How routine tasks affect labor market inequalities between vocational and tertiary graduates over the career *

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Abstract

How do routine tasks shape disparities in income and employment prospects between workers with vocational and tertiary educational qualifications? While existing research predominantly emphasizes skill differentials as the primary driver, this study proposes that group differences in the prevalence and returns to routine tasks contribute to existing disparities. Using decomposition methods on data from the German Socio-Economic Panel and the BiBB/BAuA Employment Survey, we examine how compositional differences in routine task performance between vocational and tertiary graduates impact differences in labor market outcomes over individuals' careers. We find that vocationally trained workers tend to perform more routine tasks than their university-educated counterparts. This compositional difference explains part of the income gap but does not affect unemployment risk. While group-specific levels of routine task intensity remain relatively stable, the returns to these tasks diminish over the life course, contributing substantially to the widening income gap between vocational and tertiary graduates over their careers.

keywords: routine tasks; labor market inequality; career inequality; vocational education; decomposition; life course

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1 Introduction

Research that examines disadvantages in labor market outcomes for vocationally trained workers often links those to changes in the labor market brought by technological progress (Hanushek et al. 2017, Krueger and Kumar 2004). Up to this point, research in this field has focused on skill differences as a key explanation. Occupation-specific skills obtained through vocational education are suspected to become obsolete, whereas broad skills obtained from general education enable the operation of new technologies and remain valuable. Surprisingly, little effort has been made to incorporate the role of tasks. In contrast to skills, which capture workers' abilities to perform work activities, tasks refer to actions as part of a job or occupation. The interaction between routine tasks and computer technology is a key explanation for wage and employment developments in the labor economics literature (Autor 2013, Goos and Manning 2007) but has largely been disregarded as a contributor to career inequality between workers with vocational and academic education in sociology (see e.g. Forster et al. 2016, Forster and Bol 2018, Golsteyn and Stenberg 2017, Korber and Oesch 2019).

In this article, we theorize that compositional differences in the performance of routine tasks contribute to the gap in labor market outcomes between workers with vocational and tertiary education. We hypothesize that vocational graduates are more likely to perform routine tasks than university graduates. Routine tasks, in turn, are linked to higher job displacement risk, leading to lower employment prospects and downward pressure on wages. Additionally, we analyze whether the increasing automation of routine tasks in many occupations and how workers respond to it may account for the widening of the income and employment gap between groups of graduates over the life course (Brunello and Rocco 2017, Korber and Oesch 2019).

This study adds to existing research in two fields. First, by zooming in on tasks we address a side of the labor market that has been neglected in current research on education-based disparities in labor market outcomes. So far, outcome differentials are mainly seen as the consequence of skill-driven differences in adaptive capacity. However, workers with different types of skills likely differ systematically in the tasks they perform and therefore in their exposure to external forces that require such adaptation. Hence, task measures should help explain variations in labor market outcomes that remain unobserved when focusing on skills alone (Autor and Handel 2013).

Second, existing task-based accounts of labor market change often rely on aggregate measures (see e.g. Fernández-Macías and Hurley 2016, Goos et al. 2014, Oesch and Piccitto 2019). Focusing only on the overall effects of structural change neglects how this may affect individual workers' trajectories differently and reinforce existing inequality between educational groups (Kurer and Gallego 2019). Taking a micro-level perspective, we examine the extent to which the assumed effects of routine tasks on wage and employment patterns also hold for wages and employment prospects at the individual level.

These two contributions are crucial for understanding the theoretical mechanisms underlying education-related inequalities and have important policy implications. While a skill perspective emphasizes lifelong learning and retraining as measures to address adaptability gaps between educational groups, such measures may prove ineffective or insufficient if disparities in labor market outcomes between groups are driven not only by differences in employees' skills but also by the distribution of tasks at the job level.

Our analysis focuses on Germany—a case often studied as a model case for strong VET systems (Hanushek et al. 2017) where educational credentials and occupational positions are tightly linked (DiPrete et al. 2017). We use workers with vocational and tertiary educational qualifications as comparison groups (Schulz et al. 2023). Information on routine task content from three waves of the BiBB/BAuA Employment Survey (2006, 2012, 2018) is merged with 38 waves of longitudinal data from the German Socio-Economic panel. This allows us to track changes in routine task intensity (RTI) over individual occupational trajectories while simultaneously accounting for changes in task content within occupations over time. In our analysis, we use different decomposition methods to examine how average differences in routine task intensity impact group differences in labor market outcomes and how changes in the levels and the returns to routine tasks contribute to growing disparities in labor market outcomes over the career.

Our results show that, as hypothesized, vocationally trained workers perform more routine tasks than university graduates. This difference accounts for about 11% of the average income gap but does not affect the gap in unemployment risk. Surprisingly, our results further show that levels of RTI remain relatively stable over workers' careers while income returns for routine tasks diminish. About 25% of the growth in the income gap between vocational and tertiary graduates over the life course can be explained by decreasing return to routine tasks.

