Linking Lifecycle and Cross-sectional Inequality: Cohort Dynamics and the Role of Technological Change

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Abstract

This paper examines the determinants of cross-sectional and lifecycle inequality using a lifecycle earnings process model that incorporates earnings mobility and non-employment risks across birth cohorts and over time. We show that changes in unobserved skill prices and the variance of individual fixed effects across cohorts are the primary drivers of inequality. While non-employment risk contributes little to cross-sectional inequality, it is central to explaining lifecycle inequality. To explain the increase in the variance of fixed effects, we interpret these within a Roy model as realized productivity, influenced by both ability and task choice. We provide evidence that technological change can amplify inequality beyond the canonical skill price channel by strengthening the mapping from ability to productivity through within-occupational task sorting.

Keywords: Wage Inequality, Lifecycle Earnings, Skill-biased Technological Change

JEL codes: J23, J24, J31, D31

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1. Introduction

Most research on wage and earnings inequality focuses on cross-sectional inequality (e.g., Katz and Murphy, 1992; Card and DiNardo, 2002; Lemieux, 2006; Goldin and Katz, 2007; Dustmann et al., 2009; Moretti, 2013). However, welfare implications depend on the underlying earnings dynamics, as high cross-sectional inequality could reflect rapid earnings growth and temporary wage fluctuations or stem from persistent disparities starting at labor market entry, resulting in low or high lifecycle inequality, respectively. Although income process models have been widely used to study earnings dynamics, research linking and understanding the determinants of cross-sectional and lifecycle inequality is limited. While research incorporating non-stationary shocks into earnings dynamics often focuses on age- or year-dependent variations (e.g., Haider, 2001; Baker and Solon, 2003; Moffitt and Gottschalk, 2012; Debacker et al., 2013; Blundell et al., 2015), it rarely considers heteroskedasticity in permanent wage shocks across cohorts, thus limiting our understanding of how lifecycle inequality evolves.[2] Moreover, cross-sectional wage measures often overlook the elevated non-employment risks low-wage workers face.

This paper makes two key contributions. First, it analyzes both cross-sectional wage and lifecycle earnings inequality across labor market entry cohorts in Germany, disentangling and quantifying the relative contributions of the underlying mechanisms driving each. We estimate a lifecycle earnings process model that decomposes overall inequality into structural components. The model integrates elements from Baker and Solon (2003), Guvenen (2009), and Guvenen et al. (2021) into a unified income process that allows for both cohort- and time-specific heterogeneity as well as employment–non-employment dynamics. Beyond observable factors such as the composition and returns to education, experience, and time effects, we separate the standard unobserved individual fixed effect into a cohort-specific individual productivity component and a time-varying price component. We further estimate an employment–non-employment transition process to capture the correlation between wages and job insecurity, which we

[2] Another strand of research relies on models with stationary shocks (e.g., Lillard and Willis, 1978; Lillard and Weiss, 1979; MaCurdy, 1982; Meghir and Pistaferri, 2004; Guvenen, 2009).

demonstrate is central to understanding lifecycle earnings inequality, but less so for cross-sectional inequality. Thus, we model changes in unobservable wage components through an income process that allows for multiple sources of non-stationarity in wage shocks and non-employment risks across birth cohorts and over time. Based on this framework, we decompose the evolution of lifecycle and cross-sectional inequality into their constituent components, enabling a direct comparison of the mechanisms underlying each. These decompositions show that both the price and the variance of unobserved individual productivity are key drivers of the rise in both lifecycle and cross-sectional wage inequality.

This leads to the second main contribution of the paper: we provide an economic interpretation of the increase in the variance of unobserved individual productivity across cohorts within an extended Roy framework. Earlier work typically interprets this variance as reflecting fixed differences in innate ability and, accordingly, treats it as constant over time, implying that observed increases in inequality must stem from changing skill prices. We show instead that the variance can evolve endogenously as workers adjust their task choices in response to technological change. In our model, technological change not only raises the returns to complex tasks (as in Acemoglu and Autor, 2011) but also induces individuals to sort into these tasks within occupations. This endogenous sorting amplifies the cohort-specific variance of the unobserved productivity component. We provide empirical evidence consistent with this mechanism.

Our paper begins with a descriptive analysis using German administrative data from 1975 to 2019, showing that cross-sectional inequality in Germany expanded from the late 1980s but plateaued after the Great Recession (see also Dustmann et al., 2025). Consistent with evidence for the US (Guvenen et al, 2022), we also find that wage inequality at age 25 follows a similar trend to cross-sectional inequality and that wage mobility decreases for later cohorts. These results suggest that significant inequality arises early in workers' careers and tends to persist throughout their working lives. Furthermore, lifecycle earnings inequality for birth cohorts from 1950 to 1985, defined as total labor earnings between ages 25 and 34, increased by more than 25 percent up to the 1975 cohort but declined by about 5 percent for cohorts born between 1975 and 1985.

We then turn to our model of the wage and employment process to examine the mechanisms driving the evolution of cross-sectional and lifecycle inequality. We document a substantial rise in the variance of the unobserved fixed effect. Between the 1955 and 1994 birth cohorts, this variance nearly doubled and primarily explains the evolution of cross-sectional and lifecycle inequality. Decomposing the fixed effect into a cohort-specific productivity component and its time-varying price, we show that this increase is explained about equally by both components.

Our model also replicates the recent plateau in cross-sectional inequality, which is attributed to a reduction in the magnitude of persistent wage shocks. Meanwhile, transitory wage shocks play a minor role in shaping cross-sectional and lifecycle inequality, although the magnitude of transitory shocks temporarily increased around the Great Recession.

We further investigate the effect of non-employment risk on cross-sectional inequality. While the non-employed are excluded from such analysis, selection could still lead to non-employment influencing cross-sectional inequality. We show that, although such selection is present, and non-employment has changed substantially over our study period, its magnitude is too small to affect cross-sectional inequality meaningfully. This suggests that in studies of wage inequality relying solely on cross-sectional data, selection into non-employment is unlikely to be a concern. The employment margin is, however, crucial for lifecycle earnings, given that low-wage earners experience greater job instability and non-employment is persistent over time. Our findings reveal that the decline in lifecycle inequality after the 1975 birth cohort is primarily driven by shorter and less frequent non-employment spells in recent years.[3]

Earnings mobility provides the link between cross-sectional and lifecycle inequality. Examining its evolution, we find a decline beginning with the 1966 birth cohort, which stabilizes after the 1975 cohort. This decline is primarily driven by the sharp rise in the variance of individual fixed effects, both in the unobserved individual productivity component and its price. By contrast, changes in the returns to and composition of observables had only a modest positive effect on mobility after the 1975

[3] This is consistent with Boenke et al. (2015a), who highlight the significance of non-employment in shaping lifecycle inequality through Gini coefficient analysis.

cohort, partially offsetting the adverse impact of rising variance in fixed effects.

A key finding of our analysis is that the rise in the variance of individual fixed effects is driven not only by the growing dispersion of unobserved skill prices—commonly cited as the main explanation in earlier work (e.g., Juhn et al., 1993)—but also by an increase in the variance of the unobserved productivity component. This component is often interpreted as ability or talent, yet it is implausible that successive cohorts experienced such large shifts in the distribution of innate ability. To provide an economic interpretation of this pattern, we first show that the increase in the variance of fixed effects arises predominantly within occupations, with roughly three-quarters of the total increase explained by within-occupation variation. We then develop a Roy model of task choice within occupations under skill-biased technological change. In this framework, the individual productivity component captures realized productivity—jointly determined by innate ability and task choice—rather than innate ability alone. Consequently, technological change can raise the variance of individual productivity through sorting, even when the underlying distribution of talent remains stable.

The key idea is as follows. Within occupations, workers choose between routine and complex tasks. Because ability translates more strongly into productivity in complex tasks[4], technological change—by raising the return to complex relative to routine tasks—draws a growing share of workers into complex tasks. This reallocation amplifies inequality. The mechanism complements the canonical model of technological change, where inequality rises through higher relative prices of complex tasks (e.g., Acemoglu and Autor, 2011), by providing an explanation for why technological change also increases the variance of unobserved productivity. Our framework thus accounts for the rising variance in workers' unobserved productivity without requiring changes in the underlying distribution of ability.

To test our model, we treat occupations as labor market units comprising routine and complex subsectors, with the relative size of the complex subsector varying across occupations. This focus is motivated by the observation that roughly two-thirds of the

[4] Cortes (2016) uses a similar mechanism to explain between-occupational employment polarization.

increase in the variance of unobserved individual heterogeneity—measured as residual wages net of observable components—occurs within occupations. The model generates three testable predictions. First, workers performing more complex tasks should earn higher wages than peers performing less complex tasks. Second, inequality should rise more in occupations where the share of complex tasks has expanded more strongly. Third, conditional on initial complexity, the effect of worker sorting on inequality should be largest in occupations with either low or high initial complexity and smaller in those with moderate complexity.

We test these predictions using task-complexity data from the 1986 and 2006 BIBB/IAB surveys. The estimates confirm the model's implications: within occupations, greater task complexity is associated with significantly higher wages, even after controlling for experience, gender, and managerial status. Moreover, occupations that experienced larger increases in average task complexity show greater growth in within-occupational wage dispersion, and consistent with the model's non-monotonic sorting mechanism, this relationship follows a U-shaped pattern with respect to initial complexity.

We contribute to the literature in different ways. . First, we jointly analyze cross-sectional wage and lifecycle earnings inequality through the lens of a lifecycle earnings model. Building on the longstanding literature that uses income process models to decompose sources of lifecycle inequality (MaCurdy, 1982; Abowd and Card, 1989; Moffitt and Gottschalk, 1995; Meghir and Pistaferri, 2004), we incorporate both time- and cohort-specific forms of non-stationarity in a joint model of wages and employment.[5] Explicitly modeling the employment margin distinguishes our approach from much of the prior literature, which abstracts from employment–non-employment transitions—either by focusing on workers for whom non-employment is less relevant (e.g., Guvenen, 2009) or by modeling earnings, thereby implicitly absorbing non-employment into earnings shocks (e.g., Haider, 2001; DeBacker et al., 2013; Blundell et al., 2015).[6] Our approach,

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[5] While Baker and Solon (2003) and Boenke et al. (2015b) also distinguish between cohort and time dimensions, their specifications and interpretations differ substantially and address distinct research questions.

[6] An exception is Guvenen et al. (2021), who develop a rich model that accounts for non-

therefore, allows us to quantify the relative contributions of different sources to the evolution of cross-sectional and lifecycle inequality, as well as wage mobility.

Our second contribution is to reinterpret the role of the individual fixed effect in the wage process model and to link it to the literature on technological change. The productivity component, i.e., the fixed effect net of prices, is typically viewed as capturing individual ability with a time-invariant distribution.[7] This interpretation contrasts with our finding that the variance of individual fixed effects changes systematically across cohorts. We propose that the productivity component reflects realized productivity, shaped by workers' task choices within occupations. As technological change alters task incentives, these choices increase the variance of realized productivity, while the underlying ability distribution remains constant, thereby amplifying inequality beyond the canonical skill-price channel (Katz and Murphy, 1992).

Lastly, our study contributes to the literature on German income inequality by providing new evidence on the sources of the evolution of lifecycle inequality across cohorts. Most existing research focuses on cross-sectional wage inequality (e.g., Dustmann et al., 2009; Card et al., 2013; Goldschmidt and Schmieder, 2017; Biewen et al. 2018; Biewen et al., 2019; Drechsel-Grau et al., 2022; Bossler and Schank, 2023; Dustmann et al., 2025). A few exceptions focus on Gini coefficients but do not quantify

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employment risk, but their framework does not address cohort differences in inequality.

[7] Cortes and Hidalgo-Pérez (2015) also allow the variance of the individual component to change across cohorts. They model the unobserved component as a time-invariant latent ability, delegating all other dynamics—such as lifecycle skill accumulation, permanent shocks, and task reallocations—to the residual. In principle, if their identification holds exactly, the fixed effect isolates only entry-level heterogeneity, while all persistent changes are treated as noise. In practice, however, their short-panel design (two waves) risks conflating permanent endowments with unmodeled dynamics. Lochner, Park, and Shin (2018, 2025), using the PSID, find that the variance of initial ability is essentially stable over time, and that rising dispersion reflects heterogeneous and persistent shocks to skill growth over the lifecycle. They interpret the unobserved component as a latent skill stock—initial ability augmented by heterogeneous growth shocks—whose rising variance reflects increasing dispersion in skill accumulation.

the contribution of stochastic wage determinants to lifecycle inequality (Boenke et al. 2015a), or estimate a lifecycle wage model does not consider employment-non-employment transitions (Boenke et al. 2015b). Our study jointly models the stochastic wage process and employment-non-employment transitions to disentangle the sources of the evolution of lifecycle inequality in the German context.

The remainder of this paper is structured as follows: Section 2 describes the data, and Section 3 shows our wage and employment process model. Section 4 discusses the estimation results and counterfactual simulation results. Section 5 demonstrates the economic model to interpret the estimation results. Section 6 concludes this study.

2. Data and descriptive analysis

2.1. Data

Our analysis uses administrative data for Germany from the Sample of Integrated Labour Market Biographies (SIAB) from 1975 to 2019. [8] The SIAB is a 2% random sample of the Integrated Employment Biographies (IEB), which contain detailed employment records for individuals covered by social security and records of unemployment benefit receipts. This dataset enables us to track individual employment histories across the entire 1975–2019 period. In addition to daily wages and employment duration, the data provides rich information on workers and jobs, including age, gender, educational attainment, occupation, industry, and workplace characteristics (see Frodermann et al., 2021, for further details). Dating back to 1975, it enables us to analyze wage inequality over 45 years. Since the SIAB is based on administrative records, daily wages are measured with high precision. This is crucial because measurement errors in wages can complicate the estimation of wage process models (see Bound and Krueger, 1991; Meghir and Pistaferri, 2011).

While the SIAB does not cover self-employed individuals, family workers, or civil servants, it represents about 85 percent of employment in 2019 (DESTATIS, 2023).

[8] Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

Wages in the SIAB are top-coded at the upper limit of social security contributions. To address this, we apply a two-step imputation method, following the approaches of Gartner (2005), Dustmann et al. (2009), Card et al. (2013), and Dauth and Eppelsheimer (2020).

When estimating the wage process model, we focus on males to avoid complications arising from voluntary labor force participation choices and variations in hours worked. We also exclude East Germans, as records are unavailable before 1991.[9] We restrict the sample to individuals aged 25 to 59 to focus on prime-age workers.[10] Since the SIAB does not contain detailed data on hours worked, only indicators for full-time, part-time, or marginal employment are available. Therefore, we limit the sample to full-time employment records to ensure that daily wages accurately reflect full-time work. Specifically, we exclude individuals who held part-time or marginal jobs between the ages of 25 and 59. Since most prime-age men work full-time, our results are not sensitive to this restriction and remain essentially unchanged when part-time workers are included in the analysis sample. Additionally, we exclude individuals who had not completed their apprenticeship or university studies or were not employed by age 25 (the starting point of our lifecycle definition). To address data quality concerns, we also drop the top 2% of wages to eliminate unrealistic imputed values and the bottom 2% to account for the potential misclassification of part-time employment as full-time (Fitzenberger and Seidlitz, 2020).[11]

Our analysis uses two measures of labor income: wages and lifecycle earnings. Wages are calculated as the total wages earned in full-time employment within a calendar year, divided by the total number of days spent in full-time employment during that year.[12]

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[9] Since birthplace information is unavailable in our data, we follow Boelmann et al. (forthcoming) and classify workers as West German if their first recorded workplace in the dataset is located in West Germany.

[10] Our target population is similar to Baker and Solon (2003), who analyze men between 25 and 58.

[11] The wage refers to the annual average wage defined below.

[12] In calculating wages, we assign zero weight to non-employment spells. Following Stueber et al. (2023), we allocate separately recorded one-time payments to the corresponding regular employment spells with the same employer within the same calendar year. If a worker holds multiple jobs simultaneously, we consider only the job with the highest daily wage.

While wages are helpful in analyzing the wage distribution within a given year, such as cross-sectional wage inequality, they provide limited insight into earnings over the lifecycle. Therefore, we measure lifecycle earnings as the total labor earnings accumulated between ages 25 and 34,

$$Lifecycle\ Earnings = \sum_{Age=25}^{34} Yearly\ Earnings_{Age}$$

Although our definition of "lifecycle earnings" does not capture all earnings between ages 25 and 59, we focus on these ten years to extend our analysis to recent cohorts. As Guvenen (2022) emphasizes, most wage growth occurs during the first ten years (see also Topel and Ward, 1992); in fact, we demonstrate in Section 2.2 that this period is a valid proxy for lifecycle earnings.[13]

This approach allows us to compute lifecycle inequality for cohorts born between 1950 and 1985. To ensure comparability, we calculate cross-sectional inequality also for workers aged 25 to 34 unless otherwise specified. For the lifecycle inequality analysis, we focus on workers with a total employment duration of at least three years over the ten years. All wages and earnings are adjusted to 2015 values using the consumer price index provided by the German Federal Statistical Office.

In addition to the SIAB, we utilize the BIBB/IAB Career and Qualification Survey, which inquires about the frequency of various tasks performed in workers' jobs. Task content from this survey has been used in the German context, for example, by Spitz-Oener (2006) and Black and Spitz-Oener (2010). We use this information to characterize occupations by their tasks, similar to O*NET data in the U.S. Specifically, we rely on the 1986 and 2006 survey waves to define a measure of each occupation's task complexity and merge this information with the SIAB at the occupation level. See Section 5 for further details.

2.2. Evolution of Cross-sectional and Lifecycle Inequality

Figure 1 Panel A shows the trend in cross-sectional inequality for our sample, which

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[13] To ensure strong labor market attachment, we restrict the sample to individuals employed for at least three years.

began rising in the early 1990s and accelerated during the 2000s, driven by declining earnings at the lower percentiles (see Dustmann et al., 2009). After the Great Recession, earnings grew sharply across the distribution, with no further expansion in inequality during this period. This pattern is similar when considering the entire population of male workers (see Figure 1 Panel B).[14]

Figure 1, Panel C, shows that the evolution of wage inequality at age 25 closely tracks overall cross-sectional inequality, suggesting that entry-level wages are a key driver of cross-sectional wage dispersion—a pattern also documented for the United States (Guvenen et al., 2022). Because it takes time for entry-level wage inequality to fully translate into overall inequality, the rise in entry-level dispersion unfolded gradually over the 1990s and mid-2000s, driven primarily by declines in the lower percentiles. After the Great Recession, however, entry-level wages increased across the entire distribution.

Rising entry-level inequality is driven mainly by within-occupation rather than between-occupation differences, consistent with recent U.S. evidence (Biasi et al., 2025). Figure 12 illustrates this by decomposing the variance of log wages at age 25 by birth cohort into within- and between-occupation components. The variance of entry-level wages nearly tripled—from 0.035 for the 1950 cohort to 0.09 for the 1983 cohort—with roughly two-thirds of the increase accounted for by growing within-occupation dispersion.[15]

Figure 1 Panel D plots lifecycle earnings across birth cohorts, measured as the sum of earnings between ages 25 and 34. The median and lower percentiles declined for cohorts born up to the late 1970s, although the 10th percentile shows a modest increase for early 1970s cohorts entering the labor market after 1995. By contrast, the 90th

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[14] We do not show the 90th percentile, because wages at this level are censored in the overall distribution due to the social security contribution limit.

[15] Recent work by Briskar et al. (2023) and Haltiwanger et al. (2024) highlights changes in industry composition as an important driver of rising wage inequality in Italy and the United States. To assess the relevance of this channel, Figure A9 presents a two-step variance decomposition: first separating between- and within-industry variation, and then decomposing the within-industry component by occupation. The results show that the dominant source of rising entry-level wage inequality lies within occupations within industries, rather than in shifts across industries or occupations.

percentile remained relatively flat until the 1970 cohort and then rose steadily thereafter. More recent cohorts experienced substantial gains in lifecycle earnings, particularly at the lower end of the distribution. Consequently, the 90–10 log percentile difference follows a bell-shaped pattern, peaking with the 1975 cohort (see Figure A1). Lifecycle earnings inequality increased by roughly 25 percent from the 1960 to the 1975 birth cohort, before declining by about 5 percent between the 1975 and 1985 cohorts.

As inequality in entry-level wages expanded among early cohorts, the initial rise in lifecycle inequality reflects the persistence of initial wage disparities, a mechanism we study in detail in Section 3 through our wage process model. However, the following decline in lifecycle inequality after the 1975 cohort, shown in Figure 1, Panel D, cannot be explained by entry-wage dynamics alone. Instead, the employment margin—typically neglected in analyses of cross-sectional inequality—emerges as a central driver. Over our sample period, unemployment fluctuated sharply (Figure 2, Panel A), rising from below 3 percent in 1980 to 7 percent in 1985, then falling again until German reunification in 1990. In the 1990s, unemployment climbed to 10 percent, peaking at over 11 percent in 2005, before steadily declining to just above 3 percent by 2019.[16]

Figure 2, Panel B, plots the correlation between wages at age 25 and total employment duration (in years) between ages 25 and 34. Mapping the mean and median duration against each vintile (20 bins) of the age-25 wage distribution[17] shows that low-wage workers are especially vulnerable to non-employment risk. As unemployment rates declined after 2005, this pattern aligns with the sharp rise in the 10th percentile of lifecycle earnings among recent cohorts (Figure 1, Panel D), which primarily benefited low-wage earners. Section 4 quantifies the contribution of the employment margin to the observed decline in lifecycle inequality.

To show that the first ten years of workers' careers provide a reliable proxy for lifecycle earnings, we follow Guvenen et al. (2022) and plot the median wage across ages

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[16] The Great Recession caused only a small and temporary increase in the unemployment rates.

[17] The sample covers up to ten years of employment and, to ensure consistency with our calculation of lifecycle earnings, includes only individuals employed for at least three years.

and years in Figure 3, Panel A. The solid lines depict median wages at each age across calendar years, while the dotted lines trace age profiles within cohorts from labor market entry at age 25. For example, the first dotted line on the left tracks the median log wage of the 1960 birth cohort at age 25 in 1985, age 30 in 1990, and so forth. For this cohort, wage growth between ages 25 and 55 is about 45 percent, with over 60 percent realized by age 34. A similar pattern holds for other cohorts, indicating that total earnings during the first decade of work provide a reasonable approximation of lifecycle earnings.

2.3. Earnings Mobility

A key connection between cross-sectional and lifecycle inequality is earnings mobility. In the absence of mobility, cross-sectional inequality translates directly into lifecycle inequality. By contrast, with high mobility, where earnings shocks are entirely temporary. substantial cross-sectional inequality can exist without generating lifecycle inequality. Earnings mobility thus serves as an inverse indicator of the extent to which cross-sectional inequality reflects lifecycle inequality.

To evaluate earnings mobility, we compute the Shorrocks mobility index (Shorrocks, 1978) across cohorts, following Kopczuk et al. (2010). The index is defined as the ratio of an inequality measure, in our case, the variance, of long-term average earnings to the average of that same inequality measure calculated for short-term earnings.

$$Shorrocks_c = 1 - \frac{Var\left(\frac{1}{10}\sum_{a=25}^{34} Earnings_{a,c}\right)}{\frac{1}{10}\sum_{a=25}^{34} Var\left(Earnings_{a,c}\right)}$$

The Shorrocks index ranges from 0 to 1, with higher values indicating greater earnings mobility. An index close to 1 implies that the variance of long-term earnings is much smaller than that of short-term earnings, suggesting that year-to-year earnings fluctuations are largely transitory and mobility over the lifecycle is high. By contrast, an index near 0 indicates that the variance of long-term earnings closely mirrors that of short-term earnings, meaning that annual earnings shocks are nearly permanent and mobility is low.

Figure 3, Panel B, shows the evolution of the Shorrocks index across cohorts. Earnings mobility is almost flat for the 1960–1966 birth cohorts, ranging between 0.35 and 0.40, implying that long-term variance is about 60–65% of short-term variance. It then declines to around 0.3 for the 1966-1975 cohorts, after stabilizing for later cohorts. This decline in mobility is consistent with entry-level wage inequality becoming more important and persistent among recent cohorts. In Section 4, we quantify the contribution of changes in the structure of wages and employment to the evolution of mobility.

3. Wage and Employment Process Model

We model the residual wage using a linear factor model building on Guvenen (2009) but allowing for non-stationarity across cohorts and over time (Baker and Solon, 2003). Specifically, the model includes the individual productivity components α_{ic} (representing time-invariant productivity) and associated prices p_t, along with an AR(1) persistent shock η_{it} and an idiosyncratic transitory shock ϵ_{it}. The distribution of the individual productivity component α_{ic} is allowed to vary across entry cohorts c, while its price p_t and the distributions of other shocks can differ across calendar years t.

