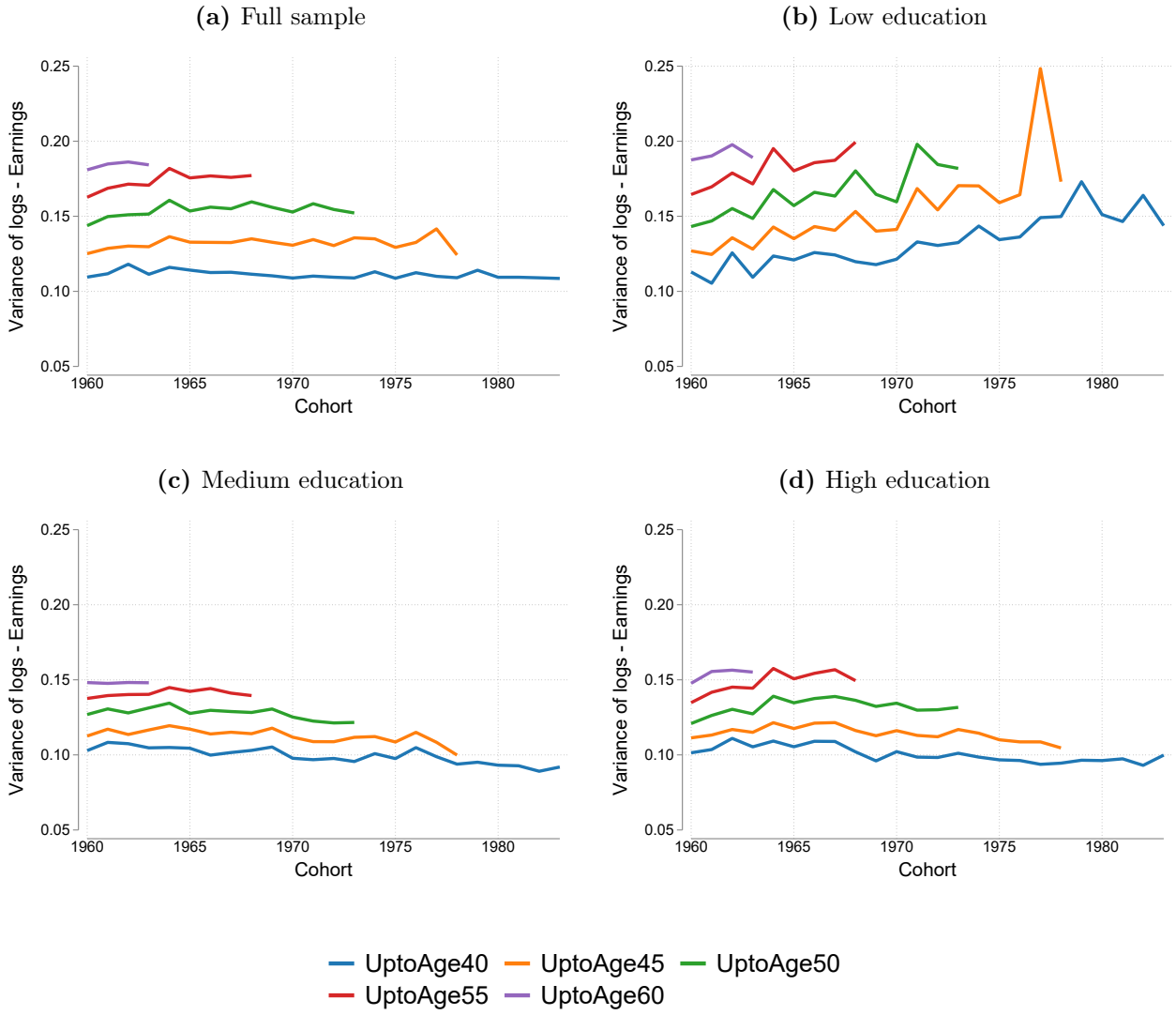
Note: Figure D.4 the Gini coefficient of lifetime employment attachment up to age 45 by birth cohort (blue), and the corresponding Gini coefficient when the attachment distribution is winsorized at the 20th percentile within each cohort (orange). The figure replicates Figure B.4 using the Gini coefficient instead of the variance of logs.