2 Theoretical background

Various studies and reports have documented that individuals who completed college or tertiary education receive better employment prospects and higher incomes than those with lesser levels of education and that returns to higher education increased over the last four decades (Boarini and Strauss 2010, Card 1999, Cheng et al. 2021, Goldin and Katz 2008, Hout 2012). While these studies largely focus on how technology affects workers who differ in their *level* of education or skill, technological change may also impact workers differently depending on the *type* of education they hold. One common hypothesis is that technological change yields advantages for workers with general education compared to those with vocational education (Krueger and Kumar 2004). It is based on the argument that general education conveys skills that facilitate further learning and adaptability allowing workers to operate new technologies. Vocational training, on the other hand, mainly conveys ready-to-use occupation-specific knowledge which increases workers' immediate productivity but also makes them inflexible and dependent on established technologies.

This argument suggests that different types of skills yield varying adaptive capacities and are crucial determinants of workers' labor market outcomes—particularly in times of technological change. In line with this argument, studies that examine differences between types of education largely take a skill-focused perspective, a perspective that is criticized in labor economic literature as it neglects the relevance of *tasks* (Acemoglu and Autor 2011). Tasks are seen as units of work activity to produce goods or services and thus differ from skills which describe workers' capabilities to perform tasks. Differentiating between skills and tasks is crucial because workers with the same type of skills may perform different job tasks and adapt their task content differently in response to changes in labor market dynamics and technology (Acemoglu and Autor 2011:1045).

While many task dimensions may matter for workers' labor market outcomes, one dimension that is assumed to carry particular relevance in the context of technological change is *routine tasks* (Autor et al. 2003). Routine tasks are repetitive activities that can be accomplished by following explicit rules. According to the *routine-biased technological change* hypothesis, these features make it possible and productive to substitute human labor for computing power and automate routine tasks. We suspect that differences in the prevalence of routine tasks contribute to the gap in labor outcomes between workers with vocational and tertiary education (Peng et al. 2018, Rohrbach-Schmidt 2019).

2.1 Types of education and routine tasks

Why do employees with different educational qualifications perform different amounts of routine tasks? The evolution of routine tasks is closely tied to changes in the division of labor. Many highly routine-intensive occupations today, like stationary plant operators or assemblers, emerged during the Industrial Revolution in the late 19th century due to work specialization. Increased production scales and new methods raised the demand for trained workers. In Germany and other European countries such as France and England, training for these professions was integrated into the existing vocational education system, which had previously focused on craftspeople (Greinert 2005, 2006). While historically, routine-intensive occupations are linked to vocational training, professions with low routine prevalence, such as university teachers, lawyers, and government officials, typically require tertiary education.

These historical linkages between routines and types of education may well be based on economic reasons. Learning routines usually requires less time than developing more abstract non-routine abilities such as problem-solving or self-directed knowledge acquisition. Hence, organizing the training for routine occupations in vocational programs with a shorter average duration than academic training is beneficial for workers and employers as students may enter the workforce more quickly.

Yet, little empirical research has examined how routine tasks are distributed between vocational and tertiary graduates in practice. Based on the Survey of Adult Skills (PIAAC), Nedelkoska and Quintini (2018) find that higher educational attainment is linked to a lower risk of automation across OECD countries. They report that upper secondary and post-secondary non-tertiary education—both include vocational education but not exclusively—reduce the automation risk by 6% and 8% compared to primary education. A bachelor's or a master's degree reduces automation risk by 15% or 20% compared to the reference category. For Germany, Helmrich et al. (2016) report that routine scores are 0.2 standard deviations lower for occupations that require vocational qualification compared to occupations with no requirement whereas routine scores are 0.45 standard deviations lower for occupations that require academic qualification. Both of these findings indicate that vocational graduates likely perform more routine tasks than workers with tertiary qualifications.

2.2 Routine tasks and labor market outcomes

How does routine task intensity impact labor market outcomes? On the one hand, the routine-biased technological change (RBTC) hypothesis assumes that as costs for computer capital decline, employers increasingly rely on computer chips to perform routine tasks (Autor et al. 2003). Workers in routine intense occupations, hence, may face negative consequences on the labor market, an increased risk of job displacement for instance. Evidence for such a link is mostly inferred indirectly from findings of decreasing employment shares in low and medium-skill occupations (see e.g. Goos et al. 2014, Oesch and Piccitto 2019) but there is also direct evidence that associates routine tasks with higher displacement risk in the US labor market (Peng et al. 2018). Automation may also exert pressure on wages as employers are inclined to only retain workers if their labor costs do not exceed those for technological substitution. Helmrich et al. (2016) find a robust negative relationship between routine scores (on individual and occupational levels) and hourly wages for workers in Germany.

On the other hand, according to Autor and colleagues (2003), computing power likely complements work that involves non-routine tasks such as problem-solving, creative thinking, or complex communication tasks putting workers who perform these tasks at a comparative advantage. Oesch and Piccitto (2019) show that employment shares for high-skill occupations rose substantially between 1992 and 2015 for Germany and other European countries. Similarly, wages were found to increase disproportionately for those occupations in the US case (Autor and Dorn 2013).