Thus, the log wage of a worker i from cohort c, with education level e, and age a in year t is modelled as:

$$\ln w_{iceat} = \mu_{ceat} + p_t \alpha_{ic} + z_{iat} + \epsilon_{it}, \tag{1}$$

$$z_{iat} = \rho_t z_{i,a-1,t-1} + \eta_{it}, \tag{2}$$

where μ_{ceat} is the mean log wage given cohort, education, and age, and z_{iat} is a non-stationary AR(1) process. In this specification, μ_{ceat} collects the observed determinants of wages, such as age, education, and calendar year fixed effects, while $p_t \alpha_{ic} + z_{iat} + \epsilon_{it}$ represents the unobserved determinants (the residual wage). The mean and variance of each component are specified as follows:

$$E[\alpha_{ic}|c] = E[\eta_{it}|t] = E[\epsilon_{it} \mid t] = 0,$$

$$Var\,(\alpha_{ic} \mid c) = \sigma^2_{\alpha c}, Var\,(\eta_{it} \mid t) = \sigma^2_{\eta t}, Var\,(\epsilon_{it} \mid t) = \sigma^2_{\epsilon t}.$$

Notably, we allow the distribution of the α_{ic} to vary across cohorts. We thus extend the variance decomposition proposed by Lemieux (2006), which assumes that the within-group variance of unobserved productivity remains constant to identify changes in skill prices. Both the price across time and the cohort-specific variance $\sigma^2_{\alpha c}$ of the unobserved individual productivity α are identified, as the autocorrelation of wages provides additional identifying variation for estimating the sources of the wage variance. Specifically, $\sigma^2_{\alpha c}$ is the baseline intercept of the autocovariance profile of each cohort, and the price p_t shifts this intercept in the same way across cohorts but differently across time. Therefore, with multiple cohorts each year, we can identify p_t across time and the cohort-specific variance $\sigma^2_{\alpha c}$ using the auto-covariance profiles of residual wages.

The model parameters are identified and estimated by using the autocovariance of the residualized wage, $\hat{y}_{iceat} = \ln w_{iceat} - \mu_{ceat}$:

$$Cov\left(\hat{y}_{iceat}, \hat{y}_{ice,a+d,t+d}\right) = p_t p_{t+d}\, \sigma^2_{\alpha c} + \left(\prod_{j=!}^{d} \rho_{t+j}\right) \sum_{k=0}^{a} \left(\prod_{s=0}^{k-1} \rho^2_{t-s}\right) \sigma^2_{\eta,t-k} + 1\{d = 0\}\sigma_{\eta t}, \quad (3)$$

where a is normalized to be zero at age 25, and p_t is normalized to be one in the initial year. We compute the empirical autocovariances for all cohorts and collect them in a single vector $\hat{\pi}$ to minimize

$$\min_{\theta \in \Theta} [\hat{\pi} - h(\theta)]' W\, [\hat{\pi} - h(\theta)],$$

where θ is the set of parameters in equations 1 and 2, $h(\theta)$ is a vector-value function represented by equation 3, and W is a diagonal weighting matrix whose element equals the number of observations for each component.[18] To manage the large number of parameters in our model, we group three consecutive calendar years and cohorts. This

[18] Although the inverse of the variance-covariance matrix of the reduced-form estimator $\hat{\pi}$ is considered the asymptotically optimal weighting matrix, Altonji and Segal (1996) argue that it performs poorly in finite samples. Therefore, following the approach of Baker and Solon (2003) and Guvenen (2009), we use the number of observations contributing to each autocovariance as weights.

approach reduces the parameter space and enhances the precision of our estimates.[19] We estimate the model on all available yearly wage observations of individuals between age 25 and 59.

We specify the employment-non-employment transition and non-employment duration as follows:

$$\text{Non-employment risk: } \Pr(U_{iat} = 1 \mid a, w_{i,t-1}, U_{i,t-1}) = q(a, t, w_{it-1}, U_{it-1}), \quad (4)$$

$$\text{Non-employment duration: } \ddot{v}_{iat} = \begin{cases} 0 \text{ if } U_{iat} = 0, \\ \min\{1, v_{iat}\} \text{ if } U_{iat} = 1, \end{cases} \quad (5)$$

where v_{iat} follows an exponential distribution as in Guvenen et al. (2021), and the distribution is characterized by calendar year, age, and the wage and employment status in the previous year with $v_{iat} \mid a, t, w_{t-1}, U_{t-1} \sim \exp\big(\lambda(a, t, w_{t-1}, U_{t-1})\big)$. In practice, we construct five groups based on individuals' wage and employment status in the previous year. Four groups comprise fully employed individuals, classified by wage quartiles in the previous year, while the fifth group consists of those with some non-employment. For each groups, we estimate the non-employment probability $q(a, t, w_{it-1}, U_{it-1})$ directly from the data as the share of workers in that group who are not employed for the full year, divided by the total number of workers in that group in that year.

Since the non-employment duration is modeled as a truncated exponential distribution, the expected non-employment duration is given by:

$$E[\ddot{v}_{iat} \mid a, t, w_{i,t-1}, U_{i,t-1} = 1] = \frac{1 - \exp\big(\lambda(a, t, w_{t-1}, U_{t-1})\big)}{\lambda(a, t, w_{t-1}, U_{t-1})}. \quad (6)$$

The parameter $\lambda(a, t, w_{t-1}, U_{t-1})$ is estimated by solving the non-linear equation (6),

[19] For example, we specify the price and individual FE as $p_{1975} = p_{1976} = p_{1977} \neq p_{1978} = p_{1979} = p_{1980} \neq p_{1981} = \cdots$, and $\sigma^2_{\alpha 1950} = \sigma^2_{\alpha 1951} = \sigma^2_{\alpha 1952} \neq \sigma^2_{\alpha 1953} = \sigma^2_{\alpha 1954} = \sigma^2_{\alpha 1955} \neq \sigma^2_{\alpha 1956} = \cdots$, and so on.

replacing the left-hand side with its empirical counterpart, $\hat{E}[\ddot{v}_{iat} \mid a, t, w_{i,t-1}, U_{i,t-1} = 1]$, estimated as the average number of days in non-employment divided by the total number of days in the year for all individuals in the respective group who are not employed full-year. The parameter λ can thus be interpreted as a hazard rate.[20]

While our model accounts for the correlation between earnings capacity and non-employment risk through equations (4)–(6), it does not explicitly capture job-displacement effects on wages. Prior studies, such as Jacobson et al. (1993) or Arulampalam (2001), show that job displacement effects tend to be persistent and would therefore be absorbed by persistent shocks in our model. Consequently, we may understate the role of non-employment risk overstate the role of persistent shocks. Despite this limitation, our model fits the data well, as we show in Section 4. Moreover, because the potential bias works against our main argument, it does not weaken our conclusion that the employment margin is crucial for explaining the evolution of the lower tail of the lifecycle earnings distribution.

Our model follows a restricted income process (RIP). An alternative, a heterogeneous income process (HIP) model, allows the age profile to vary across individuals through random coefficients, while the RIP model absorbs this heterogeneity in wage growth in the persistent shock z_{iat}. We do not adopt the HIP model for three reasons. First, as Guvenen (2009) emphasizes, identification of HIP relies heavily on higher-order autocovariances. Since few individuals contribute to these moments, the resulting estimates are difficult to interpret in the full sample. Furthermore, ensuring internal validity requires restricting the analysis to individuals with long wage histories (20 years in Guvenen's case). Such a restriction poses severe challenges for analyzing wage inequality, and especially lifecycle earnings inequality, as it would limit attention to continuously employed workers. Identification of heterogeneous profiles for more

[20] However, note that λ governs the expected duration of non-employment spells, not the timing of non-employment episodes within the annual observation window. For example, a value of $\lambda = 1.5$ corresponds to an expected non-employment fraction of roughly 50% of the year. In our model, this could correspond either to a continuous six-month non-employment spell from January to June or to two separate three-month spells, for example from January to March and July to September.

recent cohorts is also infeasible, given the limited availability of higher-order autocovariances.

Second, the evolution of cross-sectional wage inequality closely mirrors entry-level wage dynamics (see Section 2), suggesting that cohort-specific variance $\sigma_{\alpha c}^2$ of the unobserved individual productivity and their associated prices are more important than heterogeneity in wage growth. Thus, whether wage variance arises through RIP or HIP is not central to our argument.

Third, our model already requires estimating a large number of parameters. Allowing for a non-stationary HIP across cohorts would substantially increase computational complexity.

4. Results

4.1. Parameter Estimates

Panels (A) – (E) of Figure 4 show estimates of the parameters from equations (1) and (2). Panel A displays the variance of the individual productivity component, $\sigma_{\alpha c}^2$, which exhibits a clear pattern across cohorts. For the 1950 cohort, the variance is about 0.015 and nearly doubles over the next 45 years. Correspondingly, the standard deviation increases from 0.12 to 0.17, a 40 percent rise, accounting for roughly half of the growth in the standard deviation of log wages over the same period (from 0.24 to 0.34).

The price of individual productivity, p_t, rose by about 50 percent between 1975 and 2011, remained stable until 2015, and declined slightly thereafter (Panel B). This trajectory aligns with the findings of Dustmann et al. (2025), who document a trend reversal in the evolution of the skill premium for observed skills in Germany following the Great Recession. Our analysis complements their findings by demonstrating that the price for unobserved productivity also ceased to increase after the Great Recession. Together, these results reinforce our descriptive evidence that inequality at market entry is a key driver of wage inequality, which persists throughout the lifecycle.

Panel C shows estimates of the persistence parameter ρ_t of the AR(1) process. The parameter is very close to one, suggesting that persistent shocks to wages are almost permanent for most of our sample period. Panel D depicts the estimates of the variance

$\sigma_{\eta t}^2$ of the AR(1) process. This parameter fluctuates around 0.005 in the first half of the period and then declines after 2000. Since our persistence parameter $\rho_t \approx 1$, the variance of accumulated persistent shocks over s years can be approximated by $s\sigma_{\eta t}^2$. With an average variance of about 0.005, the accumulated variance $s\sigma_{\eta t}^2$ amounts to 0.05 ten years after labor market entry, which is comparable in magnitude to the composite variance of the individual productivity component and its price $(p_t^2\sigma_{\alpha c}^2)$[21]. Thus, the persistent shock η_{it} also generates substantial wage dispersion in levels at age 34, as individual wages diverge over the career due to these lasting shocks. However, its *evolution over time* is smaller than that induced by $p_t^2\sigma_{\alpha c}^2$, although we observe a non-negligible decline in persistent shocks in recent years. Consequently, changes in persistent wage shocks play a less important role in driving the overall rise in wage inequality than changes in the individual productivity component, as shown in our counterfactual simulation in Section 4.

Finally, Panel E presents estimates for the transitory shock ϵ_{it}, which remains relatively stable over time. For most of the period, the estimated variance $\sigma_{\epsilon t}^2$ ranges between 0.008 and 0.010, but rises to almost 0.012 between 2005 and 2010, coinciding with the Great Recession. This indicates that our model captures the macroeconomic shocks influencing wage volatility. The magnitude of the transitory shock is comparable to the variance of the yearly innovation of the persistent shock $\sigma_{\eta t}^2$. However, since the transitory shock does not accumulate over time, our model suggests that these temporary shocks are less influential than permanent or persistent shocks in shaping long-term wage dynamics. We confirm this in our counterfactual simulation in Section 4.

As shown in Figure 4, the parameters for persistent and transitory shocks are estimated with low precision for 1975–1977. This arises from weak identification, as our sample includes only individuals born in 1950 or later. Consequently, just one cohort is observed in 1975, two cohorts in 1976, and three in 1977. Distinguishing persistent from transitory shocks relies on the autocovariance of wages; however, for these cohorts, the

[21] For example, for the cohort born in 1971, the estimated total variance of the individual productivity component and its time-varying price component at age 34 is $p_{2005}^2\sigma_{\alpha,1971}^2 \approx 0.052$.

autocovariance matrix contains only four off-diagonal elements. Since estimating the AR(1) process requires two parameters, identification is only barely achieved, leading to large standard errors. For this reason, we use the year 1980 as the base year in our counterfactual simulations below.

Figure 5 summarizes the estimation result of the employment component of the model. The two histograms, in red and blue, show the distribution of the non-employment duration parameter λ among those non-employed (blue) and employed (red) in the previous period, plotted against the left y-axis. The black line, plotted against the right y-axis, depicts the relation between the estimated value of λ and the expected non-employment duration that corresponds to this value according to the cumulative distribution function of the truncated exponential distribution as defined in Equation (5). For example, a value of $\lambda = 0$ corresponds to full non-employment throughout the year (zero days of employment), whereas a value of $\lambda = 5$ implies a non-employment share of 20%, that is, employment for 80% of the year.

Long-term non-employment is highly persistent: The blue histogram shows the distribution of λ and the corresponding non-employment durations for individuals who experienced some non-employment in both the previous and the current year. This group tends to remain non-employed for the full year.[22] In contrast, the distribution of λ for those newly entering non-employment after being fully employed in the previous year (red histogram) is much more dispersed. For example, a worker with $\lambda = 1.5$ experiences roughly 6 months (50 percent of the year; see black solid line) of non-employment, whereas a worker with $\lambda = 0.75$ experiences about 8.4 months (70 percent) of non-employment.

4.2. Counterfactual Simulation

We conduct counterfactual simulations using the estimated wage process and non-

[22] Note that in our model, experiencing non-employment in the previous year does not necessarily imply being non-employed for the entire year. Repeated years of non-employment are also consistent with multiple short employment spells that do not last the full year, reflecting unstable or intermittent employment.

employment risk parameters to disentangle and quantify the relative importance of the various sources of cross-sectional and lifecycle inequality. The procedure consists of four steps:

1. Demographics: Replicate the demographic composition (educational distribution and cohort size) at age 25.
2. Wages: Simulate log daily wages $\ln w_{iceat}$ between the ages of 25 and 34 for all individuals using equations (1) and (2), drawing shocks from normal distributions with mean zero and the estimated year- or cohort-specific variance.
3. Employment: Based on the simulated potential wages from step 2, simulate the employment status U_{iat} and non-employment duration $\ddot{v}_{it}$ according to equations (4) and (5), assuming all individuals are employed at age 25 (consistent with our sample restriction).
4. Earnings: Compute earnings by adjusting wages for simulated employment duration$1-\ddot{v}_{it}$: $\hat{e}_{it} = (1 - \ddot{v}_{it}) \exp(\mu_{ceat} + p_t \alpha_{ic} + z_{iat} + \epsilon_{it})$.

A detailed description of the simulation procedure is provided in Appendix A.

4.2.1. Counterfactual Simulation Scenarios

To perform the counterfactual simulation, we set the variance of the individual productivity component $\sigma^2_{\alpha c}$ to its estimated value for the c =1955 birth cohort, while holding all other parameters that vary by calendar year at their estimated values for t =1980, the entry year of the 1955 cohort.[23] We then simulate the wage distribution under various scenarios, sequentially allowing additional parameters to change over time. In scenario CF1, only demographic and educational characteristics and their returns, μ_{eat}, vary. Scenario CF2 adds variation in the variance of the individual FE $\sigma^2_{\alpha c}$. Scenario CF3 instead allows the skill price p_t (but not $\sigma^2_{\alpha c}$) to change. In scenario CF4, both $\sigma^2_{\alpha c}$ and p_t vary. Scenario CF5 adds changes in the persistent shock parameters ρ_t and $\sigma^2_{\eta t}$.

[23] Our simulations start in $t = 1985$ and $c = 1960$ respectively, as these are the first years and cohorts for which we can compute a fully simulated cross-sectional distribution and a 10 year earnings inequality estimate. We use $c = 1955$ and $t = 1980$ as baseline values as we aim to approximate the cross-sectional wage inequality for these first periods by the average parameters that the first cohorts in these estimates experienced.

Scenario CF6 additionally allows in the variance of the transitory shock, $\sigma_{\epsilon t}^2$, to vary. Scenario CF7 corresponds to the full model, further incorporating changes in non-employment risk and duration. Table A1 in the Appendix summarizes the parameters that are fixed and those that vary across the different scenarios.

4.2.2. Cross-Sectional Inequality

The counterfactual simulations for cross-sectional inequality are presented in Figure 6.[24] As discussed in Section 2, the p90-p10 log difference of cross-sectional wage inequality, shown in solid black, was approximately 0.57 in 1985 and increased to around 0.83 by the onset of the Great Recession.

In Scenario CF1 (dotted black line), all parameters of the stochastic component of the wage process and non-employment probabilities are fixed at their 1980 values (for the 1955 cohort), while only the composition and returns to observables vary over time. The level of cross-sectional inequality in this scenario is relatively close to the observed data (solid black line), but increases only marginally, from approximately 0.53 to 0.58. Thus, changes in the composition and average returns to observables —specifically, age, experience, and education —account for a significant portion of the *level* of inequality but do not explain the observed trend over time. This leaves the largest share of the trend in wage inequality to be explained by the stochastic component of wages or the employment margin.

Scenario CF2 (solid blue with small dots) additionally allows the variance of the individual productivity component, $\sigma_{\alpha c}^2$, to vary across cohorts. This addition explains roughly one-third of the increase in wage inequality. Scenario CF3 (dotted blue line) instead allows observables and the skill price p_t (but not $\sigma_{\alpha c}^2$) to vary across time. Comparing the change from CF1 and CF3 with the change from CF1 to CF2, we find that the changes in the variance of the individual fixed effects and the skill price are roughly equally important in explaining the rise in cross-sectional inequality over our sample period. Scenario CF4 (solid red with symbol markers "v") allows both the variance $\sigma_{\alpha c}^2$

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[24] In the simulation, cross-sectional inequality is calculated for individuals employed for at least one day within a given year, while lifecycle inequality is measured for individuals with at least three years of employment between ages 25 and 34, ensuring alignment with our sample restrictions.

and the price p_t to vary together with observables. The combined effect explains almost the entire increase in cross-sectional inequality.

Next, to examine the role of persistent shocks, we additionally allow both the persistency ρ_t and the variance of the AR(1) innovation $\sigma^2_{\eta t}$ to vary over time (CF5, dotted red line). As suggested by the stable parameter estimates (Figure 4), the contribution of the AR(1) process, visible in the change from CF4 to CF5, is relatively modest. Although it slightly raises the p90-p10 ratio, this is primarily due to the low persistence parameter ρ_t, estimated to be around 0.9 in 1980. However, the decline in the variance of persistent shocks after 2000 (Figure 4, Panel D) helped mitigate the rise in inequality. Since the persistent shock η_{it} accumulates over time, the impact of its reduced variance was not immediately apparent in the early 2000s but became more significant during the 2010s. The stabilization of cross-sectional inequality during the 2010s can thus be attributed to a decline in the variance of persistent shocks, together with the stabilization of both price and variance of the individual productivity component. Absent the decline in the variance of persistent shocks, our model would have predicted a slight increase in inequality over this period.

Scenario CF6 also allows for changes in the transitory shock (solid green line with "x" markers). While the variance of the transitory shock increased by 20 percent during the Great Recession (Figure 4 Panel E), its contribution to the rise in inequality is much smaller than that of the combined contribution of the variance of individual fixed effects and skill prices, both in terms of magnitude and change over time.

The final scenario (CF7, dotted green line) corresponds to our full model, where all parameters, including the employment margin, are allowed to vary. The additional effect of changes in the employment margin (comparing CF6 to CF7) is negligible. Although cross-sectional wage inequality, by definition, only accounts for workers employed in a given year, non-employment can still influence inequality if selection into non-employment alters the wage distribution. However, our results suggest that changes in selection into non-employment had little impact on the observed trends in inequality.

To further examine the role of compositional changes through changes in selection into non-employment, we compute two additional counterfactual scenarios: one, an extreme case where non-employment occurs only at the bottom of the wage distribution

(*Selection)*, and another where non-employment risk is uncorrelated with wages (*No Selection*), see Appendix B and corresponding Figures A3 and A4. The Figure shows that differences in non-employment probabilities across the wage distribution do not meaningfully impact the cross-sectional wage distribution, with the *no-selection* scenario aligning closely with the model prediction without considering the employment margin. However, even if the employment margin is negligible in shaping cross-sectional inequality, the extensive margin of employment may still play an important role in shaping lifecycle inequality, as discussed below.

4.2.3. Life-Cycle Inequality

Figure 7 presents the counterfactual simulation analysis of lifecycle inequality. The solid black line shows the evolution of lifecycle inequality across birth cohorts, as discussed in Section 2. Lifecycle inequality increased by approximately 25 percent from the 1960 cohort, which entered the labor market at age 25 in 1985, to the 1975 cohort, which entered in 2000, before declining by roughly 5 percent by the 1985 birth cohort.

The decomposition reveals several parallels with cross-sectional analysis. Notably, the combined rise in the variance of the individual productivity component ($\sigma_{\alpha c}^2$) and its prices (p_t), captured in scenario CF4, drove the steady increase in lifecycle inequality over this period.[25] For example, relative to the 1960 cohort, lifecycle inequality among the 1975 cohort is almost 25 log points higher, with changes in the variance of the individual productivity component and its price alone accounting for more than 60 percent of this increase. Unlike in the cross-sectional analysis, however, about 40 percent of the rise remains unexplained. The contribution of persistent shocks (scenario CF5) and transitory shocks (scenario CF6) is limited. Additionally, changes in observables (education and age composition) and their returns (CF1) matter for the level but not for the change, mirroring the cross-sectional results.

A distinctive feature of lifecycle inequality is the role of non-employment risk. While often overlooked in studies of cross-sectional inequality—and, as shown above, it

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[25] The counterfactuals CF2 and CF3 reveal that, similar to the cross-sectional analysis in Figure 6, both factors had a roughly equal impact.

has only a minor impact in that context—non-employment risk substantially influences both the level and trend of lifecycle inequality. For example, for the 1975 birth cohort, the log p90-p10 ratio of lifecycle earnings is about 0.85 when non-employment risk is excluded (fixed at the low non-employment level of 1980, Scenario CF6), but exceeded 1.0 when employment dynamics are incorporated (CF7). Moreover, the wage process alone cannot account for the inverted U-shaped trend in lifecycle inequality. The employment margin is essential for explaining the post-1975 decline: ignoring it not only mistakes the level of inequality but also biases the estimated trend.

Non-employment is closely linked to wages: low-wage workers face substantially higher non-employment risk than their high-wage counterparts (see Figure 2, Panel B), thereby amplifying earnings inequality. Panels A and B of Figure 8 show that the 10th percentile of lifecycle earnings is far more sensitive to non-employment risk than the 90th percentile.

To better understand the role of employment dynamics in shaping the decline in lifecycle inequality after the 1975 cohort, we conduct additional counterfactual simulations that isolate changes in the parameters of the employment process. Specifically, we simulate outcomes while holding either the non-employment entry probability $q(a, t, w_{i,t-1}, U_{i,t-1})$or the expected non-employment duration $\ddot{v}_{iat}$fixed at their 1980 values, allowing all other components of the model to vary as in counterfactual CF7. These simulations show that the decline in lifecycle inequality is driven not by changes in the probability of entering non-employment but by shorter non-employment spells—particularly among individuals in the lowest wage quartile. Indeed, shorter spells for this group account for almost the entire reduction in lifecycle inequality among cohorts born after 1975.

Interpreted within a standard search-and-matching framework, non-employment risk corresponds to the separation rate, while non-employment duration reflects the job-finding rate. In job-ladder models such as Moscarini and Postel-Vinay (2018), rising job-finding rates result from more frequent matches in tighter labor markets. Dustmann et al. (2025) document a substantial increase in labor market tightness in Germany over this period and show that it reduced cross-sectional wage inequality. Our findings suggest that increasing labor market tightness also contributed to the decline in lifecycle earnings inequality—by shortening non-employment durations in addition to its documented effects on wages.

Moreover, non-employment can be viewed as a persistent shock: experiencing non-employment in one year increases both the probability and the expected duration of non-employment in the following year (see Figure 5). Thus, while non-employment has only a limited effect on cross-sectional inequality, it plays a substantial role in shaping lifecycle inequality.

4.2.4. Earnings Mobility

We now use our counterfactual simulation to study the evolution of earnings mobility. Conceptually, mobility links the cross-sectional distribution of earnings to their evolution over the lifecycle, measuring how short-term earnings fluctuations translate into long-term differences. As shown earlier, both cross-sectional wage and lifecycle earnings inequality have increased, but this does not necessarily imply lower mobility. Whether mobility rises or falls depends on which components—permanent, persistent, or transitory—drive the increase in dispersion.

Appendix G formally derives these relationships. A higher permanent component $(\sigma_{\alpha c}^2 p_t)$ reduces mobility, greater transitory variance $(\sigma_{\epsilon t}^2)$ raises it, and a higher innovation variance of the persistent shock $\left(\sigma_{\eta t}^2\right)$ has an ambiguous effect depending on persistence and the relative sizes of the other components.

Figure 9 summarizes the counterfactual simulations. Scenario CF1 shows that changes in observables and their returns (μ_{ceat}) modestly increased mobility, but cannot explain its overall decline. In contrast, the rise in the variance and price of the individual productivity component $(\sigma_{\alpha c}^2, p_t)$ generated a marked reduction in mobility beginning with the 1960 cohort (CF2–CF4). Their combined effect outweighed the modest positive contribution of observables, leading to the stabilization of mobility after the 1975 cohort. Scenarios CF5–CF6 indicate that permanent and transitory wage shocks have limited influence on the trend, while the employment margin affects the level but not the dynamics of mobility. The full model (CF7), which incorporates all channels, closely matches both the observed level and cohort evolution of mobility.

The decline in mobility reflects changes in the wage process parameters. As shown in Figure 4, both the variance of the individual productivity component and its price increased sharply until the mid-2000s, then stabilized. This pattern mirrors the observed fall and subsequent stabilization of mobility. A higher $\sigma_{\alpha c}^2$ raises the share of earnings variance fixed at labor market entry, while a higher p_t magnifies its contribution to total dispersion (see Proposition G1). As more of wage inequality becomes tied to fixed heterogeneity, the relative importance of transitory and persistent shocks declines, reducing mobility.[26]

By contrast, a higher transitory variance ($\sigma_{\epsilon t}^2$) increases mobility (Proposition G2). Although $\sigma_{\epsilon t}^2$ rose from about 0.006 in 1985 to 0.01 in 2019; its overall impact is modest given its small magnitude relative to other components. The innovation variance of the persistent shock ($\sigma_{\eta t}^2$) declined after 2005, which should have lowered mobility (Proposition G3). However, since the persistence parameter ρ is close to one, persistent shocks are almost permanent, making short- and long-term variance components similar and limiting the effect of changes in $\sigma_{\eta t}^2$ on mobility.