Figure D.5: Employment Requirement at 50 Percent: Earnings



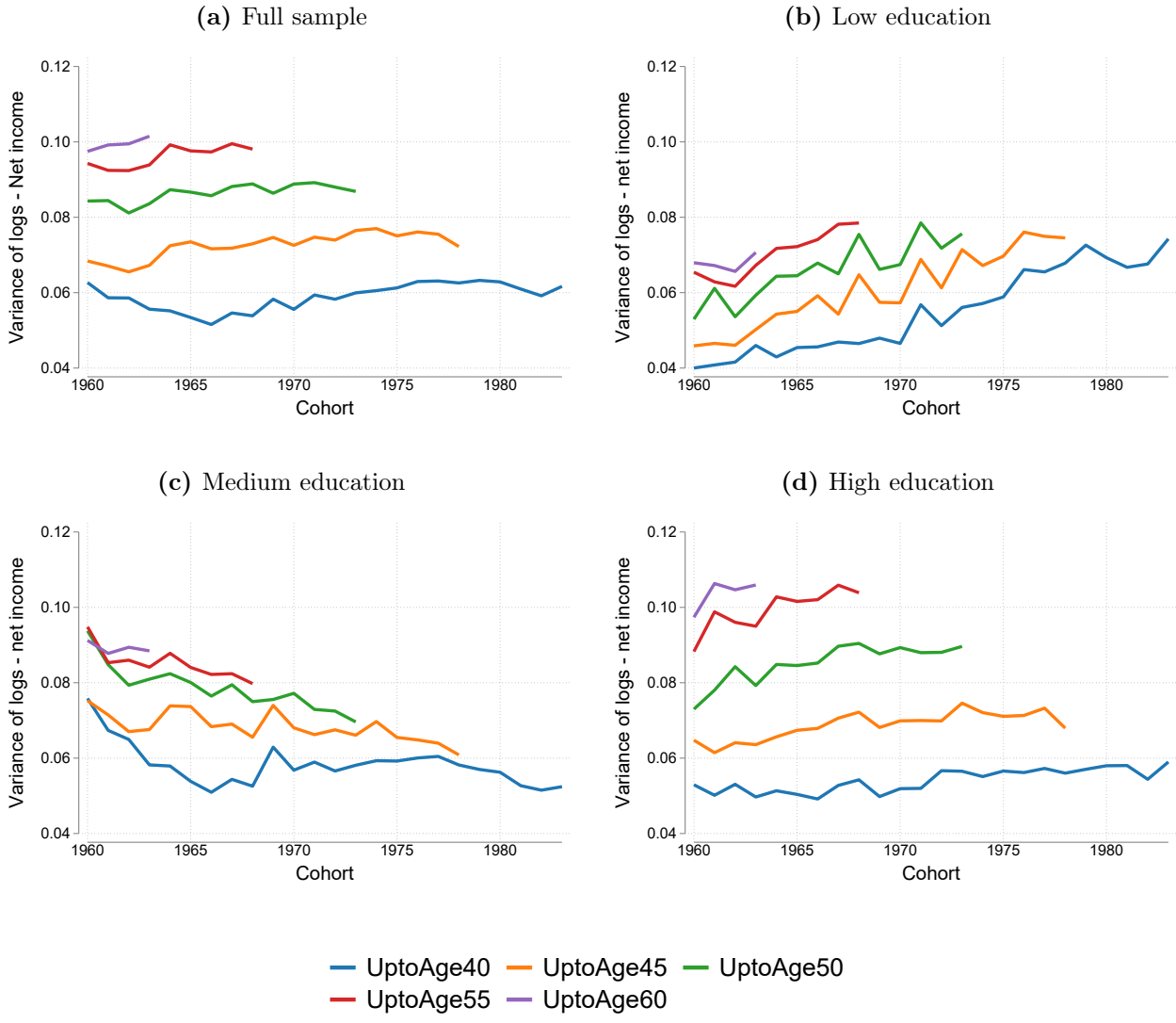
Note: Ensemble decomposition of lifetime earnings inequality using Equation (7) on a sample restricting attention to individuals with at least 50 percent employment up to age 40. Each part of the bar represents the contribution to total lifetime earnings inequality attributable to employment attachment (blue) and wages (red) at a given accumulation age. Restricting attention to a more attached sample reduces the role for employment attachment somewhat, however it is still a main driver among low educated.