5. Mechanisms for an Increase in the Variance of Individual Fixed Effects

The results in Section 4 show that a key factor influencing the development of cross-sectional wage and lifecycle earnings inequality is the growing variance of individual fixed effects ($p_t\alpha_{ic}$), with increases in both the price p_t and the variance $\sigma_{\alpha c}^2$ accounting for this trend roughly equally. This suggests that inequality at the start of careers has expanded and become more enduring over recent decades. Individual fixed effects are often seen as reflecting personal ability, but it is implausible that the spread of unobserved ability nearly doubled between the cohorts 1950 and 1994.

An alternative interpretation is that the rising variance of individual fixed effects reflects changes in how individual ability is translated into productivity. More specifically,

[26] Intuitively, the fixed component contributes equally to both long- and short-term variance, unlike shocks, which average out over time. Increasing its share of total variance raises both long- and short-term variance proportionally but reduces the relative weight of the transitory components that generate mobility—the difference between long- and short-term variance. As a result, the two variances converge, their ratio approaches one, and mobility declines.

it may capture shifts in how workers' abilities are utilized, shaped by evolving technologies, labor market frictions, and institutional factors.[27] To illustrate, consider two types of tasks: routine and complex. When demand for routine tasks is high, even high-ability workers may perform these tasks where their ability has little effect on productivity, leading to limited dispersion across the ability distribution. By contrast, when demand for complex tasks rises, more workers are drawn into the complex sector, incentivized by the higher relative price of complex tasks. In this setting, ability translates more directly into productivity, raising the variance of worker productivity—as captured by the fixed effect net of prices in our model.

To provide an interpretable benchmark, we translate the estimated cohort-specific variance of the individual productivity component into percentile productivity ratios. Since the income process is estimated in logs, the individual productivity term αrepresents log productivity, implying that productivity in levels is given by $\exp(\alpha)$. For a normal distribution, the 90–50 log percentile difference equals $1.2816\sigma_{\alpha}$. Based on our estimates, the 90th percentile worker is about 27% more productive than the median worker in the 1950 cohort, increasing to 47% in the 1994 cohort. The corresponding 90–10 ratios rise from roughly 62% to 118%. We next formalize the underlying mechanism, showing how technological change can strengthen the link between ability and productivity—and thereby widen wage inequality—without requiring changes in the ability distribution or educational attainment.

5.1. A Roy Model of Skill-biased Technological Change

Our model builds on the canonical framework of Acemoglu and Autor (2011), extending it by allowing workers to choose between complex and routine tasks within occupations.[28] Endogenizing task choice implies that sectoral composition can adjust in response to a

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[27] In line with this, Hsieh et al. (2019) suggest that a significant portion of U.S. economic growth can be attributed to improved talent allocation.

[28] In Appendix G Table A3 we illustrate how – within the same occupations – workers can specialize in performing more routine or more complex tasks.

rising skill premium. It also means that the variance of the individual productivity component α in our statistical model can rise under skill-biased technological change, even when the distribution of worker ability is unchanged. In this way, our model provides a structural interpretation of our income process estimates: rising dispersion in fixed effects net of prices reflects reallocation of workers across tasks of different complexity, rather than shifts in the underlying distribution of abilities. This mechanism operates alongside the price channel we also document, whereas in standard models the latter is typically the sole driver.

Our approach relates to Cortes (2016), who develops a Roy model in which differences in how ability maps into productivity across occupations generate sorting patterns and explain between-occupation polarization. That contribution highlights an important between-occupation mechanism. By contrast, our framework focuses on heterogeneity in task choice within occupations, motivated by the evidence presented in Section 2, which shows that most of the increase in entry-level wage inequality arises within occupations.

The model delivers three testable predictions. First, workers performing complex tasks earn more than workers performing routine tasks within the same occupation. Second, the magnitude of the increase in within-occupation variance depends on initial complexity: occupations starting with very low or very high complexity experience larger rises in inequality than those with moderate complexity. Third, increases in task complexity are associated with greater within-occupation inequality. We test both predictions in the data.

5.1.1. Model

On the demand side, consider a firm that produces output using two types of labor: workers performing complex tasks C and workers performing routine tasks R. The firm solves the following profit maximization problem:

$$\max_{(C,R)\in\mathbb{R}_+^2} [\omega C^{\varphi} + (1-\omega)R^{\varphi}]^{\frac{1}{\varphi}} - w_C C - w_R\, R\,, \tag{7}$$

where $\omega \in (0,1)$ is factor productivity of the complex (or non-routine) tasks, $\varphi \leq 1$ and the elasticity of substitution is $\frac{1}{1-\varphi}$. This gives rise to the relative demand function,

$$\frac{C^D}{R^D} = \left(\frac{\omega}{1-\omega}\frac{w_R}{w_C}\right)^{\frac{1}{1-\varphi}}, \tag{8}$$

indicating that relative demand for complex tasks increases in factor productivity ω and decreases in the relative wage $\frac{w_C}{w_R}$.

On the supply side, suppose there is a continuum of workers with population one. Each worker draws ability $S \sim \mathcal{N}(0, \sigma^2)$, which determines their effective unit of labor. Productivity depends on both ability and task type: a worker supplies $\exp(S)$ units of effective labor when preforming complex tasks and $\exp(\delta S)$ units when performing routine tasks. The parameter $\delta \in (0,1)$ captures the relative importance of ability in routine vs complex tasks. If δ is close to 0, low-ability workers are almost as productive as high-ability workers in the routine sector.

Each worker chooses the sector that maximizes earnings, selecting the complex sector if and only if

$$\exp(S)\, w_C \geq \exp(\delta S)\, w_R, \qquad \therefore\ S \geq S^* = \frac{1}{1-\delta}\ln\left(\frac{w_R}{w_C}\right). \tag{9}$$

The aggregate labor supply is

$$C^S = \int_{S^*}^{\infty} \exp(s)\ f_S(s) ds = \exp\left(\frac{\sigma^2}{2}\right)\left[1 - \Phi\left(\frac{S^*}{\sigma} - \sigma\right)\right], \tag{10}$$

$$R^S = \int_{-\infty}^{S^*} \exp(\delta s)\ f_S(s) ds = \exp\left(\frac{\delta^2\sigma^2}{2}\right)\Phi\left(\frac{S^*}{\sigma} - \delta\sigma\right), \tag{11}$$

where $f_S(\cdot)$ is the probability density function of S and $\Phi(\cdot)$ is the standard normal cumulative distribution.

Workers' sectoral choices are governed by comparative advantage, with the effective unit of labor being larger (smaller) for complex tasks than routine tasks if $S >$

0 ($S < 0$). The threshold ability level S^* decreases in the relative wage $\frac{w_C}{w_R}$, implying that the share of workers providing complex tasks rises with the relative award to complex tasks.

Through the lens of our wage process model, the *effective* unit of labor corresponds to the individual productivity component α_{ic}, whereas the relative wage ratio $\frac{w_C}{w_R}$ corresponds to the price p_t. Our comparative statics, therefore, focus on how skill-biased technological change affects the distribution of realized productivity.

Under our assumptions about the ability distribution and the functional form of the effective unit of labor, the resulting earnings distribution is log-normal, conditional on task choice. An equilibrium consists of $\left(C^D, R^D, C^S, R^S, S^*, \frac{w_C}{w_R}\right)$ that satisfies equations (8)–(11) and the market clearing conditions, $C^D = C^S$ and $R^D = R^S$. This equilibrium is uniquely determined. From equations (8) and (9) and market-clearing conditions, we obtain

$$(1-\delta)\,\mu + \frac{(1-\ \delta^2)\sigma^2}{2} + \ln\frac{1-\ \Phi\left(\frac{S^*}{\sigma}-\sigma\right)}{\Phi\left(\frac{S^*}{\sigma}-\delta\sigma\right)} = \frac{1}{1-\varphi}\left[\ln\frac{\omega}{1-\omega} + (1-\delta)S^*\right]. \quad (12)$$

Since the left-hand side of this equation is decreasing and the right-hand side increasing in S^*, the ability threshold S^* is uniquely determined. Equation (9) then pins down the relative wage, and equations (10) and (11) determine the equilibrium labor supply.

5.1.2. Model Implications and Comparative Statics

One testable implication of the model is that workers in the complex sector earn more than workers in the routine sector. This follows directly from the sorting of high-ability workers into the complex sector and low-ability workers into the routine sector.

Proposition 1.

For any $S_0 \leq S^* \leq S_1$, $\exp(\delta S_0)\, w_R \leq \exp(S_1)\, w_C$.

Proof

See Appendix C. ■

To analyze the role of skill-biased technological change, which increases factor productivity ω, we conduct comparative statics.

Proposition 2.

1. The relative wage is increasing in ω: $\frac{\partial}{\partial\omega}\frac{w_C}{w_R} > 0$.
2. The share of workers providing complex tasks is increasing in ω: $\frac{\partial}{\partial\omega}S^* < 0$.

Proof

See Appendix C. ■

This is the standard result shown, for example, by Acemoglu and Autor (2011). Intuitively, when complex tasks become more productive relative to routine tasks, the relative demand for complex task input rises, increasing the relative wage to attract more workers. The higher relative wage then induces marginal workers to transition from routine to complex tasks.

Proposition 3.

Let $\xi(S; S^*)$ denote the (realized) effective unit of labor of a worker with ability S, given the threshold value S^*.

1. For $S^* > 0$, $Var\left(\xi(S; S^*)\right)$ is inverted U-shaped. For $S^* > 0$, there exists $\bar{S} > 0$ such that for $S^* > \bar{S}$, $\frac{d}{d\,S^*}\,Var\left(\xi(S; S^*)\right) < 0$, for $S^* = \bar{S}$, $\frac{d}{d\,S^*}\,Var\left(\xi(S; S^*)\right) = 0$ and for $S^* < \bar{S}$, $\frac{d}{d\,S^*}\,Var\left(\xi(S; S^*)\right) > 0$.
2. For $S^* = 0$, $\frac{d}{d\,S^*}\,Var\left(\xi(S; S^*)\right) = 0$.
3. For $S^* < 0$, $\frac{d}{d\,S^*}\,Var\left(\xi(S; S^*)\right) < 0$.

Proof

See Appendix C. ■

Combining Propositions 2 and 3 yields the following result:

Corollary 1.

1. Skill-biased technological change increases the variance of the effective unit of labor when technology is at a low or high level.
2. Skill-biased technological change has little or no effect—and may even reduce—the variance of the effective unit of labor when technology is at a moderate level.

Proof

See Appendix C. ■

Corollary 1 highlights that skill-biased technological change has a heterogeneous impact on the variance of effective labor input. The variance rises at low or high technology levels, but the effect diminishes (and can even turn negative) at moderate technology levels, where the threshold S^* is close to 0.

To build intuition for Propositions 2 and 3 and Corollary 1, consider Figure 11. Panel A shows a situation where the level of technology ω is low, the ability threshold S^* is high, few workers are employed in the complex sector, and the average effective unit of labor across all workers (dashed line) is low. A *decline* in S^* induced by technological change incentivizes the marginal worker with ability S^* to switch from routine to complex tasks sector (illustrated by the upward shift of the orange circle). Because their abilities are now better reflected in their productivity, their effective unit of labor deviates further from the mean, thereby raising the variance of effective labor input, $Var\left(\xi(S; S^*)\right)$.

Panel B depicts the intermediate case. As S^* decreases further, the deviation of the marginal worker's effective unit of labor from the mean becomes smaller in the complex than in the routine sector. While sectoral switching still raises the variance in the complex sector, it can lower the aggregate variance of productivity due to composition effects. At the special case where $S^* = 0$, the marginal worker's effective labor is identical across sectors ($\exp(S^*) = \exp(\delta S^*) = 1$), implying no effect on variance.

Panel C considers high levels of technology ($S^* < 0$), where most workers are already in the complex sector. Here, the marginal worker´s ability is sufficiently low that they are more productive in routine tasks, yet a decrease in S^* still induces them to enter the complex sector due to its higher relative price. Because their effective labor in routine tasks lies below the mean, the deviation from the mean is larger once they switch, again increasing the variance.

Importantly, this non-monotonic relationship between technology and the variance of effective labor input remains robust when we relax the assumptions on the distribution of worker ability and on the functional form of task-specific productivity (see Appendix D).

Our model implies that technological change influences wage inequality through two channels: the price of labor efficiency $w = w_C/w_R$, and the variance of labor efficiency, $Var\ (\xi)$, induced by sorting. In our statistical model, these parameters correspond to p_t and $\sigma^2_{\alpha c}$. In Corollary 1, we show that the sorting channel generates a non-monotonic effect on the variance of labor efficiency $Var\ (\xi)$. In contrast, the price channel, captured in the Roy model as the relative price of complex to routine tasks w_C/w_R, responds monotonically to technological change.[29]

As we show in Appendix E, the combined effect of sorting and price monotonically increases the overall variance of wages, and the sorting channel generates a non-monotonic effect on the *slope* of this increase. Figure A6 illustrates that this result holds for plausible values of the elasticity of substitution between complex and routine tasks $(1/(1-\phi))$and for the task-specific ability-scaling parameter δ, which governs the extent to which innate ability translates into productivity in the routine task sector.

In empirically relevant cases, technological change increases wage variance through both channels, though the strength and direction of the sorting effect vary with task structure and ability-technology interactions.

5.2. Testing the Implications of the Model

The predictions of our theoretical framework are supported by estimates of our statistical model, where the evolution of inequality is driven by *both* the skill price p_t (corresponding to the relative wage or skill premium w_C/w_R), and the variance of the individual fixed effects $\sigma^2_{\alpha c}$ (corresponding to the variance of the effective unit of labor $Var\ (\xi)$).

The model delivers three additional testable implications:

Implication 1: Within occupations, workers performing complex tasks earn more than workers performing routine tasks (following from Proposition 1 in Section 5.1).

[29] Specifically, $\frac{w_C}{w_R}$increases in the complex task-augmenting productivity parameter ω, thereby raising the returns to performing complex tasks.

Implication 2: Changes in initial occupational complexity affect the variance of the combined price and productivity effects in a non-monotonic way, driven by the sorting channel (following from Propositions 2 and 3 / Corollary 1 in Section 5.1 and Simulation 5.2)

Implication 3: Larger increases in occupational complexity are associated with larger increases in the variance of the combined price–productivity effect (follows from Propositions 2 and 3; see Simulation 5.2)

To operationalize these tests, we construct occupation-level measures of task complexity using the 1986 and 2006 BIBB/IAB surveys. These surveys include detailed questions about work content, such as the degree of task stipulation, repetitiveness, exposure to new tasks, and opportunities for improving existing processes. The use of these measures is motivated by Deming (2021), who links technological change to shifts toward problem-solving and decision-making tasks, which are associated with higher lifecycle earnings. Following our framework, we classify tasks as more complex when they are less stipulated, less repetitive, and when workers more frequently report engaging in new tasks or improving tasks. Responses are recoded to a [0,1] scale, with higher values indicating greater complexity. Because response categories differ slightly across survey waves, we harmonize the scales to ensure comparability. The resulting complexity index is computed at the individual level as the average of the recoded items.

To connect our survey-based complexity measures to the administrative SIAB data used for estimating the income process, we impute occupational-level complexity values. Specifically, we compute weighted averages of individual complexity scores within each occupation-year cell using the BIBB survey sampling weights φ_i:

$$c_{j,t} = \sum_j \varphi_i Complexity_{i,j,t}$$

Because complexity varies systematically with age and gender, we regress it on age, age squared, gender, and occupation dummies, and use the predicted value for men aged 25 as an adjusted measure, which we refer to as *adjusted complexity*. This adjustment has little effect on the results—the correlation with the unadjusted measure is 0.98. We retain occupations with at least 20 observations per year in both the BIBB and SIAB samples and linearly interpolate complexity between 1986 and 2006. Details on the recoding and harmonization procedures are provided in Appendix Table A1.

To test Implication 1, we use data from the 2006 BIBB wave, which reports monthly wages (in €50 intervals) and actual hours worked. We restrict the sample to full-time employees working at least 34 hours per week, noting that results are robust to omitting this cutoff. We regress log monthly wages on standardized measures of task complexity. As shown in Table A2, a one–standard deviation increase in complexity is associated with a 0.170 log-point increase in monthly wages. Including occupation fixed effects reduces the coefficient to roughly 0.07, indicating that part of the wage premium reflects differences in average complexity across occupations. Importantly, the remaining effect shows that even within the same occupation, greater task complexity is associated with higher pay. Adding controls for age, supervisory status, and gender attenuates the coefficient only slightly, leaving the within-occupation relationship intact. These results support Implication 1: task complexity predicts higher wages even within narrowly defined occupations.

We next test Implications 2 and 3, which link changes in occupational complexity to the evolution of within-occupation inequality. Table A3 lists the five occupations with the largest and smallest increases in complexity. The top five occupations all originate from relatively low initial levels of complexity and are concentrated in manufacturing-related fields. For instance, turners/machinists (Dreher) exhibit one of the strongest increases in complexity, consistent with the 1987 curriculum reform in Germany, which restructured machinist apprenticeships to include computer numerical control (CNC) programming. This reform substantially raised the cognitive demands of machinists by shifting the focus from manual tool handling to programming, monitoring, and quality control of automated processes.[30] Among the occupations with the smallest changes, we find two distinct groups: highly complex professions such as chemists, engineers, and

[30] See Janssen and Mohrenweiser (2018) for evidence on the long-term effects of this reform. This observation also relates to our modeling choice, where α_c varies by cohort, reflecting the assumption that task-changing technologies are typically introduced for entry-level workers. See also Lipowski (2025) for a model in which young workers are trained on new technologies.

doctors, where there was limited scope for further increases, and occupations such as social workers, where technological change had little effect on task complexity over this period.

Using log entry-level wages of 25-year-old workers in SIAB, we compute the within-occupation variance of wages as follows. For each year, we regress log wages on occupation and year fixed effects

$$\ln(w_{itj}) = \sum_t \sum_j \Gamma_t \Lambda_j + u_{ijt}$$

The within-occupation variance in year t is then given by the variance of the residuals $\hat{\sigma}^2_{j,t} = \widehat{Var}(u_{ijt})$.

We first provide graphical evidence on the relationship between occupational complexity, its evolution, and within-occupation inequality. To study the role of baseline complexity, we regress log within-occupation inequality $\ln(\hat{\sigma}^2_{j,t})$ and baseline complexity in 1986 $c_{j,1986}$ separately on changes in complexity since 1986 $c_{j,1986,t}$ and baseline inequality in 1986 $\hat{\sigma}^2_{j,1986}$. The resulting residuals capture the components of inequality and baseline complexity orthogonal to both complexity growth and initial inequality.

Next, to study the role of complexity changes, we regress log within-occupation inequality and changes in complexity since 1986 separately on baseline complexity and baseline within-occupation inequality. These residuals represent the components of inequality and complexity growth orthogonal to initial conditions (see Appendix F for details). We then collapse the data into 200 equal-sized bins of the residualized complexity measures and plot mean residualized inequality against mean residualized complexity, overlaying a locally weighted scatterplot smoother.

Figure 13, Panel A, shows a positive association between residualized changes in complexity and within-occupation inequality, consistent with Implication 2. Panel B reveals a U-shaped relationship between residualized baseline complexity and inequality, consistent with Implication 3.

As a second test of Implications 2 and 3, we estimate a first-difference specification:

$$\Delta ln\left(\hat{\sigma}^2_j\right)_{t,t-1} = \gamma_0 + \gamma_1 \cdot \Delta c_{t,t-1} + \gamma_2 \cdot \Delta c_{t,t-1} \cdot c_{t-1}$$

$$+\gamma_3 \cdot \Delta c_{t,t-1} \cdot (c_{t-1})^2 + \epsilon_{i,j,t}$$

We regress year-to-year changes in within-occupational log wage variance on changes in occupational complexity, allowing the effect of changes to depend on the contemporaneous complexity level. The specification includes linear and quadratic interactions with the preceding year's complexity. Occupations are weighted by the inverse of the estimated sampling variance of the within-occupation variance measure, so that groups with more precise inequality estimates receive greater weight in the regression. This corresponds to a feasible GLS correction for heteroskedasticity due to differences in occupational sample size.

Table 1 presents regression results consistent with the model's predictions. Increases in occupational complexity are associated with rising within-occupation wage variance, but the magnitude of this effect depends on baseline complexity. The positive coefficient $\hat{\gamma}_1$on Δcindicates that greater task complexity generally amplifies inequality. The negative interaction with lagged complexity ($\Delta c \cdot c$) and the positive coefficient on its square ($\Delta c \cdot c^2$) imply a U-shaped pattern: the effect of complexity growth on wage variance is strongest for occupations starting from very low or very high complexity and weakest at intermediate levels. This pattern aligns with the Roy model's prediction that technological change magnifies inequality most at the extremes of the task distribution.

Using equal weighting across occupations (column 1) yields less precise estimates than the feasible GLS specification, which downweights occupations with small samples, but the overall pattern remains. However, differencing and collapsing substantially reduce the effective sample size, and the specification is relatively parameterized given available variation. As a result, the coefficients should be interpreted as illustrative evidence of the theoretical mechanism rather than precise estimates of effect magnitudes.

6. Conclusion

This paper investigates the determinants of cross-sectional and lifecycle earnings inequality using a lifecycle earnings process model that incorporates earnings mobility and non-employment risks across birth cohorts and over time. The estimated wage process accounts for multiple sources of non-stationarity, where the distribution of individual fixed effects is cohort-dependent, while skill prices and the distribution of other shocks vary by calendar year. Additionally, we estimate employment-non-employment transitions to capture the correlation between wages and job insecurity, which is crucial for understanding lifecycle earnings and may also influence cross-sectional inequality through selection effects. Using our statistical model, we decompose the evolution of inequality into its underlying determinants, enabling a direct comparison between lifecycle (cohort-specific) and cross-sectional (year-specific) inequality.

A key finding of our analysis is that the dominant determinant in the rise of both cross-sectional and lifecycle inequality is the change in the price and variance of individual fixed effects. These factors equally explain the trends in both measures of inequality. Our analysis also highlights the crucial role of non-employment, where job instability has significantly impacted lifecycle earnings among low-wage workers. Conversely, selection into employment—which could potentially influence the measurement of cross-sectional inequality—turns out to be unimportant. Consequently, failing to account for employment risk can lead to misleading welfare implications when investigating lifecycle inequality, as it plays a significant role in shaping long-term earnings disparities.

To explain how the variance of individual productivity can increase without changing the underlying talent distribution, we develop a Roy model incorporating skill-biased technological change, which amplifies wage inequality by strengthening the relationship between ability and realized productivity. This leads to greater sorting of workers into tasks where their abilities are most productive, contributing to rising inequality without changes in the underlying distribution of ability.

We empirically test key predictions of our model and find evidence supporting the proposed mechanisms. Our findings contribute to the literature on wage inequality by providing new insights into the link between cross-sectional and lifecycle inequality and its interaction with technological change.