Figure D.6: Employment Requirement at 50 Percent: Earnings



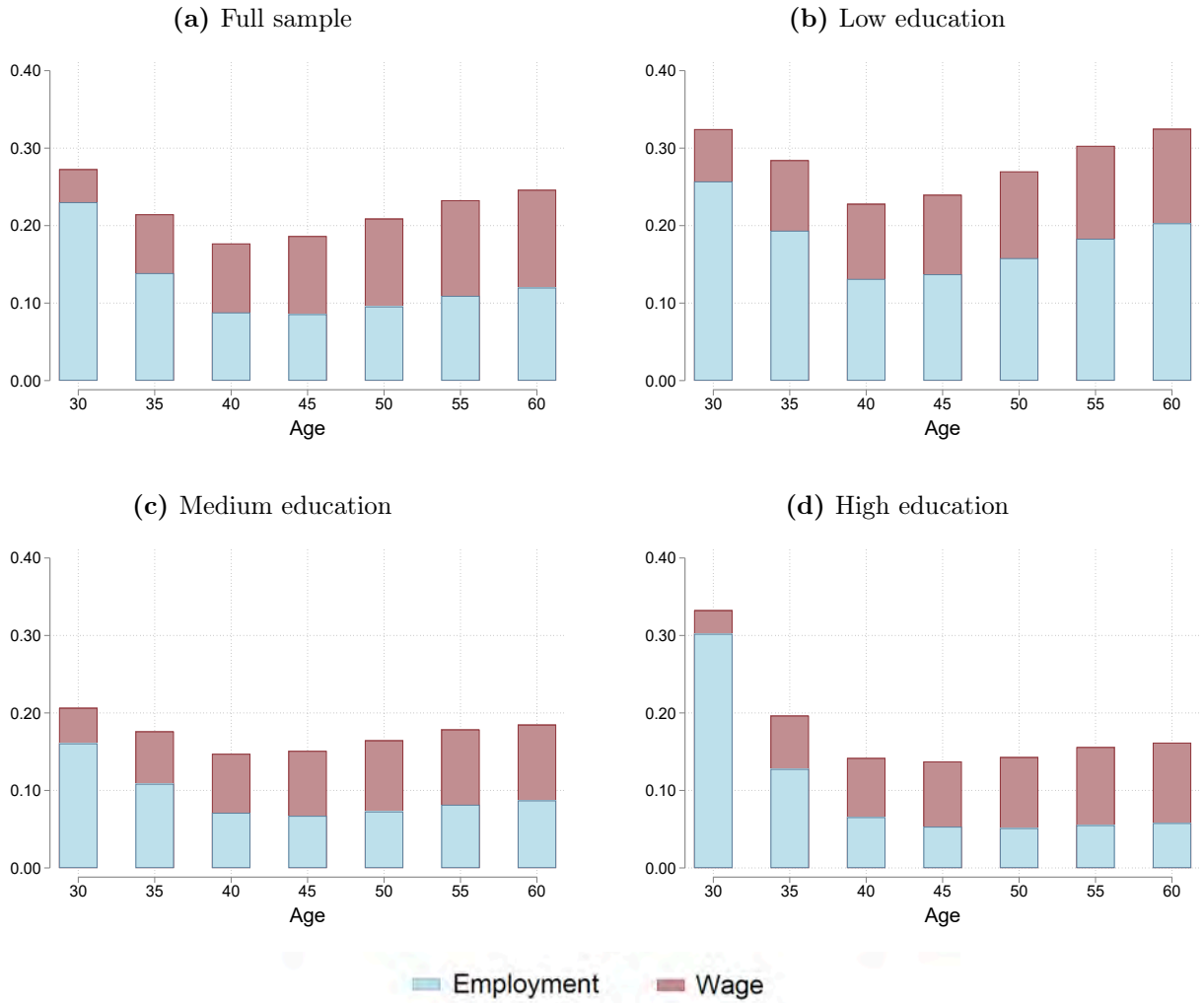
Note: Variance of log lifetime earnings by birth cohort when sample inclusion requires employment in at least 50 percent of the possible years up to age 40, compared with 25 percent in the baseline (see Section 2.3). Lines are as in Figure 4. Inequality is lower than in the baseline, but it still increases across cohorts among the low educated, indicating that our cohort patterns are not driven by the specific employment requirement.