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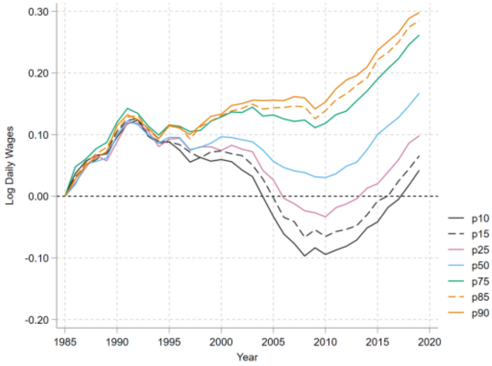
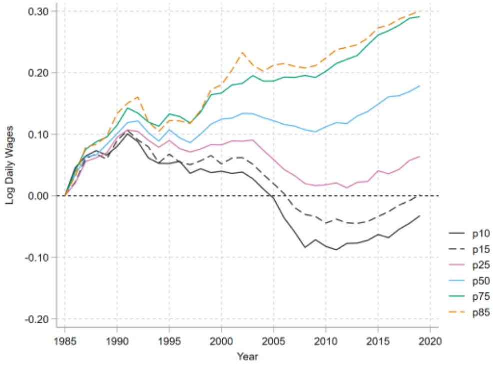
Figures

Figure 1 Distribution of wages and lifecycle earnings



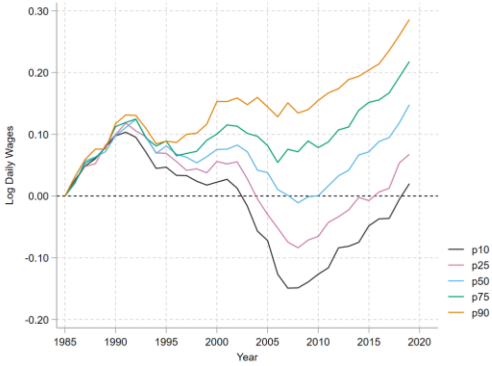
(a)

Distribution of cross-sectional wage in our sample



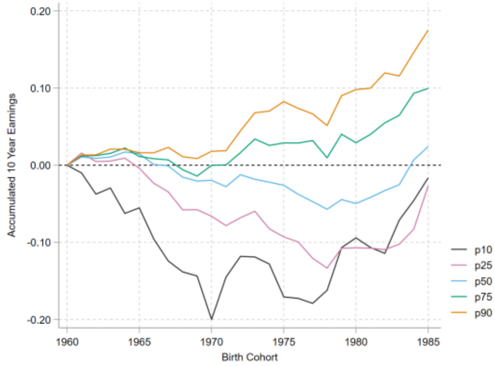
(b)

Distribution of cross-sectional wage for West German males



(c)

Distribution of wage at age 25

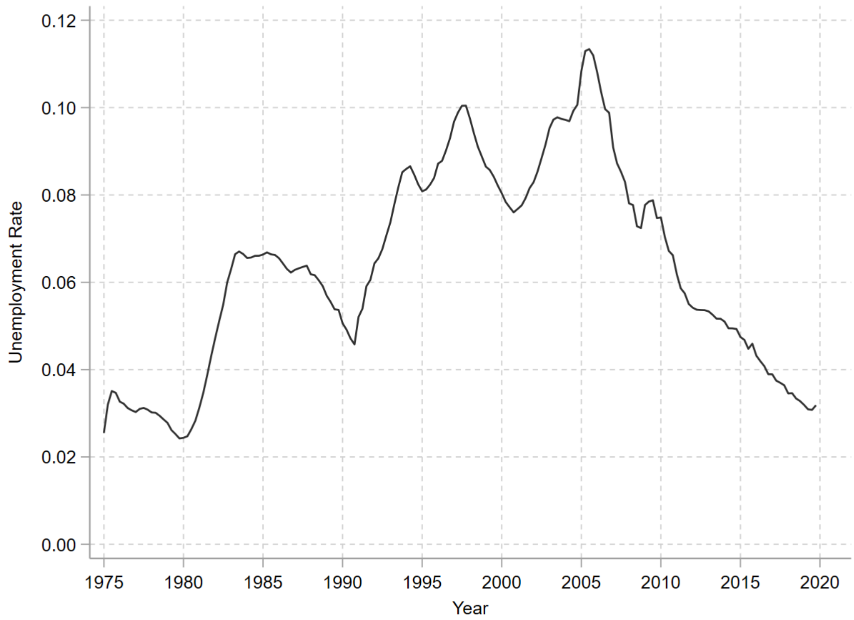


(d)

Distribution of lifecycle earnings across cohorts

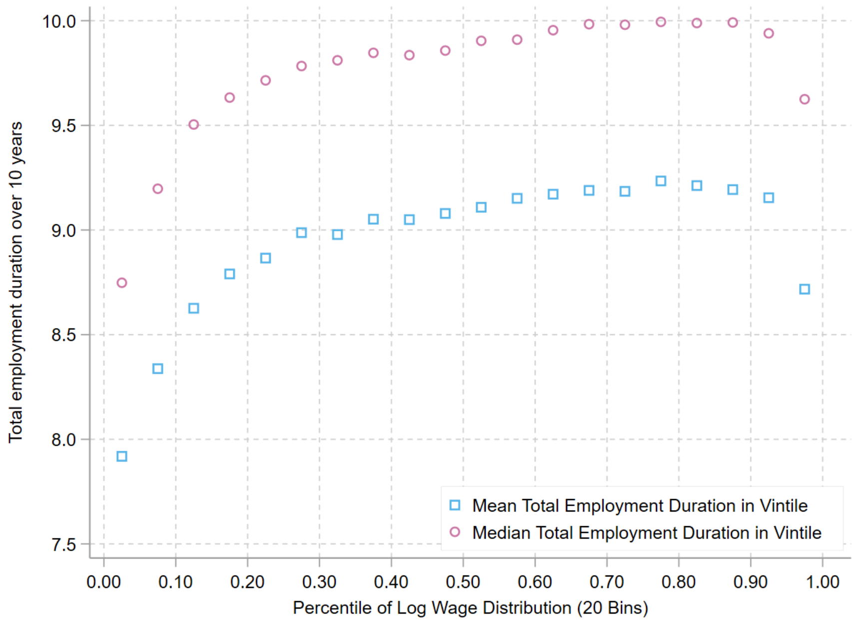
Note: Panel (a) shows the distribution of log wages of workers across calendar years in our sample aged 25 to 34. Panel (b) shows the distribution of log wages for West German males. Panel (c) shows the distribution of log wages of workers at age 25 in our sample. Panel (d) shows the distribution of our measure of lifecycle earnings calculated as the total earnings from age 25 to 34.
Source: Own calculations based on IAB data

Figure 2 Unemployment



(a)

Unemployment Rate (15 Years or over)



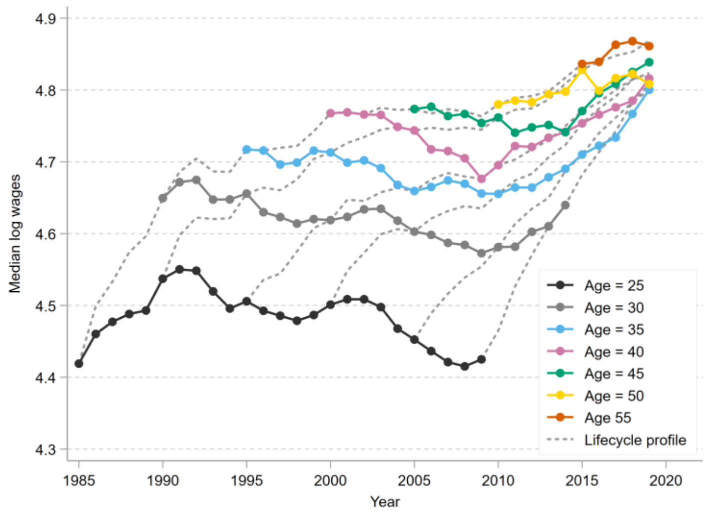
(b)

Total duration of employment over wage distribution at age 25

Note: Panel (a) shows seasonally adjusted quarterly unemployment rate for 15 years or over for Germany. Panel (b) shows the mean and median of total duration of non-employment in each Vintile (20 bins) over the wage distribution at age 25. For example, the first bin corresponds to the total duration of employment for the earners below the 5% percentile of wage at age 25

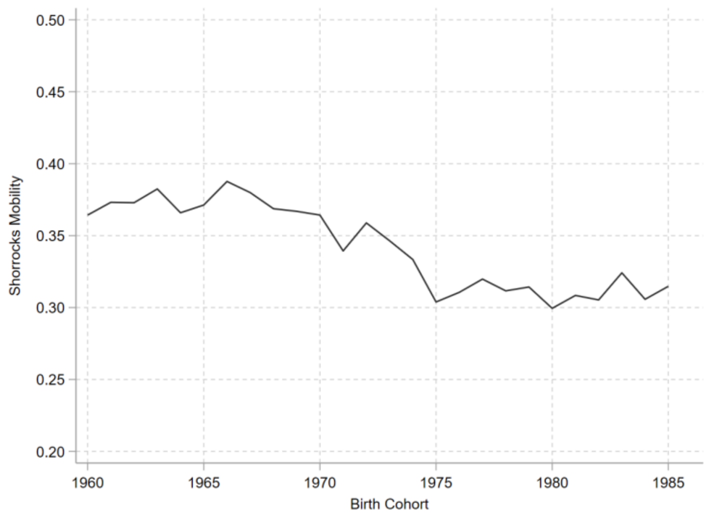
Source: Panel (a): OECD (2024). Panel (b): Own calculations based on IAB data

Figure 3 Median log wage across cohorts and lifecycle and earnings mobility across cohorts



(a)

Median log wage across cohorts and lifecycle

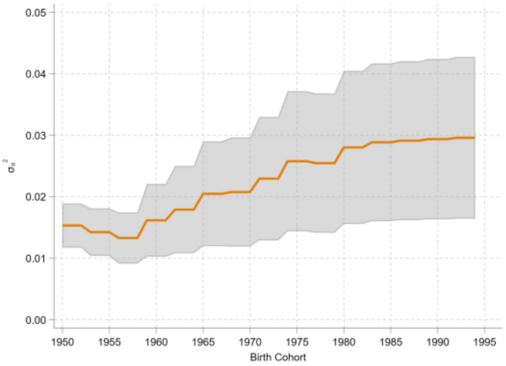


(b)

Shorrocks Index of Variance in Earnings

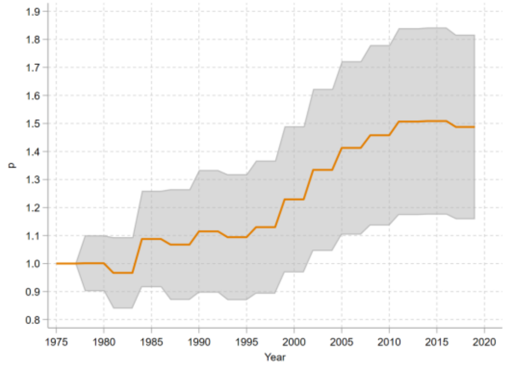
Note: Panel (a) shows the log median wage for different labor market entry cohorts at different ages. The solid lines with points allow us to follow the median log wage for a given age across calendar year. For example, the black dotted line follows the median wages of workers at age 25 across years. The dotted lines allow to follow lifecycle profiles of the median log wage of a given cohort. For example, the first dotted line from the left hand allows to track the log wage of the cohort born in 1960 at age 25 in year 1985, age 30 in year 1990 and so on. Panel (b) shows the Shorrocks index of the variance of earnings across birth cohort.
Source: Own calculations based on IAB data

Figure 4 Parameter estimates



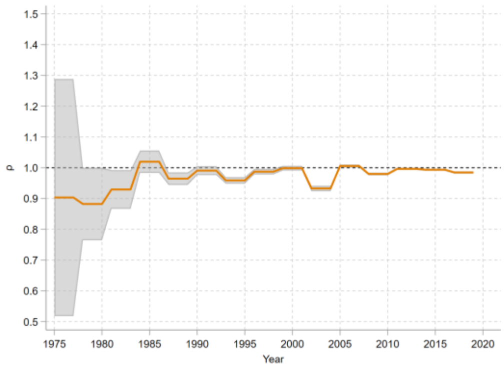
(a) Variance of individual FE

$\boldsymbol{\sigma^2_{\alpha c}}$



(b) Skill price

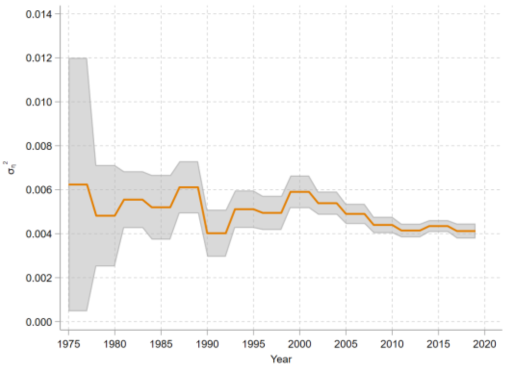
$\boldsymbol{p_t}$



f

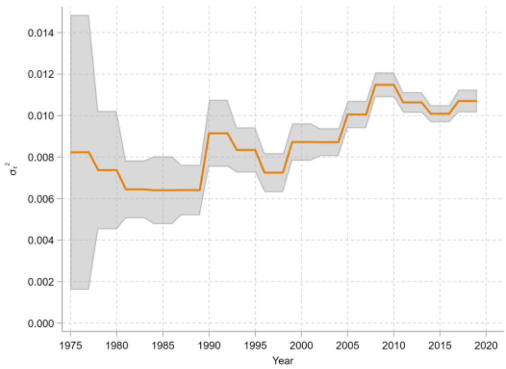
(c) Persistency of AR(1) process

$\boldsymbol{\rho_t}$



(d) Variance of persistent shock (AR(1) innovation)

$\boldsymbol{\sigma^2_{\eta t}}$

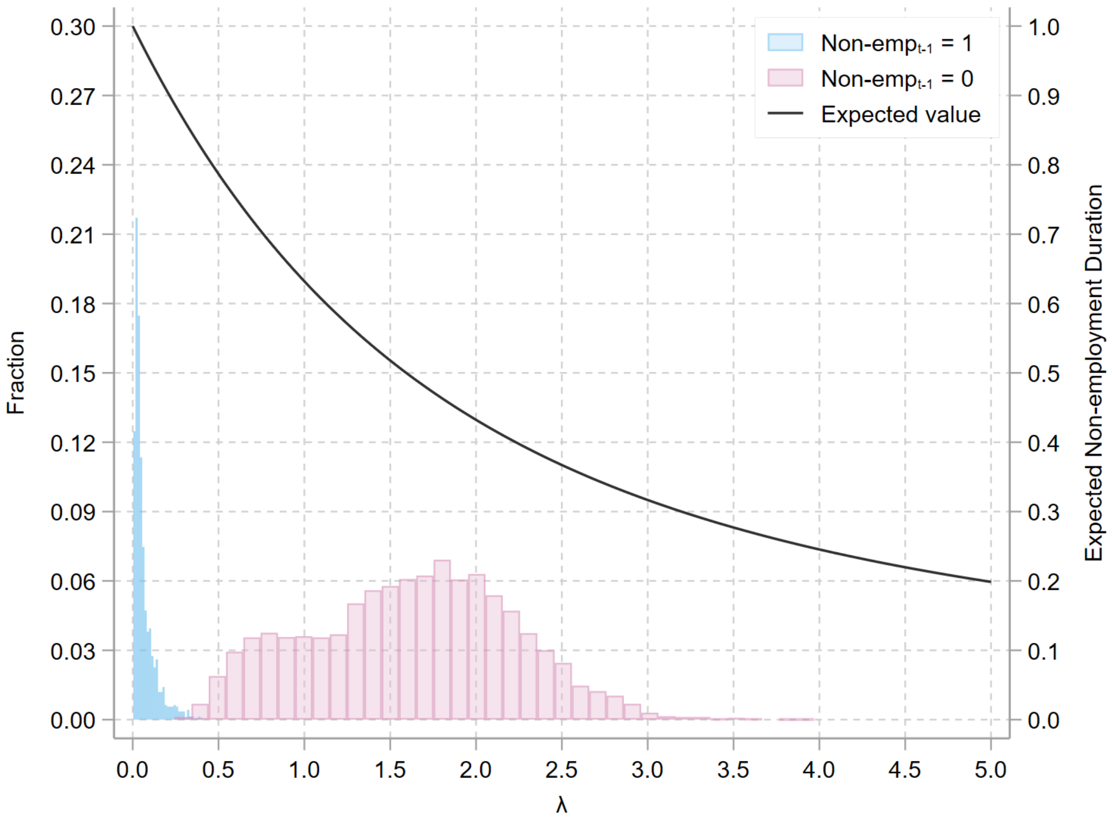


(e) Variance of transitory shock

$\boldsymbol{\sigma^2_{\epsilon t}}$

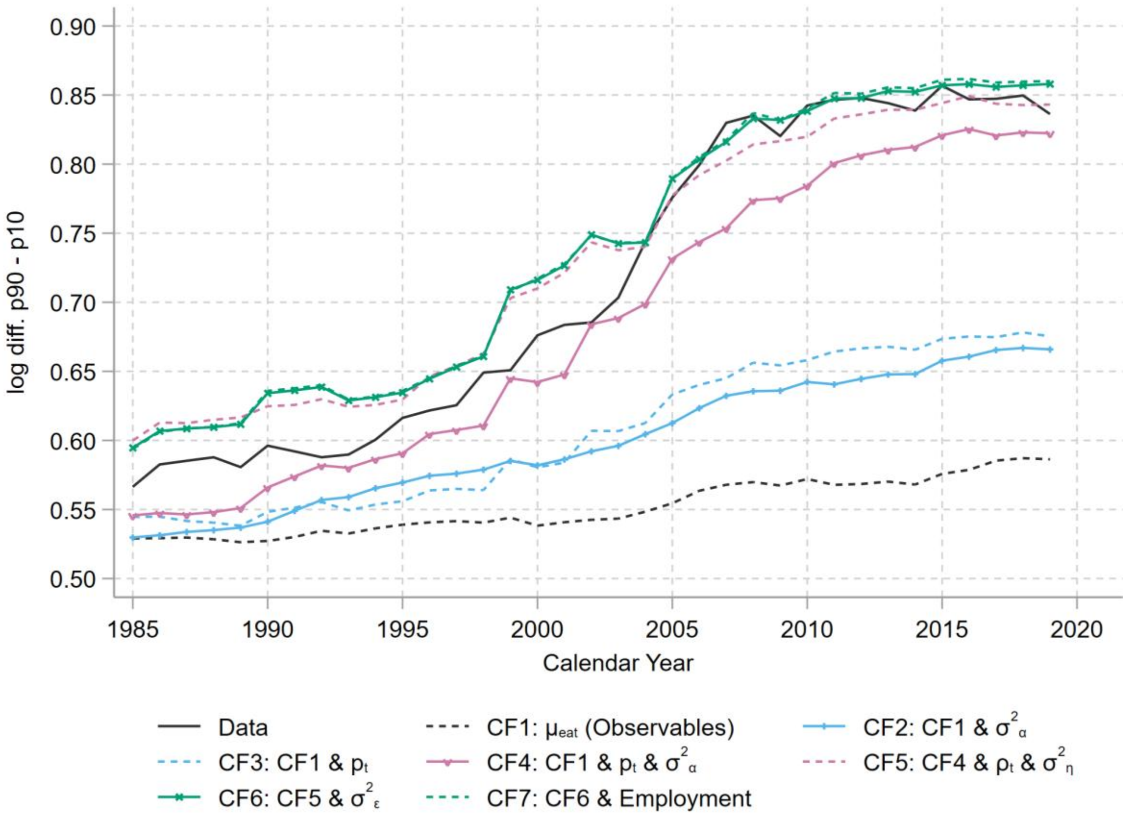
Note: The figure shows the estimated parameters of the stochastic wage growth model according to Equations 1 and 2 for West German workers born between 1950-1994. All parameters are indexed by calendar year, expect the variance of individual fixed effects $\sigma^2_{\alpha c}$ which varies by cohort. For estimation three cohorts and calendar years are group together respectively. Estimation was performed by minimization of the Euklidian norm of the covariance matrix of residual wages according to Equation 3. Shaded areas represent 90% confidence intervals.
Source: Own calculations based on IAB data

Figure 5 Parameter estimates: Non-employment duration



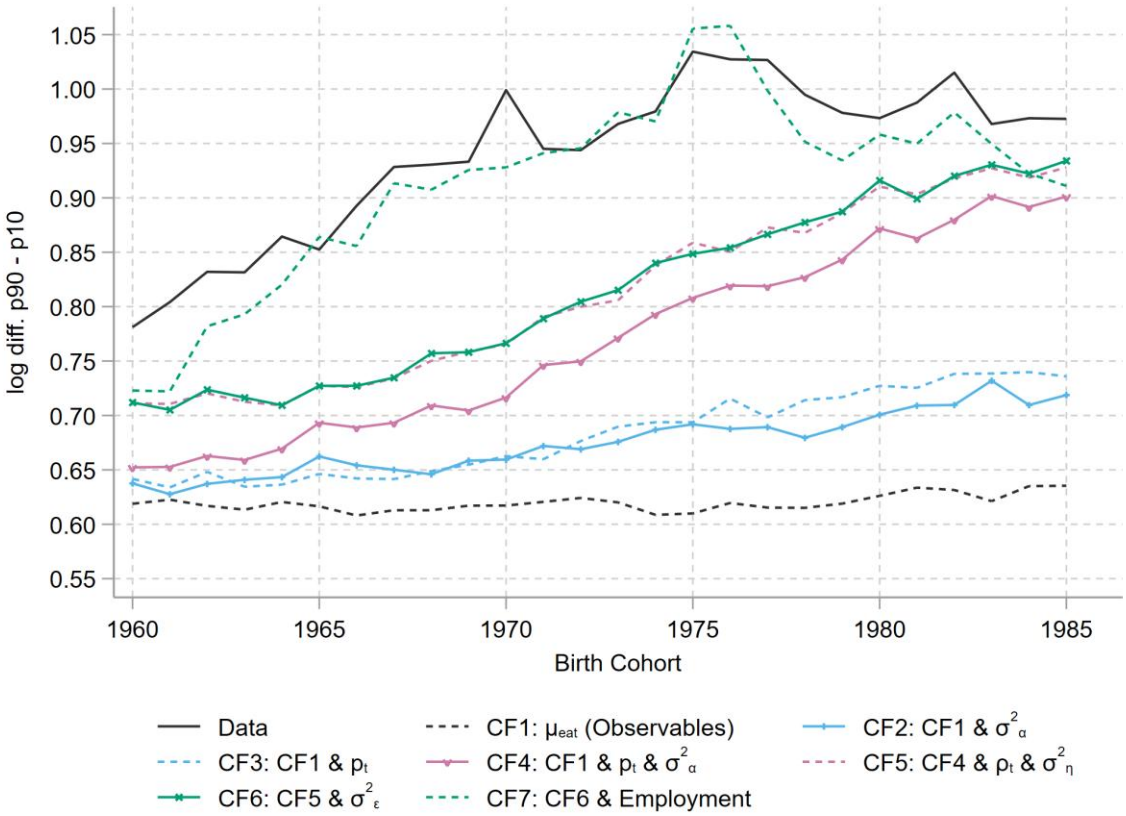
Note: This figure presents the distribution of the estimated non-employment duration parameters λ (left scale) for individuals who are non-employed in period t. The numerical values corresponds to the fraction of a year the individual is non-employed. The parameter λ represents the hazard rate of transitioning back to employment and is estimated separately basd on employment status in the previous period $t-1$. The blue distribution corresponds to individuals who were unemployed in $t-1$., while the red distribution corresponds to those who were employed in $t-1$. The solid line shows the expected non-employment duration, expressed as a fraction of a year, implied by each lambda value. Non-employment duration follows a truncated exponential distribution, where smaller values of lambda indicate longer expected durations out of employment. Estimates are constructed using individual-level data gruped by prior year's wage and employment status according to Equation 5.
Source: Own calculations based on IAB data

Figure 6 Counterfactual simulation: Cross-sectional inequality (p90-p10 ratio)



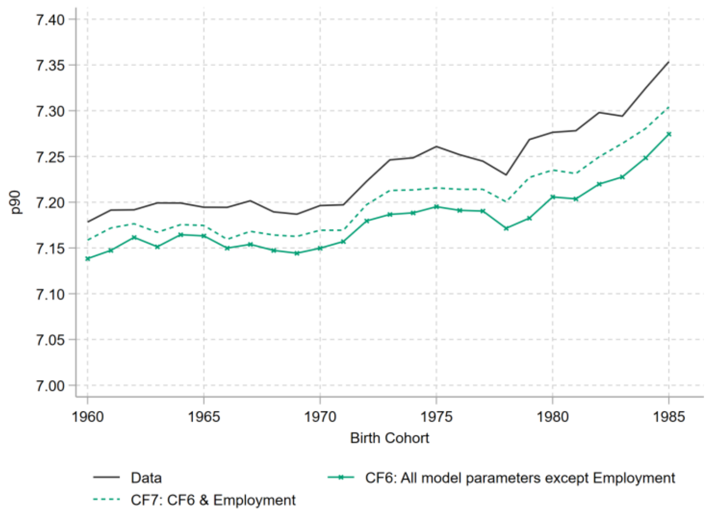
Note: The figure shows the p90-p10-ratio of the distribution of the cross-sectional wages across calendar years for different simulated counterfactual scenarios described in section 4.2 The Cross-sectional wage distribution in calendar year t consists of a rolling sample of the workers in our sample between age 25 and 34 at the given year. Data is calculated using the empirical distribution from our sample. Wages for CF1 to CF7 are simulated from a normal distribution with mean zero and variances according to our estimated parameters and employment/non-employment probabilities according to Equations (4) and (5). CF1 fixes all parameters at base year 1985 except the observable wage component μ_{ceat}. CF2 allows the observables and additionally the variance of skill $\sigma^2_{\alpha c}$ vary across cohort and time. CF3 allows the observables and the price for skill p_t vary across time (but not $\sigma^2_{\alpha c}$). CF4 allows observables and both variance of skill $\sigma^2_{\alpha c}$and price for skill p_t vary. CF5 allows observables, variance and price of skill as well as the components of the AR(1) process (the persistent shock), ρ_t and $\sigma^2_{\eta t}$, vary. In CF6 observables, variance and price of skill, the components of the AR(1) process (the persistent shock) and additionally the variance of the transitory shock $\sigma^2_{\epsilon t}$ are allowed to vary. CF7 additionally lets the parameters governing the employment process (non-employment probabilities and duration) to vary and corresponds to our full model.
Source: Own calculations based on IAB data

Figure 7 Counterfactual simulation: Lifecycle inequality (p90-p10 ratio)

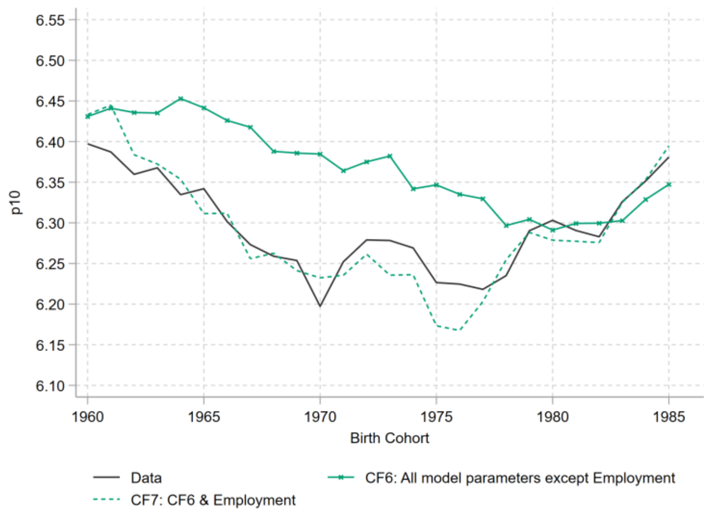


Note: The figure shows the p90-p10-ratio of the distribution of the lifecycle earnings across birth cohort for different simulated counterfactual scenarios described in section 4.2 The Lifecycle Earnings for workers in cohort c are calculated as the total earnings from age 25 to 34. The sample is restricted to individuals with at least 3 years of positive earnings between age 25 to age 34. Earnings are set as yearly wages in the case of full-time employment and 0 otherwise. Data is calculated using the empirical distribution from our sample. Wages and Earnings for CF1 to CF7 are simulated from a normal distribution with mean zero and variances according to our estimated parameters and employment/non-employment probabilities according to Equations (4) and (5). CF1 fixes all parameters at base year 1985 except the observable wage component μ_{ceat}. CF2 allows the observables and additionally the variance of skill $\sigma^2_{\alpha c}$ vary across cohort and time. CF3 allows the observables and the price for skill p_t vary across time (but not $\sigma^2_{\alpha c}$). CF4 allows observables and both variance of skill $\sigma^2_{\alpha c}$and price for skill p_t vary. CF5 allows observables, variance and price of skill as well as the components of the AR(1) process (the persistent shock), ρ_t and $\sigma^2_{\eta t}$, vary. In CF6 observables, variance and price of skill, the components of the AR(1) process (the persistent shock) and additionally the variance of the transitory shock $\sigma^2_{\epsilon t}$ are allowed to vary. CF7 additionally lets the parameters governing the employment process (non-employment probabilities and duration) to vary and corresponds to our full model.
Source: Own calculations based on IAB data

Figure 8 Counterfactual simulation: p10 and p90 of lifecycle earnings



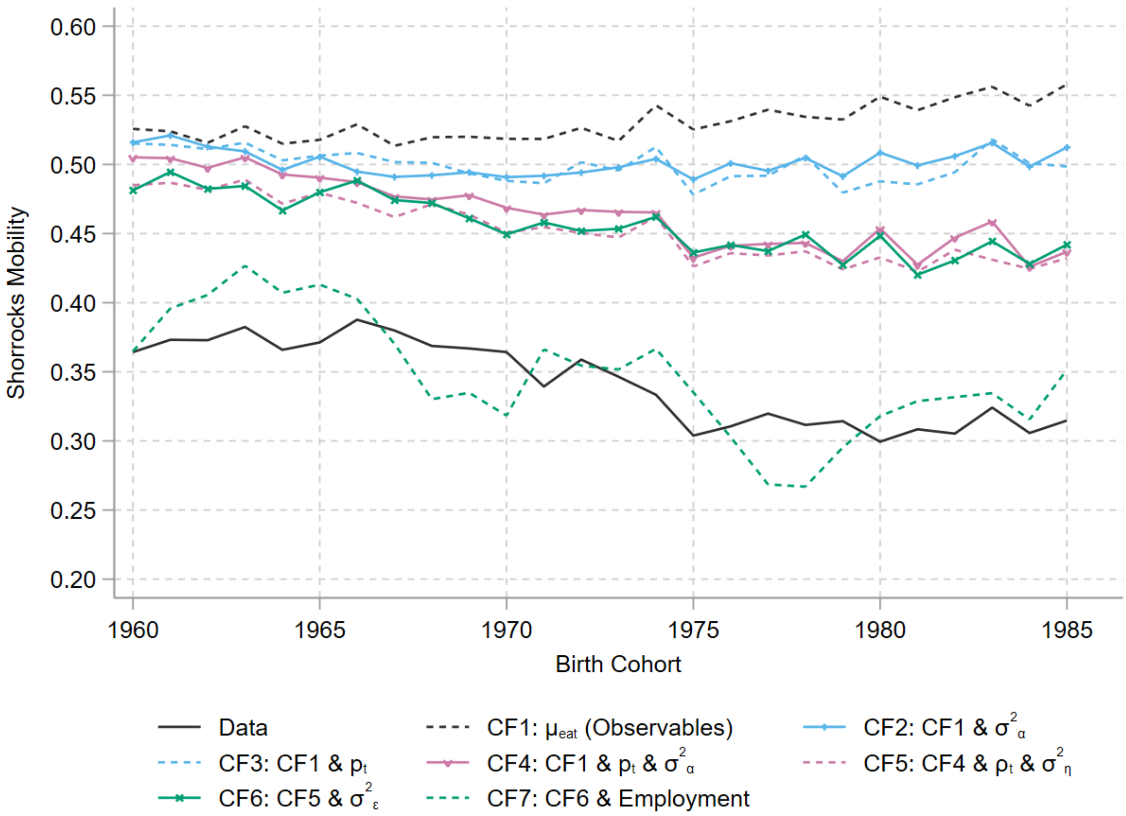
(a) p90



(b) p10

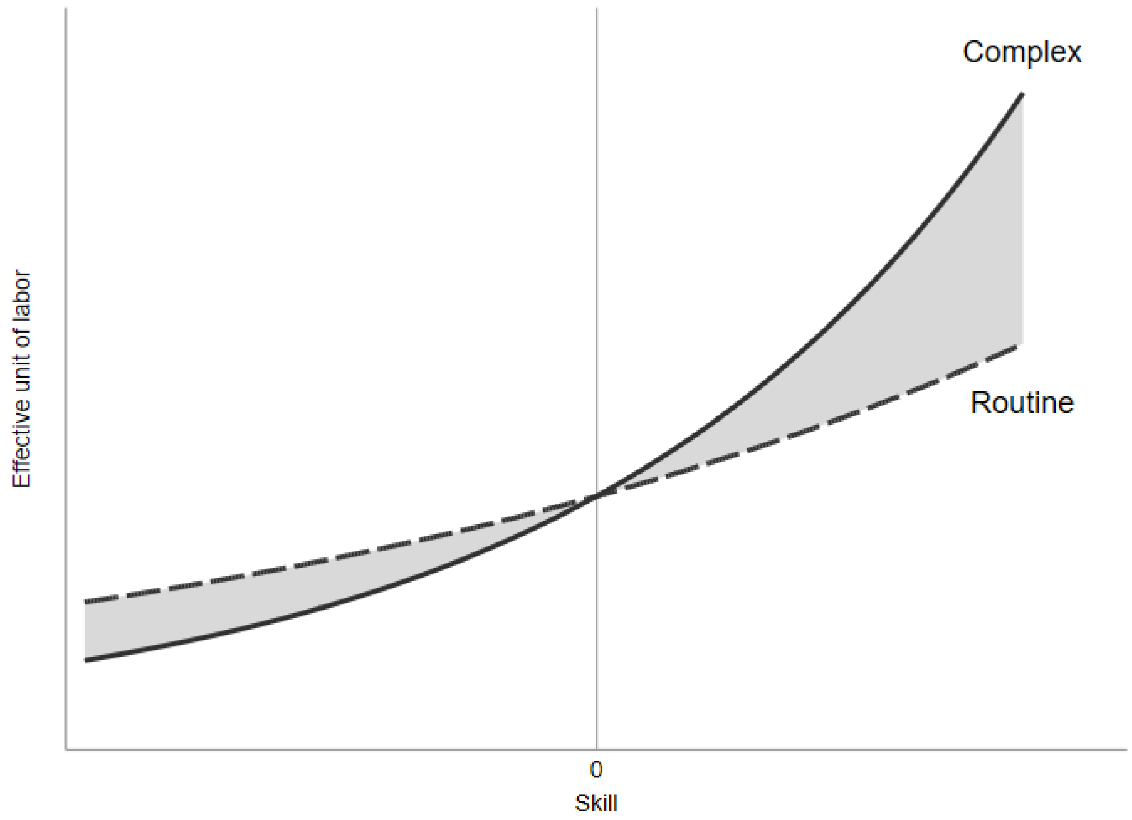
Note: The figure shows the 10th and 90th percentile of the distribution of the lifecycle earnings across birth cohort for different simulated counterfactual scenarios described in section 4.2 The Lifecycle Earnings for workers in cohort c are calculated as the total earnings from age 25 to 34. The sample is restricted to individuals with at least 3 years of positive earnings between age 25 to age 34. Earnings are set as yearly wages in the case of full-time employment and 0 otherwise. Data is calculated using the empirical distribution from our sample. Wages and Earnings for CF1 to CF7 are simulated from a normal distribution with mean zero and variances according to our estimated parameters and employment/non-employment probabilities according to Equations (4) and (5). CF1 fixes all parameters at base year 1985 except the observable wage component μ_{ceat}. CF2 allows the observables and additionally the variance of skill $\sigma^2_{\alpha c}$ vary across cohort and time. CF3 allows the observables and the price for skill p_t vary across time (but not $\sigma^2_{\alpha c}$). CF4 allows observables and both variance of skill $\sigma^2_{\alpha c}$and price for skill p_t vary. CF5 allows observables, variance and price of skill as well as the components of the AR(1) process (the persistent shock), ρ_t and $\sigma^2_{\eta t}$, vary. In CF6 observables, variance and price of skill, the components of the AR(1) process (the persistent shock) and additionally the variance of the transitory shock $\sigma^2_{\epsilon t}$ are allowed to vary. CF7 additionally lets the parameters governing the employment process (non-employment probabilities and duration) to vary and corresponds to our full model.
Source: Own calculations based on IAB data

Figure 9: Counterfactual simulation: Shorrocks Index of Variance in Earnings



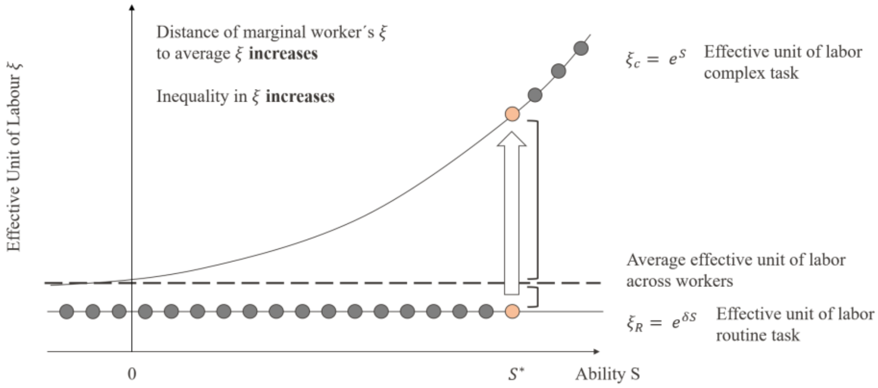
Note: The figure shows the Shorrocks index of the variance of earnings across birth cohort for different simulated counterfactual scenarios described in section 4.2. The sample is restricted to individuals with at least 3 years of positive earnings between age 25 to age 34. Earnings are set as yearly wages in the case of full-time employment and 0 otherwise. Data is calculated using the empirical distribution from our sample. Wages and Earnings for CF1 to CF7 are simulated from a normal distribution with mean zero and variances according to our estimated parameters and employment/non-employment probabilities according to Equations (4) and (5). CF1 fixes all parameters at base year 1985 except the observable wage component μ_{ceat}. CF2 allows the observables and additionally the variance of skill $\sigma^2_{\alpha c}$ vary across cohort and time. CF3 allows the observables and the price for skill p_t vary across time (but not $\sigma^2_{\alpha c}$). CF4 allows observables and both variance of skill $\sigma^2_{\alpha c}$and price for skill p_t vary. CF5 allows observables, variance and price of skill as well as the components of the AR(1) process (the persistent shock), ρ_t and $\sigma^2_{\eta t}$, vary. In CF6 observables, variance and price of skill, the components of the AR(1) process (the persistent shock) and additionally the variance of the transitory shock $\sigma^2_{\epsilon t}$ are allowed to vary. CF7 additionally lets the parameters governing the employment process (non-employment probabilities and duration) to vary and corresponds to our full model.
Source: Own calculations based on IAB data

Figure 10 Comparative advantage in complex and routine sectors by skill

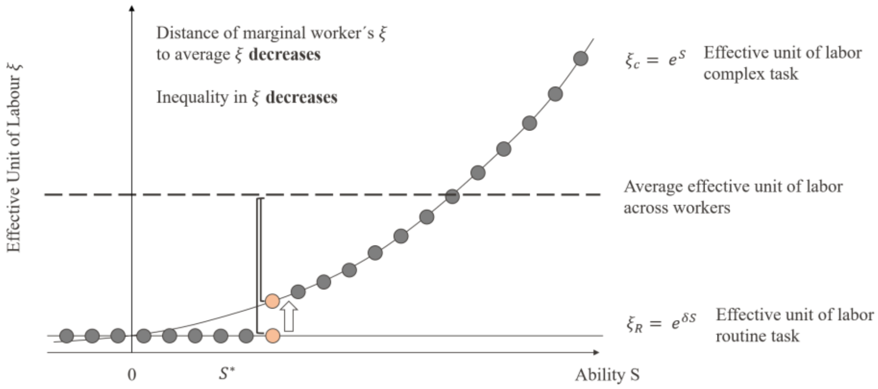


Note: The figure shows the effective unit of labor for complex and routine tasks by skill level.
Source: Own illustration

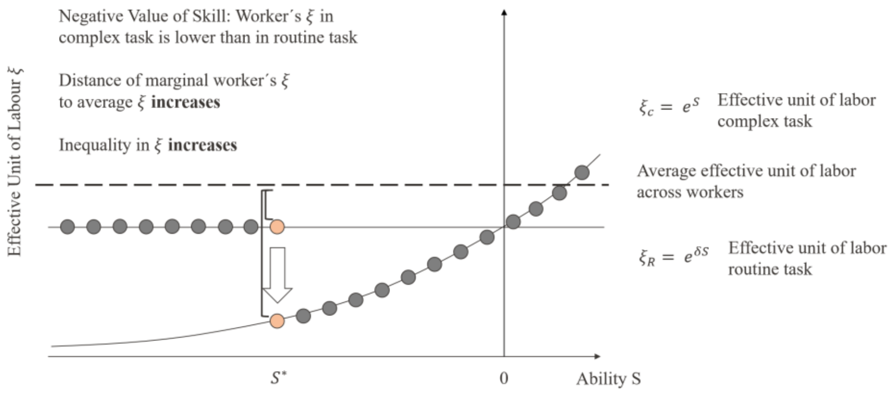
Figure 11 Job switching of the marginal worker under different levels of technology



(a) Low level of technology



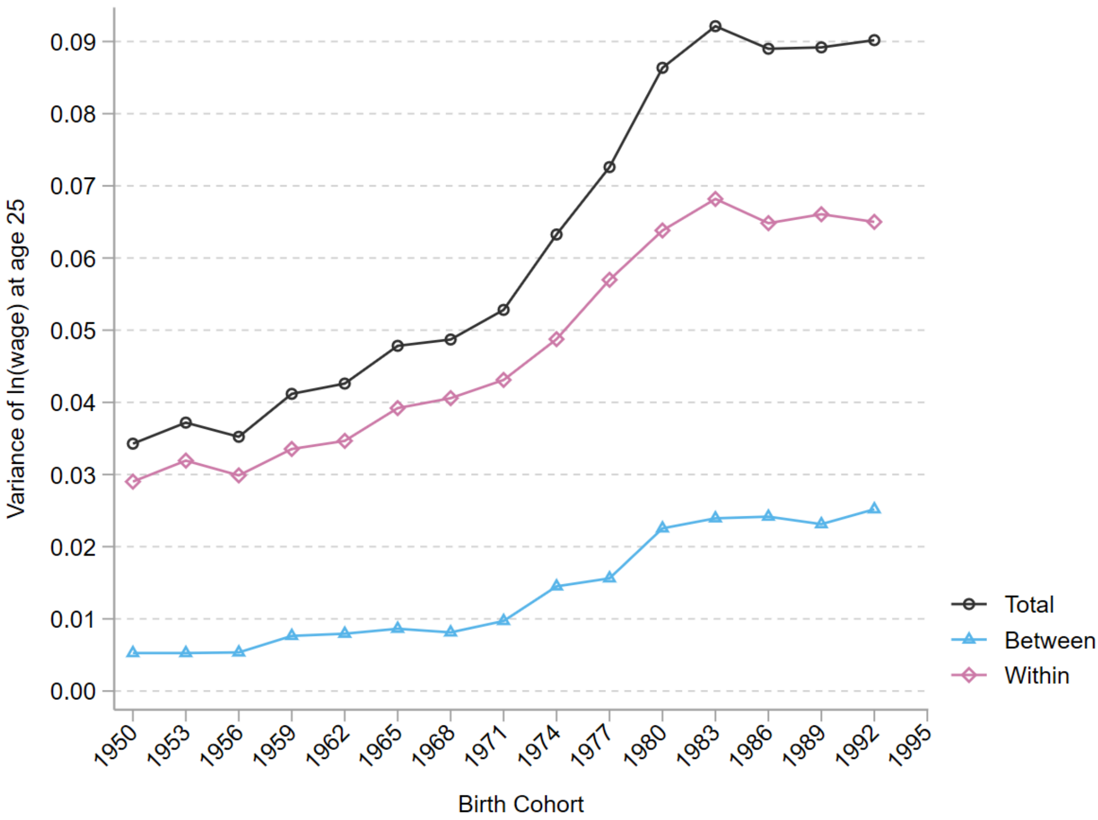
(b) Moderate level of technology



(c) High level of technology

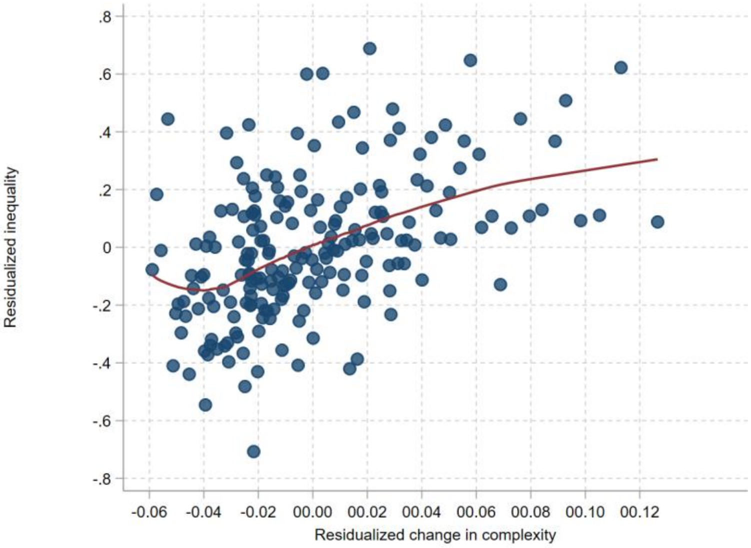
Note: The figure shows the effective unit of labor across skill leave. Each dot represents one worker. The orange dots represent the effective unit of labor of the marginal worker with skill S^* depending on whether he works in the complex or routine task sector. Note that the complex workers payoff working in complex tasks is equal working in routine tasks but his effective unit of labor differs.
Source: Own illustration

Figure 12 Between- and within-occupation variance of wage at age 25

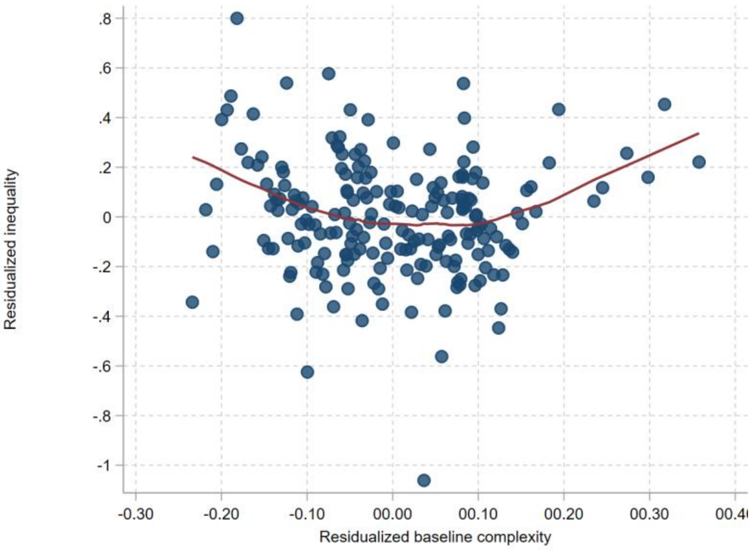


Note: The figure shows the evolution of the variance in log wages of workers at age 25 across birth year decomposed into changes between and within 120 occupations.
Source: Own calculations based on IAB data

Figure 13 Residualized Inequality and Complexity



(a) Residualized Change in Complexity



(b) Residualized Complexity in 1986

Note: The figure plots residualized within-occupation inequality against residualized measures of occupational complexity. In Panel A, both inequality and baseline complexity (1986) are residualized on subsequent changes in complexity (1986–2006) and on baseline inequality (1986). In Panel B, inequality and changes in complexity (1986–2006) are residualized on baseline complexity (1986) and baseline inequality (1986). Data are collapsed to the occupation–year level. Occupations are grouped into equal-sized quantile bins of the residualized complexity measure (200 bins). Each point shows the weighted mean of residualized inequality and residualized complexity within a bin, with weights equal to the number of observations in the underlying occupation–year cells. The solid line is a lowess smoother (bandwidth 0.8).
Source: Own calculations based on IAB and BIBB data

Tables

Table 1 Regression Results Within-occupational variance on complexity

	(1)	(2)	(3)
Dep. Variable	log wage	log wage	log wage
$\Delta c_{t,t-1}$	13.530	29.518***	46.392***
	(9.216)	(10.548)	(13.986)
$\Delta c_{t,t-1} \cdot c_{t-1}$	-84.048*	-175.042***	-256.068***
	(45.748)	(56.468)	(72.367)
$\Delta c_{t,t-1} \cdot c_{t-1}^2$	103.665*	213.244***	305.201***
	(54.289)	(67.990)	(84.189)
Constant	0.036***	0.037***	0.023**
	(0.011)	(0.011)	(0.009)
R^2	0.001	0.004	0.003
Observations	1,038	1,038	1,038
Occ. Clusters	75	75	75
Weighting	Raw	FGLS	FGLS
Complexity Measure	Adjusted	Adjusted	Unadjusted

Note: This table report the result of the regression of year-to-year changes in the variance of within-occupational log wages on change in complexity. We restrict to occupations for which we observe at least 20 observations in 1986 and 2006.
Source: Own calculations based on IAB and BIBB data

Appendix

A Simulation

To test how well our model fits the data and how the components of our both our earnings model contribute to the evolution of inequality we simulate our data. Our simulation is performed in 4 steps.

1. In the first step, we replicate the demographic composition, in our case the educational distribution and the cohort size at age 25. The number of observations in the simulation to be ten times larger than the original cohort size to minimize simulation errors.
2. In the second step we simulate for all workers the 10 wage observations $\ln w_{iceat}$ from age 25 to 34 (we can call this potential wage). To do this we simulate separately the three components of which residual wages are composed according to Equation (1) and (2): the FE $p_t \alpha_{ic}$, the persistent shock z_{iat} and the transitory shock ϵ_{it}. To simulate the three wage components, we draw the components from a normal distribution with mean zero (because the components are residual wages) and the variance depending on the estimated parameters of our model (Figure 4). The simulated FE $p_t \alpha_{ic}$ depends on the variance of the FE in the workers birth cohort $\sigma^2_{\alpha c}$ as well as the skill price p_t for the respective year the wage should be generated. For example, if we compute the fixed effect for a worker born in 1950 at age 30, we use the skill price in year 1980 and the variance of cohort 1950: $p_{1980}\alpha_{i1950}$. The variance of the transitory shock $\sigma^2_{\epsilon t}$ depends on the year in which the wage of the worker should be generated. The permanent shock is computed sequentially: first we compute the wage innovation at age 25. Then at age 26, the depreciated wage innovation from age 25 is added to the new wage innovation at age 26 which is based on the variance estimate of the new year. For example, for a worker aged 26 in year 1981 we compute: $z_{i,26,1981} = \rho_{1981} z_{i,25,1980} + \eta_{i1981}$. Finally, we also add the non-stochastic component of wages μ_{ceat} which is based on the average wage in each interacted cell of the observables age, year and education. After this procedure, every worker now has 10 simulated observations of a potential wage from age 25 to 34.

3. In the second step, we generate for each worker the employment status based on his potential wage from step 2. According to equation (4) each worker faces in every of his 10 periods a different probability to become unemployed $\Pr(U_{iat} = 1 \,|a, w_{i,t-1}, U_{i,t-1})$ which depends on a) the calendar year t b) his age a c) the wage quartile of his potential wage in the last period $w_{i,t-1}$ and d) whether he was employed in the last period or not $U_{i,t-1}$. Using these probabilities and the information of the potential wage from step 2 (which gives us the information in which wage quartile the worker is), we simulate sequentially for each worker if he will be unemployed from age 25 to 34.[31] If the worker is simulated to be unemployed in a given year, then we also draw their length of non-employment $\ddot{v}_{iat}$ from the truncated exponential distribution according to Equation (6), The estimate for Equation (6) was computed from the data. In some cases, an unemployed worker will be unemployed for the full year. In that case we exchange his potential earnings (based on his potential wage we computed in step 1) with 0. The worker could however also be simulated to be 75% of the year unemployed. We then exchange his potential earnings from step 1 for the fraction of the year with 0 according to $(1 - \ddot{v}_{it}) \exp(\mu_{ceat} + p_t\alpha_{ic} + z_{iat} + \epsilon_{it})$. For example, a worker with potential wage that equals 20.000 EUR earnings in a year who is 75% unemployed he is simulated to receive earnings of 5000 EUR. What happens to workers who are unemployed in the following period? We draw again from the probability distribution to simulate if he is employed or unemployed in the next year. Non-employment in our model can be persistent, because a worker faces a different (higher) probability to be unemployed if they were unemployed already in the previous period as can be seen in Figure 5. If the unemployed worker becomes employed again, he goes back to his original wage path which we calculated in step 2.
4. After this procedure we have for each individual 10 simulated values (for age 25-34) of a potential log wages $\ln \widehat{(w_{\iota ceat})}$ for which some could be missing if the person

[31] We simulate this sequentially, as the probability to become unemployed depends on the employment status in the previous period.

is unemployed[32]. and 10 simulated values of annual earnings $\hat{e}_{it}$ for which some could be 0 if the person is unemployed for the full year. We then sum up the 10 years of earnings to arrive at the total accumulated earnings over the period. Here we also condition on workers whose accumulated working days are at least the equivalent of 3 out of 10 years to ensure we only consider worker with a minimum of attachment to the labor market.