Figure D.7: Employment Requirement at 50 Percent: Net Income



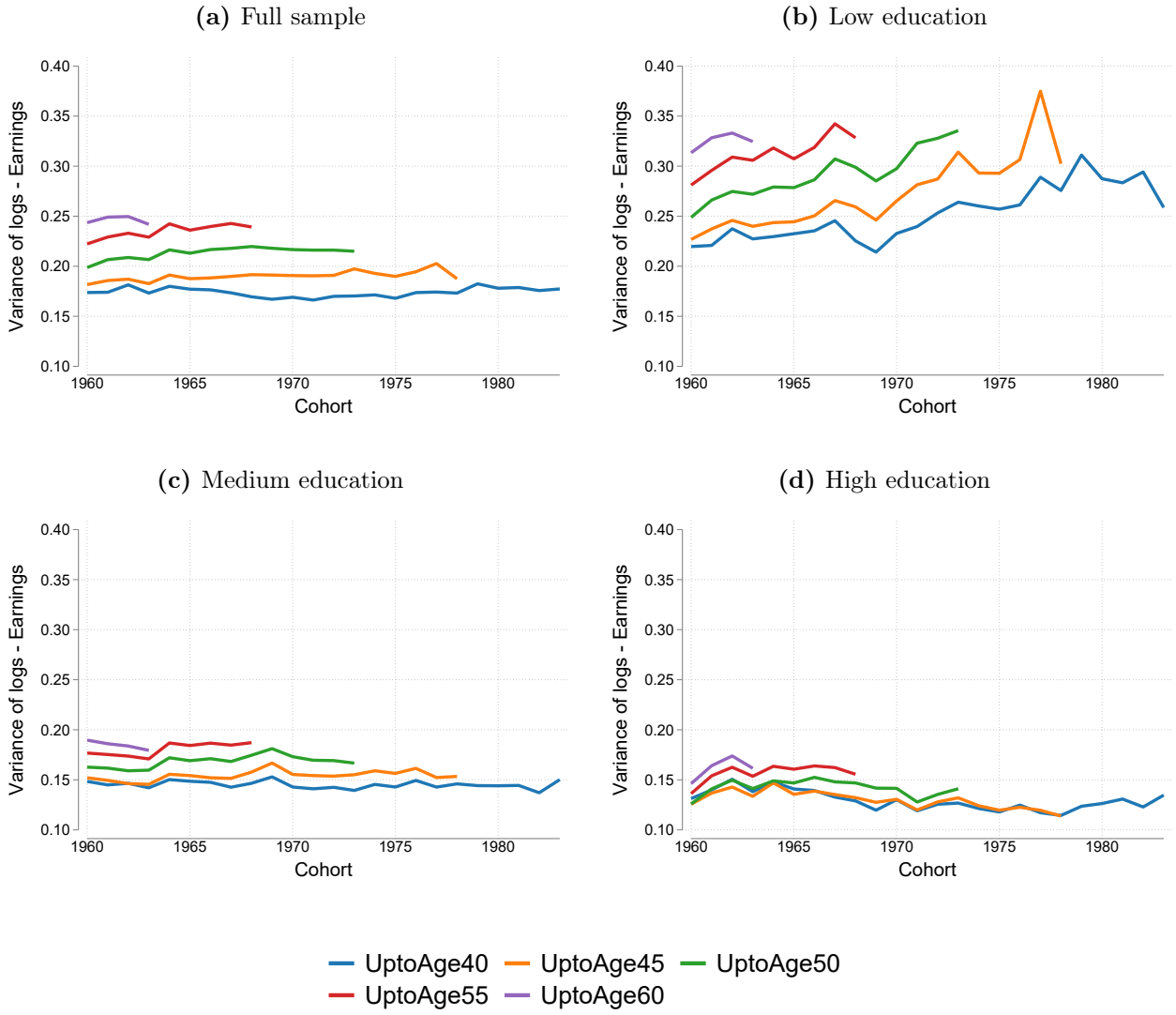
Note: Net income counterpart to Figure D.6, using the 50 percent employment requirement. As in the baseline (Figure C.4), net income inequality still increases across cohorts among the low educated.