B Selection into Non-employment

In principle, changing non-employment rates could affect the cross-sectional distribution of wages if selection into non-employment is sufficiently based on the wage and we explicitly consider this in our employment process. In this section we perform two additional decompositions to explain why in our counterfactual decomposition in Section 4.2 the employment margin - despite large changes in the non-employment rate and positive correlation between non-employment and wages - does not affect the evolution of cross-sectional wage inequality. Looking at the non-employment probability across the potential wage decile in Figure A2 we note that the probability to become unemployed is considerably higher for low wage earners than for high wage earners. We also note that the slope of this relationship becomes more negative in years of high unemployment. However, the question is, if this difference in non-employment probability across wages is strong enough to influence the distribution of wages when the non-unemployment probability varies across years.

To understand this, we perform two additional counterfactual scenarios of our employment process. Our employment process estimates for each simulated individual the employment status stochastically in each period based on his age, year and importantly his potential wage decile. This means workers with lower simulated wage having a higher probability of non-employment than simulated individuals with higher simulated wage.

We now change this scenario to account for the two possible extremes which are

[32] In that case we do not consider it in the cross-section.

illustrated in Figure A3 for an non-employment rate of 10%:

The first scenario is a scenario of full or perfect selection into non-employment. In this scenario the non-employment in a given year (determined by the aggregate non-unemployment rate in the data) is fully faced by the lowest earners (the individuals in our simulation which have the lowest potential wage in our first step estimation). Those individuals are assigned 0 earnings and missing wage and they are not considered in the cross-sectional wage inequality. In this scenario an increasing aggregate non-employment rate across years should ceteris paribus decrease the cross-sectional wage inequality because with more non-employment more low-wage earners leave the wage distribution.

In the second scenario, The *No Selection* Scenario, non-employment does not depend on the wage and changes in the non-employment rate should not affect the cross-sectional wage distribution at all.

Figure A4 shows the result of this counterfactual decomposition. We see that if the labor market operated under a system of perfect selection, where the lowest earners were systematically sorted into non-employment, cross-sectional inequality would (i) have been lower on average during the period we examine, and (ii) would have continued to rise after 2010 as non-employment rates declined and the lowest wage earners re-entered the wage distribution. Furthermore, our analysis shows that both the full model and the data closely align with a *No Selection* scenario, suggesting that the differences in non-employment probabilities along the wage distribution as we saw in Figure B1 are too small to significantly impact the cross-sectional distribution. Consequently, the employment margin has a minimal effect on shaping cross-sectional inequality during the period we study.

C Proof of Propositions

To show Proposition 1, note that the maximum earnings among workers in the routine sector are $\exp(\delta S^*)\ w_R$, whereas the minimum earnings among workers in the complex sector are $\exp(S^*)\ w_C$, since the effective unit of labor is increasing in ability S and workers engage in complex tasks if and only if $S \geq S^*$. Considering that $\exp(\delta S^*)\ w_R = \exp(S^*)\ w_C$ by the definition of S^*, we observe that for any $S_0 \leq S^* \leq S_1$,

$$\exp(\delta S_0)\, w_R \leq \exp(\delta S^*)\ w_R = \exp(S^*)\ w_C \leq \exp(S_1)\ w_C. \quad \blacksquare$$

To show Proposition 2, note that $S^* = \frac{1}{1-\delta}\ln\frac{w_R}{w_C}$, and thus, $\frac{\partial S^*}{\partial\omega} < 0 \Leftrightarrow \frac{\partial}{\partial\omega}\frac{w_C}{w_R} > 0$. From equation (12), we have

$$\left[\frac{\Phi(z-\delta\sigma)}{1-\Phi(z-\sigma)}\cdot\frac{\partial}{\partial z}\frac{1-\Phi(z-\sigma)}{\Phi(z-\delta\sigma)}\cdot\frac{1}{\sigma}-\frac{1-\delta}{1-\varphi}\right]\frac{\partial S^*}{\partial\omega}=\frac{1}{1-\varphi}\frac{\partial}{\partial\omega}\ln\frac{\omega}{1-\omega} > 0,$$

where $z = \frac{S^*-\mu}{\sigma}$. Since $\frac{\partial}{\partial z}\frac{1-\Phi(z-\sigma)}{\Phi(z-\delta\sigma)} < 0$ and $\frac{\Phi(z-\delta\sigma)}{1-\Phi(z-\sigma)}\cdot\frac{\partial}{\partial z}\frac{1-\Phi(z-\sigma)}{\Phi(z-\delta\sigma)}\cdot\frac{1}{\sigma}-\frac{1-\delta}{1-\varphi} < 0$, it follows that $\frac{\partial S^*}{\partial\omega} < 0$. ■

To show Proposition 3, we first show that the expectation of the effective unit of labor is inverted U-shaped and peaked when $S^* = 0$. In fact,

$$E[\xi(S;S^*)] = \int_{S^*}^{\infty}\exp(s)\ f_S(s)ds + \int_{-\infty}^{S^*}\exp(\delta s)\ f_S(s)ds,$$

and hence,

$$\frac{\partial E[\xi(S;S^*)]}{\partial S^*} = f_S(S^*)[\exp(\delta S^*)-\exp(S^*)] < 0 \Leftrightarrow S^* > 0. \qquad (C1)$$

In addition, it follows that

$$E[\xi(S;0)] > \lim_{S^*\to-\infty} E[\xi(S;S^*)] = E[\exp(S^*)] = \exp\left(\frac{\sigma^2}{2}\right) \geq 1. \qquad (C2)$$

Note also that $Var\big(\xi(S;S^*)\big) = E[\xi^2(S;S^*)] - E[\xi(S;S^*)]^2$, and $E[\xi^2(S;S^*)] = \int_{S^*}^{\infty}\exp^2(s)\ f_S(s)ds + \int_{-\infty}^{S^*}\exp^2(\delta s)\ f_S(s)ds$. Thus, we observe

$$\frac{d}{dS^*}Var\big(\xi(S;S^*)\big) = f_S(S^*)[\exp(\delta S^*)-\exp(S^*)]\big[\exp(\delta S^*)+\exp(S^*)-2\,E[\xi(S;S^*)]\big].$$

Proposition 3.2 immediately follows from this equation since if $S^* = 0$, we have $\exp(\delta S^*)-\exp(S^*) = 0$. ■

We next show Proposition 3.1. To this end, define $g(S^*) = \exp(\delta S^*) + \exp(S^*) - 2\,E[\xi(S;S^*)]$. For $S^* > 0$, since $\exp(\delta S^*)-\exp(S^*) < 0$, and equation (B1) implies that $g(S^*)$ is monotonically increasing, $\frac{d}{dS^*}Var\big(\xi(S;S^*)\big)$ is monotonically decreasing. Hence, Proposition 3.1 holds if we show that there exists $S_0 > 0$ such that $g(S_0) = 0$, or equivalently, $\frac{\exp(\delta S^*)+\exp(S^*)}{2} = E[\xi(S;S^*)]$. Since the left-hand side is continuous and monotonically increasing from 1 to ∞ for

$S^* > 0$, and since the right-hand side is continuous and monotonically decreasing for $S^* > 0$ with $1 < E[\xi(S;0)] < \infty$ from equation (C2), these two lines cross at one point S_0. ■

For Proposition 3.3, we next consider the case with $S^* < 0$, and since $\exp(\delta S^*) - \exp(S^*) > 0$ in this case, it is sufficient to show $g(S^*) < 0$. Given that $0 < \frac{\exp(\delta S^*) + \exp(S^*)}{2} < 1$ for $S^* < 0$, equations (C1) and (C2) imply that

$$\frac{\exp(\delta S^*) + \exp(S^*)}{2} < 1 \leq \lim_{S^* \to -\infty} E[\xi(S;S^*)] < E[\xi(S;S^*)],$$

and therefore, $g(S^*) < 0$ for $S^* < 0$. ■

Finally, we show Corollary 1. Since

$$\frac{\partial}{\partial \omega} Var\left(\xi(S;S^*)\right) = \frac{d}{d\,S^*} Var\left(\xi(S;S^*)\right) \cdot \frac{\partial}{\partial \omega} S^*,$$

and $\frac{\partial}{\partial \omega} S^* < 0$ from Proposition 2, the sign of $\frac{\partial}{\partial \omega} Var\left(\xi(S;S^*)\right)$ is opposite to $\frac{d}{d\,S^*} Var\left(\xi(S;S^*)\right)$. Therefore, given Proposition 3, it is sufficient to show that the equilibrium threshold $S^* = S^*(\omega, \varphi, \mu, \sigma, \delta)$ ranges $(-\infty, \infty)$ for $\omega \in (0,1)$. To this end. we first show that $S^*(\omega, \varphi, \mu, \sigma, \delta)$ is continuous and monotonically decreasing in ω. Rewriting equation (12) as

$$\Xi(S^*, \varphi, \mu, \sigma, \delta) = (1-\varphi)\left[(1-\delta)\,\mu + \frac{(1-\delta^2)\sigma^2}{2} + \ln \frac{1 - \Phi\left(\frac{S^* - \mu}{\sigma} - \sigma\right)}{\Phi\left(\frac{S^* - \mu}{\sigma} - \delta\sigma\right)} - \frac{(1-\delta)}{1-\varphi} S^*\right]$$
$$= \ln \frac{\omega}{1-\omega}, \tag{C3}$$

we note that $\Xi(S^*, \varphi, \mu, \sigma, \delta)$ is continuous and monotonically decreasing in S^*. Hence, there exists a continuous and monotonically decreasing inverse function $\Xi^{-1}(\omega, \varphi, \mu, \sigma, \delta) = S^*(\omega, \varphi, \mu, \sigma, \delta)$. In addition, it is evident from equation (C3) that $\lim_{\omega \to 0} S^*(\omega, \varphi, \mu, \sigma, \delta) = \infty$ and $\lim_{\omega \to 1} S^*(\omega, \varphi, \mu, \sigma, \delta) = -\infty$. Therefore, given the continuity and monotonicity, $S^*(\omega, \varphi, \mu, \sigma, \delta)$ ranges $(-\infty, \infty)$ for $\omega \in (0,1)$. ■

D Model extension

This section generalizes our Roy model. In particular, we relax the distributional assumption on workers' skill and the functional form assumption on the effective unit of labor. For skill distribution, we assume that S has the cumulative distribution function $F_S(\cdot)$ with support $\mathcal{S}$. We assume that $\inf \mathcal{S} < 0 < \sup \mathcal{S}$, so that there are workers who are more productive in routine (complex) tasks. We denote the effective unit of labor of a worker with ability S by $\psi(S)$ for complex tasks and $\psi(\delta S)$ for routine tasks, where $\psi: \mathcal{S} \to \mathbb{R}^2_{++}$ is continuous and monotonically increasing on $\mathcal{S}$. In addition, we assume that the first and second moments of $\psi(S)$ exist, and $h(S;\delta) = \frac{\psi(S)}{\psi(\delta S)}$ is monotonically increasing for all $S \in \mathcal{S}$, which serves as the single crossing condition. In fact, the worker chooses routine tasks if and only if

$$\psi(S)w_C \geq \psi(\delta S)w_R, \qquad \therefore S \geq S^* = h^{-1}\left(\frac{w_R}{w_C};\delta\right), \qquad (D1)$$

where $h^{-1}(\cdot\,;\delta)$ exists due to the monotonicity of $h(\cdot\,;\delta)$. Then, the effective unit of aggregate labor supply to each sector is

$$C^S = \int_{S^*}^{\sup \mathcal{S}} \psi(S) dF_S, \qquad R^S = \int_{\inf \mathcal{S}}^{S^*} \psi(\delta S) dF_S. \qquad (D2)$$

The equilibrium is $\left(C^D, R^D, C^S, R^S, S^*, \frac{w_C}{w_R}\right)$ that satisfies equations (8), (D1) and (D2) and the market clearing conditions, $C^D = C^S$ and $R^D = R^S$. The existence and uniqueness of the equilibrium are shown similarly to our baseline model in Section 5.1. Furthermore, it is obvious that Proposition 2 holds with almost identical proof. That is, we observe that $\frac{\partial}{\partial\omega}\frac{w_C}{w_R} > 0$ and $\frac{\partial}{\partial\omega}S^* < 0$. We now show the non-monotonic nature of the variance of effective unit of labor:

Proposition 4

Suppose that $\inf_{S\in\mathcal{S}} \psi(\delta S) < E[\psi(S)]$ and $\xi(0) \neq E[\psi(S;0)]$. Then, the variance of the realized effective unit of $Var(\xi(S;S^*))$ is non-monotonic in S^*.

Proof

Note first that with similar argument in our baseline model, we observe that $E[\xi(S;S^*)]$ is inverted U-shaped with peak at $S^* = 0$, and the derivative of the variance is given by

$$\frac{d}{dS^*}Var(\xi(S;S^*)) = f_S(S^*)[\psi(\delta S^*) - \psi(S^*)][\psi(\delta S^*) + \psi(S^*) - 2\,E[\xi(S;S^*)]].$$

We first show that the variance is decreasing when S^* is sufficiently small or large. Define $g(S^*) = \psi(\delta S^*) + \psi(S^*) - 2\,E[\xi(S;S^*)]$. Since $\psi(S)$ is increasing in S, we have

$$g(\inf \mathcal{S}) = \frac{\psi(\delta \inf \mathcal{S}) + \psi(\inf \mathcal{S})}{2} - E[\xi(S; \inf \mathcal{S})] < \psi(\delta \inf \mathcal{S}) - E[\psi(S)] < 0,$$

where $E[\xi(S; \inf \mathcal{S})] = E[\psi(S)]$ by the definition of $\xi(\cdot)$ and the last inequality follows from the assumption of Proposition 3. As $g(\cdot)$ is continuous, there exists $\underline{S} \in \mathcal{S} \cap \mathbb{R}_-$ such that for all $S^* \leq \underline{S}$, $g(S^*) < 0$, and thereby, $\frac{d}{dS^*} Var\big(\xi(S; S^*)\big) < 0$. On the other hand, since $\psi(S)$ is increasing, we observe $E[\psi(S; \sup \mathcal{S})] = E[\psi(\delta S)] < \sup_{S^* \in \mathcal{S}} \psi(\delta S^*) \leq \sup_{S^* \in \mathcal{S}} \frac{\psi(\delta S^*) + \psi(S^*)}{2}$, implying $g(\sup \mathcal{S}) > 0$. So, there exists $\bar{S} \in \mathcal{S} \cap \mathbb{R}_+$ such that for all $S^* \geq \bar{S}$, $g(S^*) > 0$, and $\frac{d}{dS^*} Var\big(\xi(S; S^*)\big) < 0$.

Therefore, to show the non-monotonicity of the variance, it is sufficient to show $\frac{d}{dS^*} Var\big(\xi(S; S^*)\big) > 0$ for some S^*. If $\psi(0) < E[\xi(S; 0)]$, we have $g(0) < 0$. Since $g(\cdot)$ is continuous, there exists $\ddot{S}_+ \in \mathcal{S} \cap \mathbb{R}_+$ such that for all $S^* \in \big(0, \ddot{S}_+\big)$, $g(S^*) < 0$, and $\frac{d}{dS^*} Var\big(\xi(S; S^*)\big) > 0$ since $\psi(\delta S^*) - \psi(S^*) < 0$ for $S^* > 0$. Similarly, if $\psi(0) > E[\xi(S; 0)]$, we have $g(0) > 0$, and there exists $\ddot{S}_- \in \mathcal{S} \cap \mathbb{R}_-$ such that for $S^* \in \big(\ddot{S}_-, 0\big)$, $g(S^*) > 0$, and $\frac{d}{dS^*} Var\big(\xi(S; S^*)\big) > 0$ since $\psi(\delta S^*) - \psi(S^*) > 0$ for $S^* < 0$. ■

Note that with assumption $\psi(0) \leq E[\psi(S)]$, we can generalize Proposition 3:

Proposition 5

Let $\xi(S; S^*)$ be the (realized) effective unit of labor of a worker with skill S, given the threshold value S^*. Suppose that $\psi(0) \leq E[\psi(S)]$.[33] Then,

1. For $S^* > 0$, $Var\left(\xi(S; S^*)\right)$ is inverted U-shaped.
2. For $S^* = 0$, $\frac{d}{d\,S^*} Var\left(\xi(S; S^*)\right) = 0$.
3. For $S^* < 0$, $\frac{d}{d\,S^*} Var\left(\xi(S; S^*)\right) < 0$.

Proof

[33] This assumption holds when ability S has mean-zero distribution and $\psi(\cdot)$ is convex by Jensen's inequality.

First, Proposition 5.2 is trivial. To show Proposition 5.3, note that by the definition of $\xi(\cdot)$, we have $E[\xi(S;\inf\mathcal{S})] = E[\psi(S)]$, and so, the assumption of the proposition implies that for $S^* < 0$,

$$\frac{\psi(\delta S^*) + \psi(S^*)}{2} < \psi(0) \leq E[\psi(S)] = E[\xi(S;\inf\mathcal{S})] < E[\xi(S;S^*)],$$

where the last inequality follows since $E[\xi(S;S^*)]$ is inverted U-shaped with peak $S^* = 0$. Therefore, for $S^* < 0$, we have $g(S^*) < 0$, and thus, $\frac{d}{dS^*}Var\big(\xi(S;S^*)\big) < 0$. To show Proposition 5.1, consider the case with $S^* > 0$. By the definition of $\xi(\cdot)$, $E[\xi(S;\inf\mathcal{S})] = E[\psi(S)]$ and $E[\xi(S;\sup\mathcal{S})] = E[\psi(\delta S)]$. The assumption implies that $\psi(0) \leq E[\psi(S)] = E[\xi(S;\inf\mathcal{S})] < E[\xi(S;0)]$, so that $g(0) < 0$. Furthermore, since $\psi(S)$ is monotonically increasing, we have $E[\xi(S;\sup\mathcal{S})] = E[\psi(\delta S)] < \sup_{S^*\in\mathcal{S}}\psi(\delta S^*) \leq \sup_{S^*\in\mathcal{S}}\frac{\psi(\delta S^*)+\psi(S^*)}{2}$, so that $g(\sup\mathcal{S}) > 0$. Hence, $g(0) < 0 < g(\sup\mathcal{S})$. Since $g(S^*)$ is continuous and monotonically increasing for $S^* > 0$, there exists $\tilde{S} \in \mathcal{S} \cap \mathbb{R}_+$ such that $g(S^*) < 0$ for $0 < S^* < \tilde{S}$, $g(S^*) = 0$ for $S^* = 0$, and $g(S^*) > 0$ for $S^* > 0$. Therefore, given that $\psi(\delta S^*) - \psi(S^*) < 0$ for $S^* > 0$, we observe that $Var\big(\xi(S;S^*)\big)$ is inverted U-shaped for $S^* > 0$ with peak $S^* = \tilde{S}$. ■

E Model Simulation

Our model implies that technological change influences wage inequality through two primary channels: the price of labor efficiency $w = w_C/w_R$, and the variance of labor efficiency, $Var\,(\xi)$, induced by sorting. In our statistical model, these parameters correspond to p_t and $\sigma^2_{\alpha c}$.

In Corollary 1, we show that the sorting channel generates a non-monotonic effect on the variance of labor efficiency $Var\,(\xi)$. In contrast, the price channel, captured in the Roy model as the relative price of complex to routine tasks w_C/w_R, responds monotonically to technological change. Specifically, w_C/w_R increases in the complex task-augmenting productivity parameter ω, thereby raising the returns to performing complex tasks.

The individual effects on w_C and w_R, and thus on the overall variance of total wages $Var(w\xi)$[34], depend non-trivially on two key functional form assumptions: First, the elasticity of substitution between complex and routine tasks, $\frac{1}{1-\varphi}$, determines the extent to which firms can substitute across tasks types. Second, the task-specific ability-scaling parameter δ governs the degree to which innate ability translates into productivity in the routine task sector.

In our empirical analysis below, we observe the equivalent of $\Delta Var(w\xi)$, i.e., the change in the variance of the combined effect of productivity and price. To assess how its relationship with initial complexity (capturing the initial technology level of an occupation) and changes in complexity reflects the implications of our model, as stated in Propositions 2 and 3 and Corollary 1, we rely on simulations. Specifically, to distinguish whether changes in $Var(w\xi)$ associated with higher initial complexity or larger increases in complexity are driven by price increases or sorting, we simulate a baseline scenario in which complex and routine tasks are gross complements $\frac{1}{1-\varphi} = 0.5 \left(\frac{1}{1-\varphi} = 0.5\right)$ and ability plays only a limited role in routine task productivity ($\delta = 0.1$).

Figure A6 presents the simulation results. Panel (a) shows that a decline in S^*, induced by technological progress (increasing ω), consistently raises the variance of wages $Var(w\xi)$ through the combined effect of price and sorting channels. Panel (b), however, shows that the *slope* of this increase is non-monotonic and flattens at intermediate levels of ω. This pattern reflects the sorting channel, whose impact weakens in the mid-range of ω. Thus, while the positive, monotonic price effect dominates overall, the non-monotonic sorting effect modulates the rate at which inequality grows within occupations.

In most empirically relevant settings, technological change increases wage variance through both channels. The relative importance and direction of the sorting effect, however, can depend on the task structure and ability-technology interaction within

[34] The variance is the weighted sum of the overall renumeration of all workers: $Var(w\xi) = Var\left(\sum_{i\epsilon C} w_c \cdot \xi_i + \sum_{i\epsilon R} w_r \cdot \xi_i\right)$.

occupations.

We next examine the sensitivity of our Roy model simulation to alternative values of the two key parameters: the elasticity of substitution between complex and routine tasks, $\frac{1}{1-\varphi}$, and the degree to which ability maps into productivity in routine tasks, δ. Our baseline assumes $\delta = 0.1$ and $\frac{1}{1-\varphi} = 0.5$ implying that ability plays a minimal role in routine tasks and that complex and routine tasks are relative complements.

Figure A7 presents the simulated relationship between the level of technology ω and the variance of wages $Var(w\xi)$, where wages are the product of task price and labor efficiency. Each panel (a) through (f) corresponds to a different value of the elasticity of substitution $\frac{1}{1-\varphi}$, and within each panel, the curves represent varying values of δ.

Across most relevant parameter combinations, wage variance increases monotonically with technology ω. Exceptions occur at low levels of ω when is δ high. These cases are inconsistent with the conceptual foundation of our model, which assumes that ability has limited influence on productivity in routine tasks.

For example, in our baseline scenario with $\frac{1}{1-\varphi} = 0.5$, the variance of wages exhibits a negative slope for $\delta \geq 0.6$, a scenario in which ability contributes more and more equally to productivity in both tasks. This violates the core logic of our model, which rests on differential relevance of ability across tasks.

A monotonic increase in wage variance with technological progress emerges as long as at least one of the following conditions is met: (i) ability plays a relative limited role in routine task productivity, (ii) routine and complex tasks are not highly substitutable, or (iii) the empirically relevant range of technological change avoids extreme values of ω

Next, we examine the *slope* of the wage variance with respect to ω. In Figure A8, we plot the first derivative of the variance of wages $Var(w\xi)$ with respect to ω. This derivative captures the rate of change in wage variance at different levels of technological progress. A positive derivative indicates that technological change increases wage inequality at that level ω.

For our baseline case with $\delta = 0.1$ and $\frac{1}{1-\varphi} = 0.5$, the slope is positive throughout but exhibits a U-shaped pattern: the rate of increase in wage variance is lowest at intermediate levels of ω. This aligns with the mechanism identified in our model—non-monotonic sorting into tasks causes realized labor efficiency variance $Var(\xi)$ to flatten at medium technology levels, slowing the overall growth in wage inequality despite the monotonic price effect.

We observe that the U-shaped pattern holds also for other relatively low values of δ reinforcing that sorting effects dominate when ability is largely irrelevant in routine tasks[35].

Similarly, the U-shape holds for low values of δ in cases where complex and routine tasks are stronger complements—i.e., when the elasticity of substitution is at 0.1 or 0.001. As routine and complex tasks become increasingly substitutable, the U-shape flattens and eventually disappears, as task-specific sorting loses influence over the task price effect.

Taken together, a U-shaped pattern in the slope of wage variance emerges when (i) ability plays a relative limited role in routine task productivity, and (ii) routine and complex tasks are not highly substitutable.

F Construction of Residualized Measures of Complexity and Complexity Change for Graphical Analysis

To provide nonparametric evidence on the link between the level of complexity in 1986, complexity change since 1986 and within-occupotional inequality, we residualize the variables against relevant controls. The procedure is carried out at the occupation–year level after collapsing the SIAB–BIBB matched data. We distinguish two cases: (i) Residualized Baseline complexity and (ii) Residualized Complexity change.

We regress log within-occupation inequality and baseline complexity (1986)

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[35] The strength of the U-shaped pattern is however not strictly monotonically increasing with lower ω for all parameter choices of the elasticity of substitution.

separately on changes in complexity between 1986 and 2006 and on baseline inequality in 1986:

$$(1)\quad \ln\left(\hat{u}^2_{i,t,j}\right) = \gamma_0 + \gamma_1 \cdot \Delta Complexity[t-1986]_{j,t} + \gamma_2 \cdot \sigma^2_{j,1986} + \epsilon_{i,j,t}$$

$$(2)\quad \ln\left(Complexity_{j,t}\right) = \xi_0 + \xi_1 \cdot \Delta Complexity[t-1986]_{j,t} + \xi_2 \cdot \sigma^2_{j,1986} + \eta_{i,j,t}$$

Residuals from these equations represent the components of inequality and baseline complexity orthogonal to both subsequent complexity growth and initial inequality.

For the Residualized Complexity change measure we regress log within-occupation inequality and changes in complexity on baseline complexity (1986) and baseline inequality:

$$(1)\quad \ln\left(\hat{u}^2_{i,t,j}\right) = \theta_0 + \theta_1 \cdot c_{j,1986} + \theta_2 \cdot \left(c_{j,1986}\right)^2 + \theta_3 \cdot \sigma^2_{j,1986} + \kappa_{i,j,t}$$

$$(2)\quad \ln\left(\Delta c_{j,t,1986}\right) = \tau_0 + \tau_1 \cdot c_{j,1986} + \tau_2 \cdot \left(c_{j,1986}\right)^2 + \tau_3 \cdot \sigma^2_{j,1986} + \varphi_{i,j,t}$$

Residuals from these equations represent the components of inequality and complexity growth orthogonal to initial conditions.

For visualization, we sort occupations into equal-sized quantile bins of the relevant residualized complexity measure, compute the weighted mean of residualized inequality and complexity within each bin, and use the number of individuals in each occupation–year cell as weights. We exclude bins with fewer than 20 observations and, e exclude bins with extreme values of residualized complexity change (mean values above 0.1. We then plot the bin means against each other, overlaying a lowess smoother with bandwidth 0.8.

G Parameter Effects on Shorrocks Income Mobility

In this subsection we derive how the different components of our earnings process contribute to short-term and long-term variance, and thus to the Shorrocks mobility index.[36] For simplicity, we abstract here from the influence of the observables and the employment margin on the wage and only consider the effect of our income process parameters on the residual wage $\hat{y}_t$.

$$\hat{y}_t = p_t \alpha_{ic} + z_{iat} + \epsilon_{it}, \tag{1a}$$

$$z_{iat} = \rho_t z_{i,a-1,t-1} + \eta_{it}, \tag{2a}$$

The environment for our analysis is static: all structural parameters and prices are fixed within the observed window of length T. We will consider the effect of level changes in single parameters for the entire holding the other parameters constant. As a result, we define $p_t \alpha_{ic} = p\alpha$, $\epsilon_{it} = \epsilon$ and $z_{iat} = z_a$ for all t.

Define the short-term variance of residual wages as

$$S = \frac{1}{T} \sum_{t=1}^{T} Var(\hat{y}_t)$$

and the long-term variance as

$$L = \frac{1}{T} \sum_{t=1}^{T} Var(\hat{y}_t)$$

The Shorrocks mobility index, with variance as the inequality measures, is then

$$M = 1 - \frac{L}{S}$$

A lower value of L/S implies higher earnings mobility, because less of short-term dispersion translates into persistent, long-term inequality. Because the permanent effect $p_t \alpha_{ic}$, the persistent shock z_{iat} and the transitory shock ϵ_{it} are independent we can write short- and long-term inequality as

$$S = \frac{1}{T} \sum_{t=1}^{T} Var(p_t \alpha_{ic}) + \frac{1}{T} \sum_{t=1}^{T} Var(z_{iat}) + \frac{1}{T} \sum_{t=1}^{T} Var(\epsilon_{it}) = S_{FE} + S_P + S_T$$

[36] We abstract here from the influence of the observables and the employment margin on the wage and only model the effect of our income process parameters on the residual wage

and

$$L = Var\left(\frac{1}{T}\sum_{t=1}^{T} p_t \alpha_{ic}\right) + Var\left(\frac{1}{T}\sum_{t=1}^{T} z_{iat}\right) + Var\left(\frac{1}{T}\sum_{t=1}^{T} \epsilon_{it}\right) = L_{FE} + L_P + L_T$$

Lemma G0: The short term-variance of each sub-component of our income process is always lower or equal than the long-term variance

Proof: Because the fixed effect is constant over time, it contributes equally to both short- and long-term variance:

$$S_{FE} = \frac{1}{T}\sum_{t=1}^{T} Var(\alpha p) = \frac{1}{T}\sum_{t=1}^{T} p^2\sigma_\alpha^2 = p^2\sigma_\alpha^2$$

$$L_{FE} = Var\left(\frac{1}{T}\sum_{t=1}^{T} \alpha p\right) = Var(\alpha p) = p^2\sigma_\alpha^2$$

Therefore $S_{FE} = L_{FE}$

Because the transitory component is independent across time t, positive and negative shocks are more likely offset each other, this effect is stronger the longer the time-horizon T.

$$S_T = \frac{1}{T}\sum_{t=1}^{T} Var(\epsilon_t) = \sigma_\epsilon^2$$

$$S_T = Var\left(\frac{1}{T}\sum_{t=1}^{T} \epsilon_t\right) = \frac{1}{T^2}\sum_{t=1}^{T} Var(\epsilon_t) = \frac{\sigma_\epsilon^2}{T}$$

So $S_T \geq S_T$

In the stationary distribution with persistency $\rho \leq 1$ the variance of the persistent shock is

$$Var(z_a) = \frac{\sigma_\eta^2}{1-\rho^2}$$

And the autocovariance between two periods i, j is

$$Cov(z_i, z_j) = \sigma_z^2 \rho^{|i-j|}$$

The short-term variance is the average of the one-year variances within a window of length T

$$S_P = \frac{1}{T}\sum_{t=1}^{T} Var(z_a) = \frac{\sigma_\eta^2}{1-\rho^2}$$

Thus, the contribution of the persistent component to the short-term variance increases in its variance and increases in the persistency parameter.

$$L_P = Var\left(\frac{1}{T}\sum_{t=1}^{T} u_t\right) = \frac{1}{T^2}\sum_{i=1}^{T}\sum_{i=1}^{T} Cov(u_i, u_j)$$

Substitute $Cov(u_i, u_j) = \sigma_z^2 \rho^{|i-j|}$

$$L_P = \frac{\sigma_z^2}{T^2}\left[T + 2\sum_{k=1}^{T-1}(T-k)\rho^k\right]$$

Because $\sigma_u^2 = \frac{\sigma_\eta^2}{1-\rho^2}$, we can rewrite this as

$$L_P = \frac{\sigma_\eta^2}{1-\rho^2} g(\rho, T)$$

With $g(\rho, T) = \frac{1}{T^2}[1 + 2\sum_{k=1}^{T-1}(T-k)\rho^k]$

The term $g(\rho, T)$ now captures how averaging across years attenuates the variance.

Because $0 < \rho < 1$,

$$\frac{1}{T} < g(\rho, T) < 1$$

Therefore

$$L_P = S_P \, g(\rho, T)$$

And thus $L_P < S_P$

Intuitively: with positive serial correlation, u_t moves slowly, so when we average earnings over time, the ups and downs partly cancel. The stronger the persistence the smaller the attenuation.

Proposition G1: An increase in the variance of the FE $p^2\sigma_\alpha^2$, that is either the variance of the individual productivity component α or its price, p, decreases mobility M

Proof:

$$\frac{L}{S} = \frac{p^2\sigma_{\alpha c}^2 + L_P + L_T}{p^2\sigma_{\alpha c}^2 + S_P + S_T}$$

Differentiation with respect to $p^2\sigma_\alpha^2$ yields

$$\frac{\partial(\frac{L}{S})}{\partial p^2\sigma_\alpha^2} = \frac{L_P + L_T - S_P + S_T}{(p^2\sigma_\alpha^2 S_P + S_T)^2}$$

From Lemma G0 we have $L_P + L_T < S_P + S_T$, and therefore the numerator is negative, which means the fraction $\frac{L}{S}$ increases toward 1 as $p^2\sigma_{\alpha c}^2$ rises (because L grows faster than S by the same fixed amount, narrowing their difference). The fixed component enters both the long- and short-term variance equally — it is not averaged out like the shocks. When we increase its share of the total variance, we add proportionally to both L and S, but we also reduce the relative weight of the attenuated terms that create mobility (the difference between S and L). As a result, L and S become more similar, the ratio $\frac{L}{S}$ rises toward 1, and mobility $M = 1 - \frac{L}{S}$ declines. ■

Proposition G2: An increase in the variance of the transitory shock σ_ϵ^2 increases income mobility M

Proof: Lemma G0 showed that

$$S_T = \frac{1}{T}\sum_{t=1}^{T} Var(\epsilon_t) = \sigma_\epsilon^2$$

$$L_T = Var\left(\frac{1}{T}\sum_{t=1}^{T} \epsilon_t\right) = \frac{1}{T^2}\sum_{t=1}^{T} Var(\epsilon_t) = \frac{\sigma_\epsilon^2}{T}$$

Therefore

$$\frac{L}{S} = \frac{L_{FE} + L_P + \frac{\sigma_\epsilon^2}{T}}{S_{FE} + S_P + \sigma_\epsilon^2}$$

For tractability, we define $A = L_{FE} + L_P$ and $B = S_{FE} + S_P$ and rewrite

$$\frac{L}{S} = \frac{A + \frac{\sigma_\epsilon^2}{T}}{B + \sigma_\epsilon^2}$$

Differentiation with respect to σ_ϵ^2 yields

$$\frac{\partial(\frac{L}{S})}{\partial\sigma_\epsilon^2} = \frac{\left(\frac{1}{T}\right)(B + \sigma_\epsilon^2) - (A + \frac{\sigma_\epsilon^2}{T})}{(B + \sigma_\epsilon^2)^2} = \frac{\frac{B}{T} - A}{(B + \sigma_\epsilon^2)^2}$$

The denominator is always positive. The nominator can be rewritten as

$$\frac{B}{T} - A = \frac{S_{FE} + S_P}{T} - L_{FE} - L_P$$

Because $S_{FE} = L_{FE}$ and $L_P = S_P\, g(\rho, T)$

$$\frac{S_{FE} + S_P}{T} - L_{FE} + L_P = -\frac{T-1}{T}p^2\sigma_\alpha^2 + \frac{S_p - T\, S_P\, g(\rho,T)}{T}$$

$$= -\frac{T-1}{T}p^2\sigma_\alpha^2 + \frac{1}{T}S_p\big(1 - T\, g(\rho,T)\big)$$
$$= -\frac{T-1}{T}p^2\sigma_\alpha^2 + \frac{1}{T}S_p(1 - T\, g(\rho,T))$$

From $\frac{1}{T} < g(\rho,T) < 1$ follows that $T\, g(\rho,T) > 1$ and therefore this expression is negative.

As a result

$$\frac{\partial(\frac{L}{S})}{\partial\sigma_\epsilon^2} < 0$$

Therefore, an increase in the transitory variance lowers the ratio $\frac{L}{S}$, which means the Shorrocks mobility $M = 1 - \frac{L}{S}$ increases. The intuition for this result is that the transitory shock inflates the short-term variance by a factor of 1 but the long-term variance only by $\frac{1}{T}$, so as its weight grows, L/S declines.■

Proposition G3: An increase in the variance of the persistent component σ_η^2 increases mobility if variance of the FE is sufficiently large.

Holding ρ fixed, S_P and L_P are both proportional to σ_η^2, but L_P is smaller by the factor $g(\rho,T)$. Differentiating L/S with respect to σ_η^2 gives

$$L_P =$$

$$\frac{\partial\left(\frac{L}{S}\right)}{\partial\sigma_\eta^2} = \frac{\frac{g(\rho,T)}{1-\rho^2}S - \left(\frac{1}{1-\rho^2}\right)L}{S^2} = \frac{g(\rho,T)S - L}{(1-\rho^2)S^2} \propto g(\rho,T)S - L$$

as the denominator is always positive.

We can now substitute the transitory and permanent shocks into S and L in the nominator

$$g(\rho,T)S - L = g(\rho,T)(S_{FE} + S_P + S_T) - L_{FE} - L_P - L_T$$

$$= g(\rho,T)(S_{FE} + S_P + S_T) - L_{FE} - L_P - L_T$$

$$(g(\rho,T) - 1)p^2\sigma_\alpha^2 + (g(\rho,T)S_P - L_P) + \left(g(\rho,T) - \frac{1}{T}\right)\sigma_\epsilon^2$$

Because $g(\rho,T)S_P = L_P$ this simplifies to

$$(g(\rho,T) - 1)p^2\sigma_\alpha^2 + \left(g(\rho,T) - \frac{1}{T}\right)\sigma_\epsilon^2$$

The effect is negative if

$$\frac{\partial\left(\frac{L}{S}\right)}{\partial\sigma_\eta^2} < 0 <-> \left(1 - g(\rho,T)\right)p^2\sigma_\alpha^2 > \left(g(\rho,T) - \frac{1}{T}\right)\sigma_\epsilon^2$$

This condition can be rewritten as

$$\frac{p^2\sigma_\alpha^2}{\sigma_\epsilon^2} > \frac{g(\rho,T) - \frac{1}{T}}{1 - g(\rho,T)}$$

For any $T \geq 2$ and $\rho < 1$, $g \epsilon \left(\frac{1}{T}, 1\right)$ so the right hand side is finite and positive.

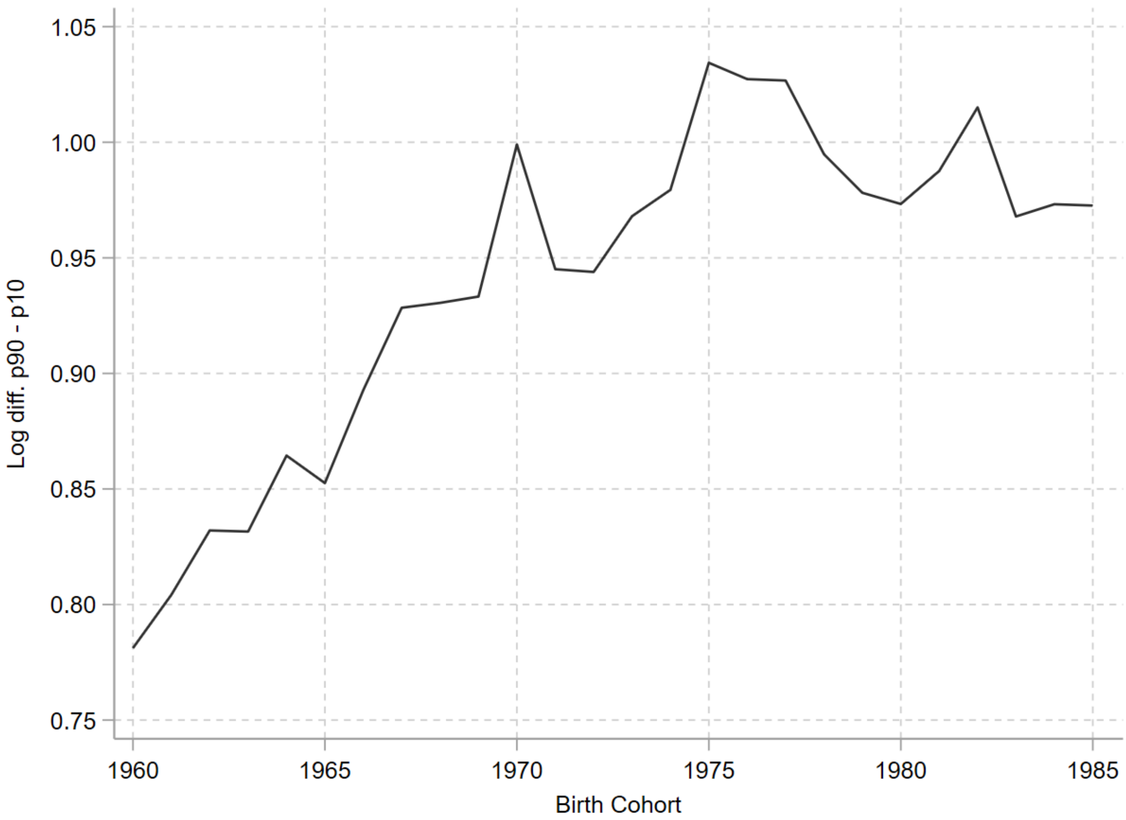
If the variance of the permanent component is sufficiently larger than the transitory variance, than this holds and an increasing σ_η^2 lowers $\frac{L}{S}$ and raises mobility.

If the transitory variance is extraordinarily large relative to $p^2\sigma_\alpha^2$, this sign can flip.

Also if $\rho \to 1$, $g(\rho,T) \to 1$ and $\frac{\partial\left(\frac{L}{S}\right)}{\partial\sigma_\eta^2} \to 0$ so it has little effect. ■

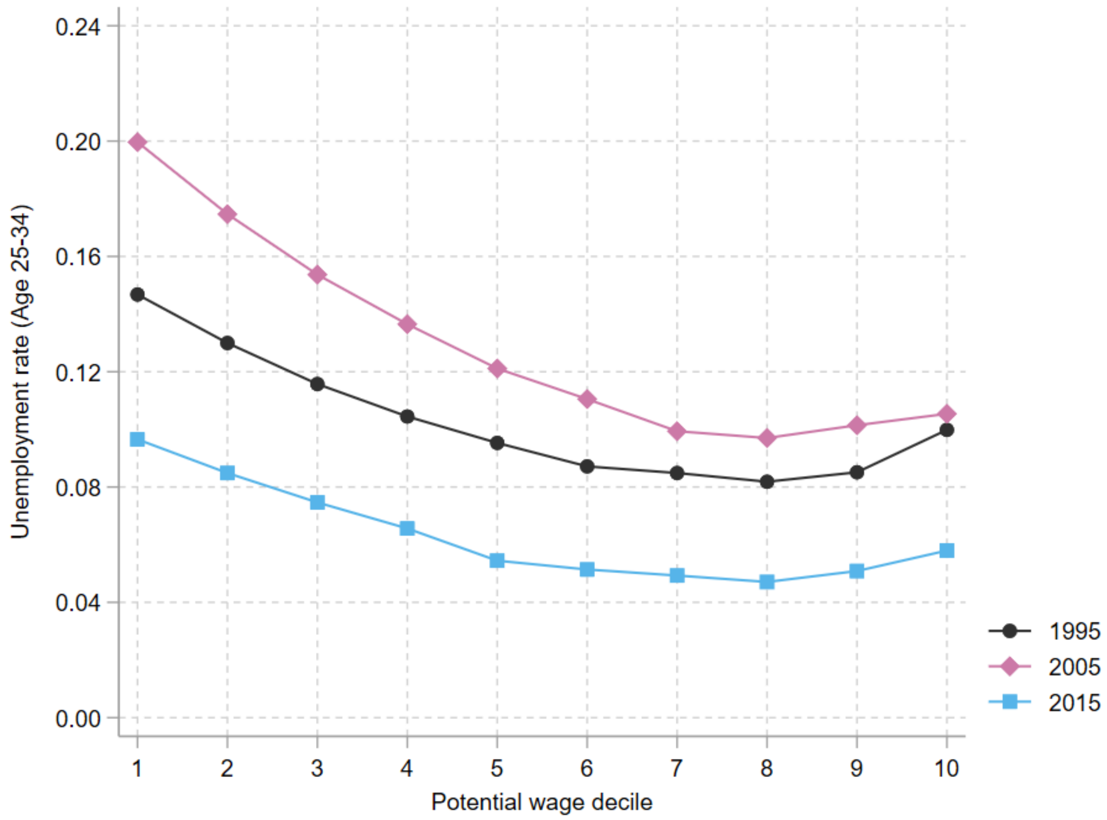
H Figures

Figure A1 p90-p10 ratio of lifecycle earnings



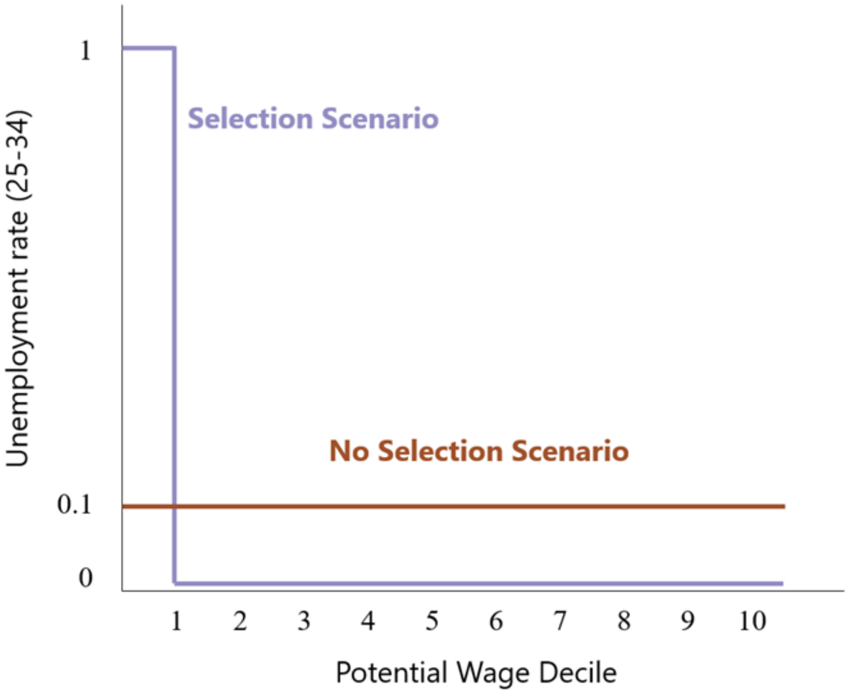
Note: This graph shows the p90p10 log ratio of our measure of lifecycle earnings calculated as the total earnings from age 25 to 34.
Source: Own calculations based on IAB data

Figure A2 Non-employment rate across the potential wage distribution



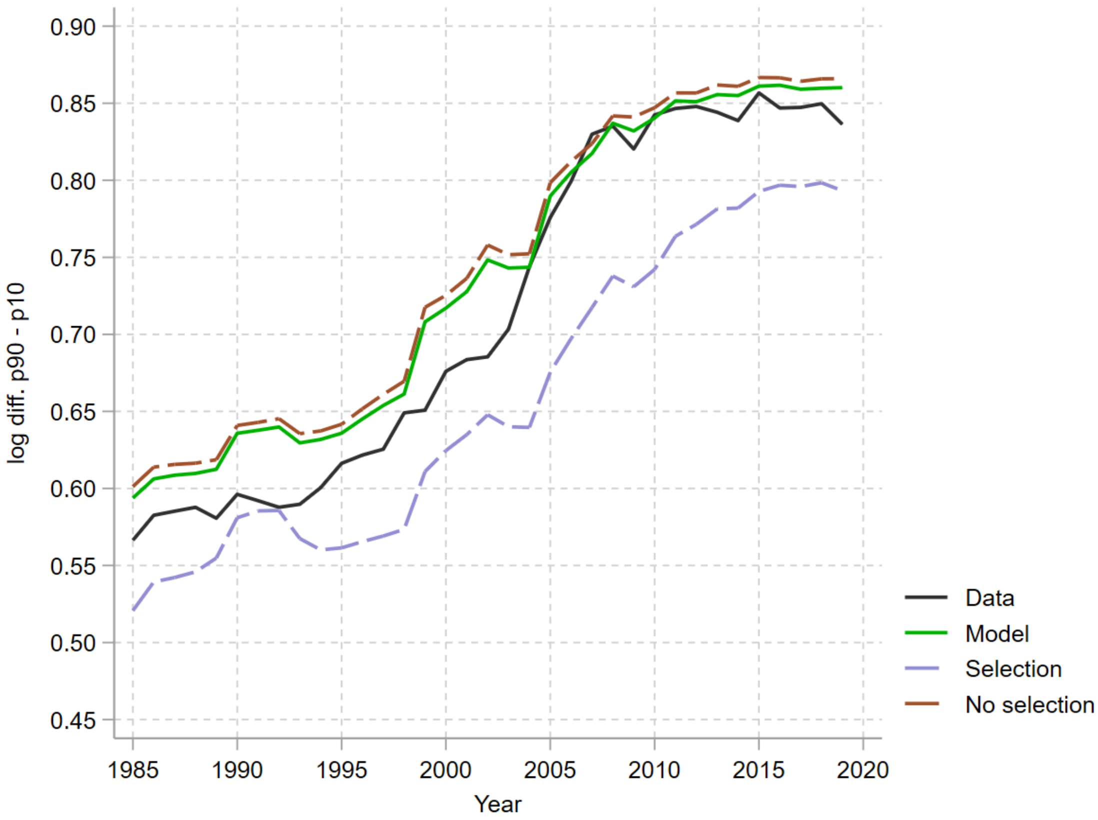
Note: The figure shows the rate of non-employment across potential wage deciles in our simulated data across the calendar years 1995, 2005 and 2015.
Source: Own calculations based on IAB data