Figure D.8: Winsorizing at 5th and 95th Percentiles: Wage hours decomposition



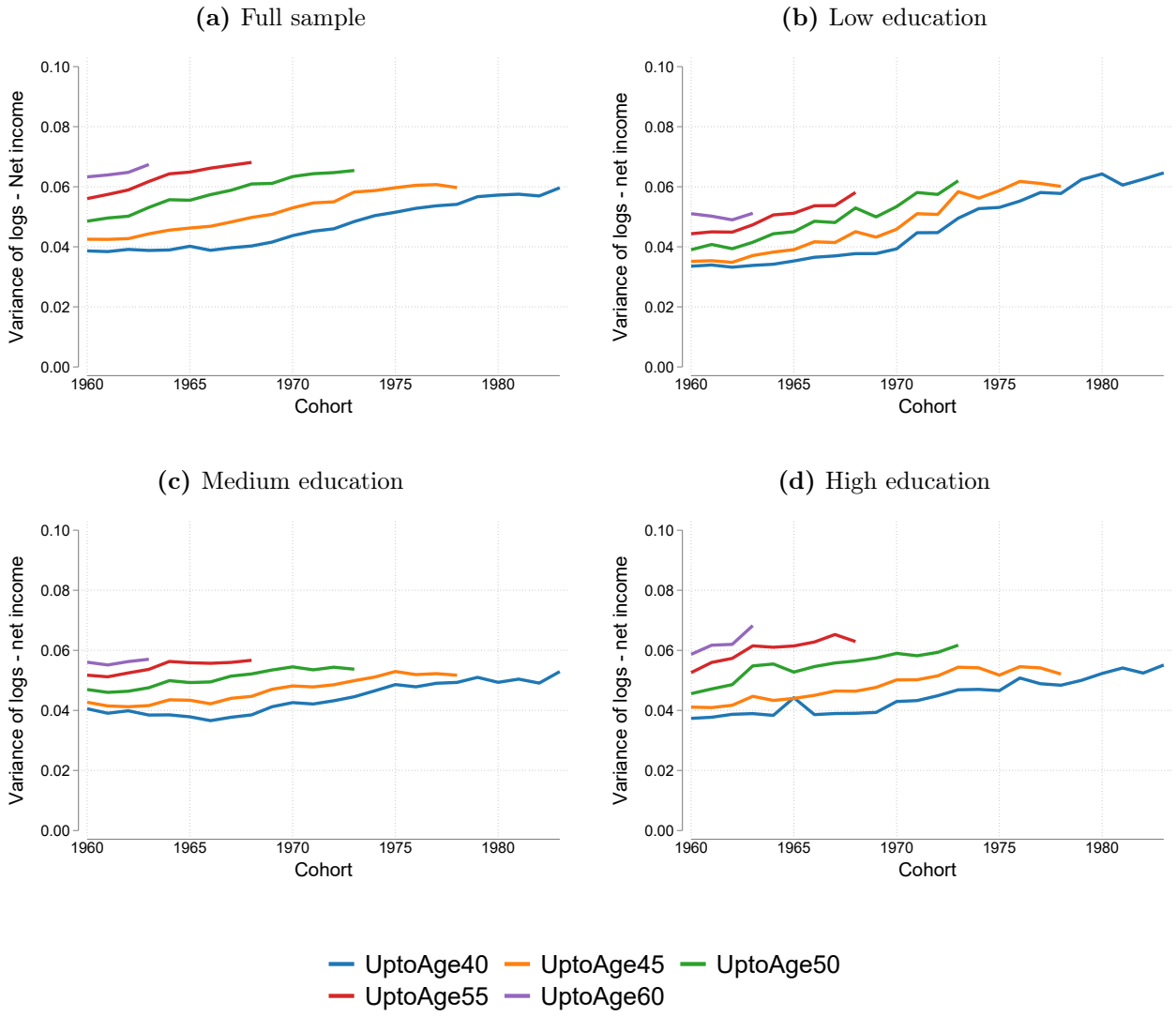
Note: Ensemble decomposition of lifetime earnings inequality using Equation (7) on a sample winzorizing at the 5th and 95th percentiles rather then 1st and 99th as in Figure 2. Each part of the bar represents the contribution to total lifetime earnings inequality attributable to employment attachment (blue) and wages (red) at a given accumulation age. Trimming reduces levels slightly but leaves age trend and education pattern essentially unchanged.

Figure D.9: Winsorizing at 5th and 95th Percentiles: Earnings



Note: Variance of log lifetime earnings by birth cohort when annual earnings are winsorized at the 5th and 95th percentiles within year and cohort, rather than at the 1st and 99th percentiles. Trimming reduces levels slightly but leaves the upward cohort trend and education pattern essentially unchanged.

Figure D.10: Winsorizing at 5th and 95th Percentiles: Net Income



Note: Net income counterpart to Figure D.9, with annual net income winsorized at the 5th and 95th percentiles. Inequality levels are lower than in the baseline (Figure C.4), but net income inequality still rises across cohorts.