Figure A3 Selection and No Selection Counterfactual Scenario



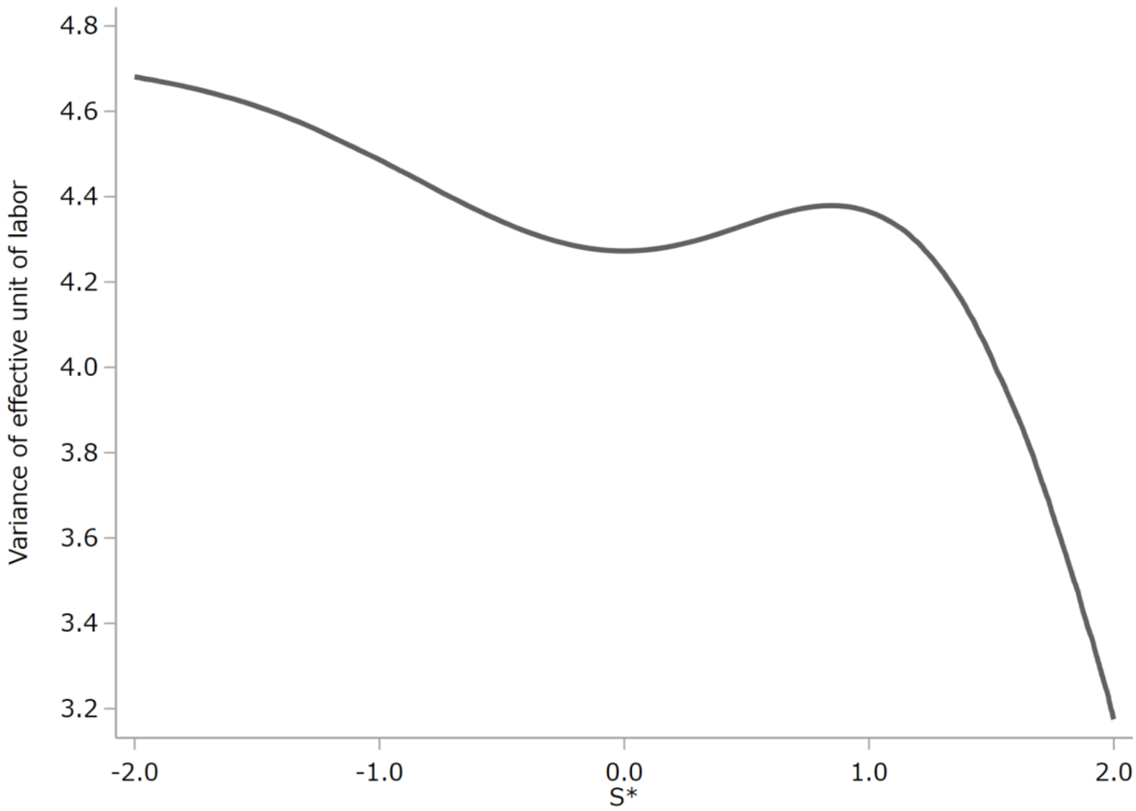
Note: The figure shows the probability of non-employment for an aggregate 10% non-unemployment rate under the counterfactual Selection and No Selection Scenario across the Potential Wage Distribution. In the Selection Scenario, the bottom wage decile has a 100% probability of being unemployed while the rest of the wage distribution has a 0% probability of being unemployed. In the No Selection Scenario, the probability of non-employment is 10% across the distribution.
Source: Own illustration

Figure A4 Selection and No Selection Counterfactual Simulation



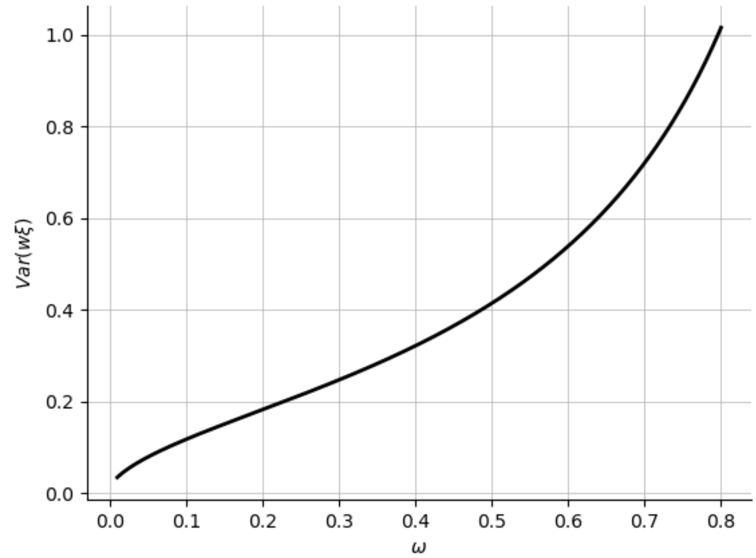
Note: The figure shows the results of the counterfactual decomposition under the full model, the Selection scenario and the No Selection Scenario.
Source: Own calculations based on IAB data

Figure A5 Simulation of the Roy Model – Variance of Effective Unit of Labor



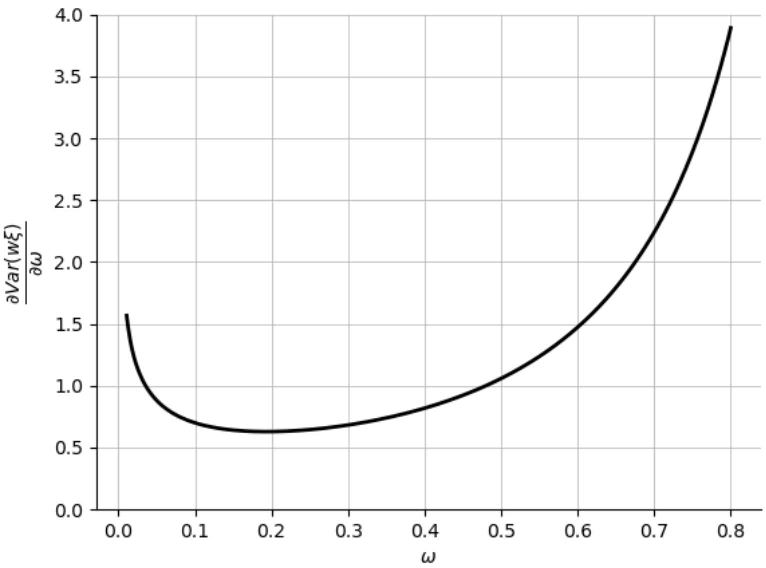
Note: This graph shows the simulated variance of the effective unit of labor across different values of S^*. To simulate the model we draw skill $S \sim N(0,1)$ for 100,000 individuals and set $\delta = 0.1$. Given the value of S^*, the worker with skill S is assigned the effective unit of labor $\xi = exp(S)$ if $S > S^*$ and $\xi = exp(\delta S)$ otherwise. We then compute $Var(\xi)$ for different levels of S^*.
Source: Own illustration

Figure A6 Simulation of the Roy Model – Variance of Wage



(a)

Level of Wage $\boldsymbol{Var(w \cdot \xi)}$



(b)

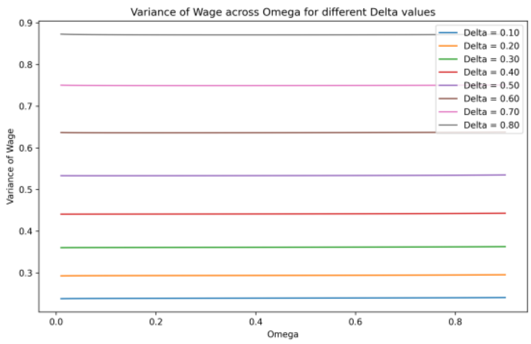
First derivative of the Variance of Wage $\boldsymbol{Var(w \cdot \xi)}$ with respect to the level of technology $\boldsymbol{\omega}$

Note: To simulate the model we draw skill $S \sim N(0,1)$ for 100,000 individuals and set $\delta = 0.1$ and $\frac{1}{1-\varphi} = 0.5$. Given the value of S^*, the worker with skill S is assigned the effective unit of labor $\xi = exp(S)$ if $S > S^*$ and $\xi = exp(\delta S)$ otherwise.

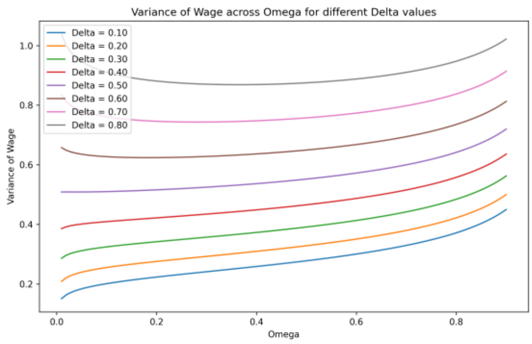
Source: Own calculations based on IAB data

Figure A7 Simulation of Roy Model – Choice of Parameters

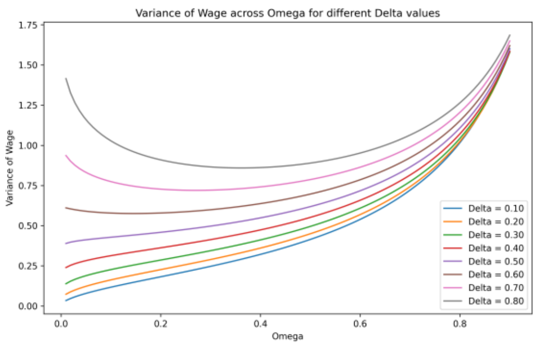
Variance of Wage



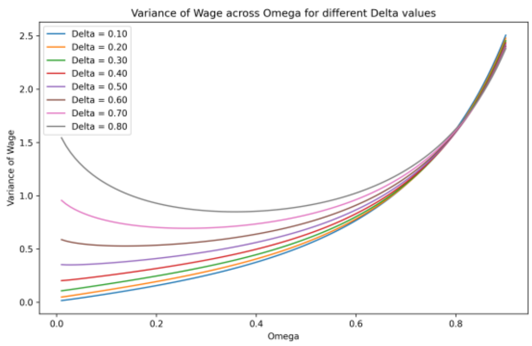
(a) $\frac{1}{1-\varphi} = \mathbf{0.001}$



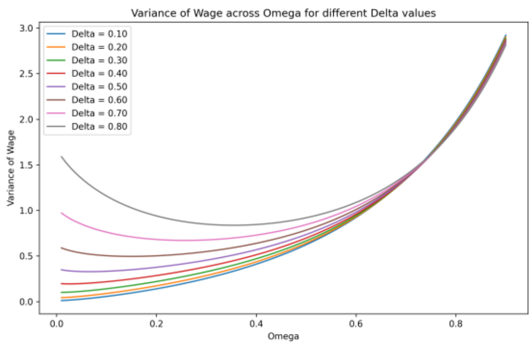
(b) $\frac{1}{1-\varphi} = \mathbf{0.1}$



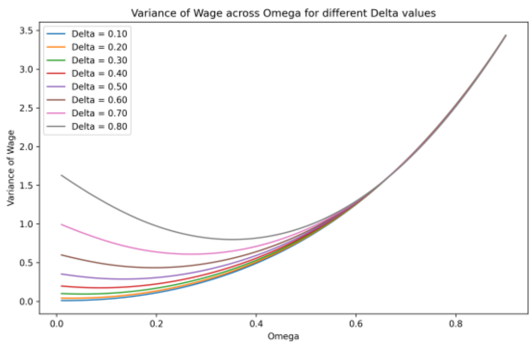
(c) $\frac{1}{1-\varphi} = \mathbf{0.5}$



(d) $\frac{1}{1-\varphi} = \mathbf{0.999999}$



(e) $\frac{1}{1-\varphi} = \mathbf{1.5}$

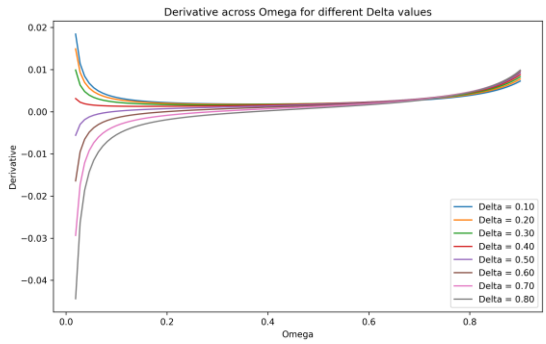


(f) $\frac{1}{1-\varphi} = \mathbf{4}$

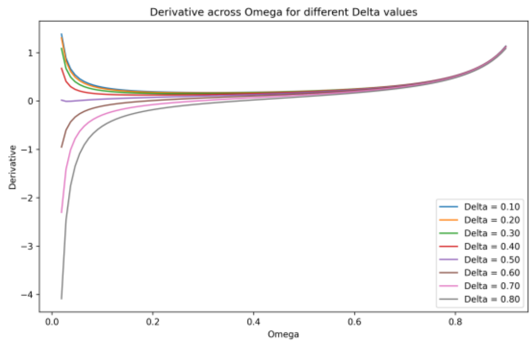
Note: To simulate the model we draw skill $S \sim N(0,1)$ for 100,000 individuals and set the parameter δ and the elasticity of substitution $\frac{1}{1-\varphi}$ accordingly. Given the value of S^*, the worker with skill S is assigned the effective unit of labor $\xi = exp(S)$ if $S > S^*$ and $\xi = exp(\delta S)$ otherwise.
Source: Own calculations based on IAB data

Figure A8 Simulation of Roy Model – Choice of Parameters

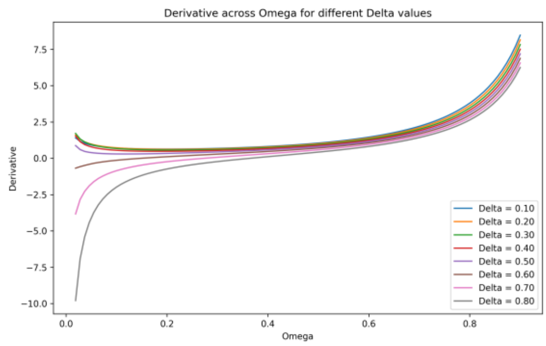
Derivative of Variance of Wage



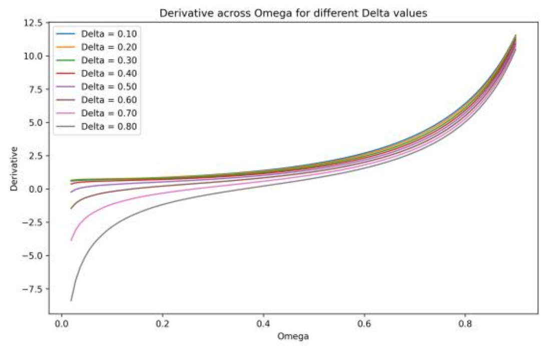
(a) $\frac{\mathbf{1}}{\mathbf{1-\varphi}} = \mathbf{0.001}$



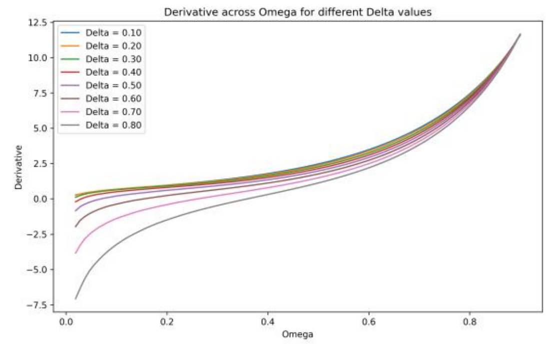
(b) $\frac{\mathbf{1}}{\mathbf{1-\varphi}} = \mathbf{0.1}$



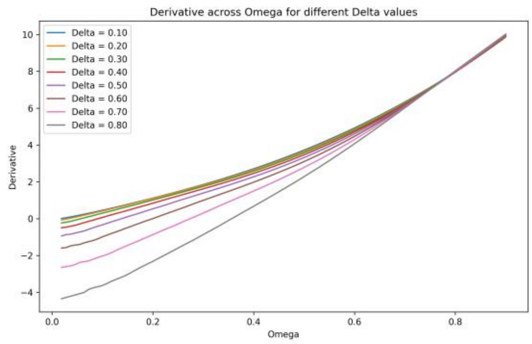
(c) $\frac{\mathbf{1}}{\mathbf{1-\varphi}} = \mathbf{0.5}$



(d) $\frac{\mathbf{1}}{\mathbf{1-\varphi}} = \mathbf{0.999999}$



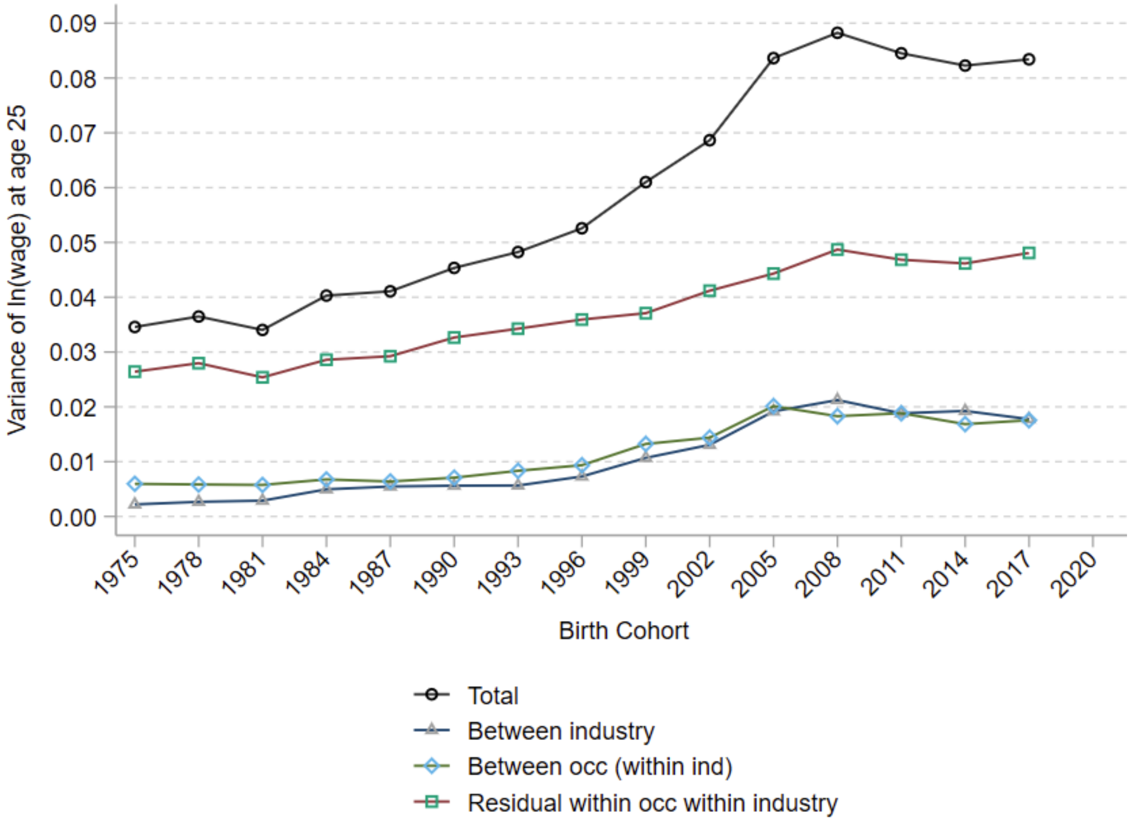
(e) $\frac{\mathbf{1}}{\mathbf{1-\varphi}} = \mathbf{1.5}$



(f) $\frac{\mathbf{1}}{\mathbf{1-\varphi}} = \mathbf{4}$

Note: To simulate the model we draw skill $S \sim N(0,1)$ for 100,000 individuals. Given the value of S^*, the worker with skill S is assigned the effective unit of labor $\xi = exp(S)$ if $S > S^*$ and $\xi = exp(\delta S)$ otherwise.
Source: Own calculations based on IAB data

Figure A9



Note: The figure shows a two-step decomposition of the variance of log wages at age 25 by birth cohort. The first step separates between- and within-industry variation. The second step further decomposes the within-industry component into between-occupation and residual within-occupation variation.
Source: Own illustration

I Tables

Table A1 Overview Counterfactual Scenarios

Scenario	Free Parameters	Parameters fixed at estimated value of $c = 1955$ and $t = 1980$
CF1	μ_{eat}	$\sigma^2_{\alpha t}$, p_t, $\sigma^2_{\eta t}$, ρ_t, $\sigma^2_{\epsilon t}$, Employment (q, λ)
CF2	μ_{eat}, $\sigma^2_{\alpha t}$	p_t, $\sigma^2_{\eta t}$, ρ_t, $\sigma^2_{\epsilon t}$, Employment (q, λ)
CF3	μ_{eat}, p_t	$\sigma^2_{\alpha t}$, $\sigma^2_{\eta t}$, ρ_t, $\sigma^2_{\epsilon t}$, Employment (q, λ)
CF4	μ_{eat}, $\sigma^2_{\alpha t}$, p_t	$\sigma^2_{\eta t}$, ρ_t, $\sigma^2_{\epsilon t}$, Employment (q, λ)
CF5	μ_{eat}, $\sigma^2_{\alpha t}$, p_t, $\sigma^2_{\eta t}$, ρ_t	$\sigma^2_{\epsilon t}$, Employment (q, λ)
CF6	μ_{eat}, $\sigma^2_{\alpha t}$, p_t, $\sigma^2_{\eta t}$, ρ_t, $\sigma^2_{\epsilon t}$	Employment (q, λ)
CF7 (Full Model)	μ_{eat}, $\sigma^2_{\alpha t}$, p_t, $\sigma^2_{\eta t}$, ρ_t, $\sigma^2_{\epsilon t}$, Employment (q, λ)	

Note: This table gives an overview of the different counterfactual scenarios described in Section 4. For each counterfactual scenario we allow the free parameters to vary over time or for the case of $\sigma^2_{\alpha c}$ across cohort, while the other parameters are fixed at the level of year $t = 1980$ or cohort $c = 1955$.

Table A2 Regression results wage on complexity

Dependant Variable: Log Monthly Wage	(1)	(2)	(3)	(4)
Complexity	0.170***	0.069***	0.072***	0.052***
	(0.013)	(0.014)	(0.014)	(0.014)
Age			0.044***	0.041***
			(0.008)	(0.008)
Age^2			-0.000***	-0.000***
			(0.000)	(0.000)
Supervisor				0.170***
				(0.027)
Female				-0.184***
				(0.031)
Constant	8.363***	8.563***	7.320***	7.386***
	(0.013)	(0.206)	(0.261)	(0.261)
Occupation Controls		x	x	x
R^2	0.015	0.063	0.078	0.085
Number of Observations	11,716	11,716	11,716	11,716

Note: This table shows the results of OLS regressions of monthly log wages in 2006 on our measure of task complexity (standardized), age and supervisor status and 3-digit occupation controls. Significance levels are denoted by *10%, **5% and ***1%.
Source: Own calculations based on BIBB data

Table A3 Examples of Routine and Complex Tasks within Occupations

Occupation	Routine Task	Complex Task
Car Mechanic	Change tires, oil, battery	Repair engine damage
Bank Clerk	Open checking account	Advise on financial situations
Gardener	Mow the lawn	Select draught-resistant plants
Journalist	Rewrite press releases	Conduct investigative research
Warehouse Assistant	Move boxes	Deal with system failures

Note: This table shows examples of routine and complex tasks within occupations

Table A4 Occupations with the highest and lowest change in complexity

Highest Change	Lowest Change
Goods inspectors, sorters	Chemists, chemical engineers, physicists
Welders, flame cutters	Farmers, livestock breeders, animal caretakers
Other assemblers	Social workers, carers, pastoral assistants
Plastics processing workers	Surveying engineers, other engineers
Turners (lathe operators)	Physicians, pharmacists

Note: This table shows the occupations with the lowest and highest increase in average complexity across 120 occupations from 1986 to 2006
Source: Own calculations based on BIBB Data

Table A5 Coding of complexity measures

Dimension	Question wording (translated)	1986 Response categories and coding	2006 Response categories and coding
Non-Stipulation	How often does it occur in your work that the execution of the work is stipulated to you in every detail?	"Practically always (*praktisch immer*)" = 0 "Often (*häufig*)" = 0 "From time to time (*immer mal wieder*)" = 0.5 "Rarely (*selten*)" = 1 "Practically never (*praktisch nie*)" = 1	 "Often (*häufig*)" = 0 "Sometimes (*manchmal*)" = 0.5 "Rarely (*selten*)" = 1 "Never (*nie*)" = 1
Non-Repetitiveness	And how often does it occur that one and the same work process is repeated in every detail?	"Practically always (*praktisch immer*)" = 0 "Often (*häufig*)" = 0 "From time to time (*immer mal wieder*)" = 0.5 "Rarely (*selten*)" = 1 "Practically never (*praktisch nie*)" = 1	 "Often (*häufig*)" = 0 "Sometimes (*manchmal*)" = 0.5 "Rarely (*selten*)" = 1 "Never (*nie*)" = 1
New Tasks	And how often does it occur in your work that you are confronted with new tasks in which you first have to familiarize yourself and work your way in?	"Practically always (*praktisch immer*)" = 1 "Often (*häufig*)" = 1 "From time to time (*immer mal wieder*)" = 0.5 "Rarely (*selten*)" = 0 "Practically never (*praktisch nie*)" = 0	 "Often (*häufig*)" = 1 "Sometimes (*manchmal*)" = 0.5 "Rarely (*selten*)" = 0 "Never (*nie*)" = 0
Improving Tasks	And how often does it occur in your work that you improve existing procedures or try out something new?	"Practically always (*praktisch immer*)" = 1 "Often (*häufig*)" =1 "From time to time (*immer mal wieder*)" = 0.5 "Rarely (*selten*)" = 0 "Practically never (*praktisch nie*)" = 0	 "Often (*häufig*)" = 1 "Sometimes (*manchmal*)" = 0.5 "Rarely (*selten*)" = 0 "Never (*nie*)" = 0

Note: Description of coding of complexity sub-measures across the 1986 and 2006 BIBB survey. Question wording is unchanged, apart from negligible linguistic adjustments (orthographic variant: *reindenken* vs. *hineindenken*; minor syntactic change in word order: *Arbeitsgang sich* vs. *sich Arbeitsgang*). These do not affect interpretation.
Source: Own illustration