Following the RBTC approach, we argue that routine tasks may contribute to differences in labor market outcomes between vocational and tertiary graduates in two ways. First, if performing routine tasks yields substantial disadvantages in terms of employment and/or wages over non-routine tasks whereas performance of these tasks is distributed unequally between vocationally trained workers and workers with university education, computerization should exacerbate the income and employment gap between these two groups beyond initial differences based on skills. We therefore hypothesize that if workers with vocational training performed the same amount of routine tasks as tertiary graduates differences in labor market outcomes between vocational and tertiary graduates would *decrease* (**hypothesis 1**).

Second, routine tasks may contribute to disparities in labor market outcomes over group differences in the *returns*. We suspect that workers with university degrees face larger penalties for performing routine tasks than vocationally trained workers. Routine intense occupations frequented by tertiary graduates—administrative jobs in the public sector or mid-tier management for instance—offer lower salaries compared to non-routine professional occupations. Vocational programs, in turn, don't prepare workers for complex and high-paying non-routine occupations. Task routineness should therefore matter less as a determinant of labor market outcomes for vocational graduates. This suggests that group differences in the returns to routine tasks may not amplify but attenuate disparities in labor market outcomes between vocational and tertiary graduates. We, therefore, hypothesize if workers with vocational training received the same returns to routine tasks as tertiary graduates differences between vocational and tertiary graduates would *increase* (**hypothesis 2**).

The initial approach of Autor and colleagues on the relevance of routine tasks and their assumed implications for the labor market was critically discussed and extended over the last two decades. Below, we discuss three relevant additions and their implications for this study.

First, since most jobs do not involve routine tasks exclusively, their substitution rarely renders entire jobs obsolete. Instead, workers may adopt new tasks or focus on their remaining ones, altering occupational task profiles over time (Dengler and Matthes 2018). Analyzing local labor markets in the US, Autor and colleagues (2015) find neutral effects of technological change on overall employment but substantial shifts in occupational composition within sectors. This indicates that technological change may primarily promote occupational mobility without lasting effects on employment. Mobility between occupations, however, is often negatively linked to wages, particularly involuntary mobility. In the US, displaced workers experience an average 15% decrease in weekly earnings over the next five years (Kambourov and Manovskii 2009). These findings suggest that the impact of routine tasks on employment may be smaller and less relevant for the employment gap between vocational and tertiary graduates than assumed, whereas negative effects on income are maintained through involuntary occupational mobility.

Secondly, automation is not the only mechanism that links routine tasks to differences in labor market outcomes. Technological progress largely coincided with growth in emerging economies and increases in global trade. Falling trade costs permit firms to offshore specific production tasks (Grossman and Rossi-Hansberg

2008). Some assume that many job tasks that are susceptible to automation are also suitable for offshoring (Autor et al. 2015, Baumgarten 2015, Reijnders and de Vries 2018). Consequently, observed shifts in labor market outcomes for workers in routine heavy occupations could be based on both, automation, and offshoring. This distinction is inconsequential for capturing the extent to which routine tasks contribute to discrepancies in income or employment between educational groups, but it shapes the underlying theoretical explanation. Disentangling the respective roles of these macro phenomena is complex and beyond the scope of this paper. We return to this point in the discussion of the results.

Lastly, some studies question the relevance of routine tasks and automation for predicting labor market outcomes in general (Caines et al. 2017a, 2017b). They argue that the main driver for changes in wages and employment shares in the last decades is not the degree of routine of tasks, but their *complexity*. We address this issue further in our analysis.

2.3 Routine tasks over the career

Some studies show that differences in labor market outcomes between workers with vocational and tertiary education tend to grow over their careers (see e.g. Brunello and Rocco 2017, Korber and Oesch 2019, but see Forster and Bol 2018). We expect that changes in the *prevalence* and the *effects* of routine tasks impact these growing differences.

There are two reasons for the prevalence of routine tasks to decrease with age. First, following the idea of a routine-biased technological change, technological substitution leads to a decrease in the amount of routine work over time. Such decreasing time trends have been identified for Germany (Helmrich et al. 2016, Spitz-Oener

2006). This development should also become visible through decreasing levels of routine work over individual working careers. Second, as workers collect work experience, they are likely to trade operative tasks for more organizational and managerial work which leads to a reduction in routine task intensity.

Changes in the levels of routine tasks likely differ between occupations and industries. If—as argued above—vocationally trained workers perform routine tasks more often than university graduates, automation should occur more frequently and declines in the prevalence of routine tasks over the career should be more pronounced for them relative to university-educated workers. The effect of work experience may also be more pronounced for vocationally trained workers considering that low starting levels of routine tasks among tertiary graduates limit the potential for change over the career. However, the effect of experience may be bounded for vocational graduates by more limited career advancement opportunities.

How does this impact workers' income and employment trajectories? If routine tasks yield income and employment disadvantages, decreasing levels of routine-task intensity for vocationally trained workers that outpace those of tertiary graduates may naturally mitigate the divergence of income and employment probability trajectories over the life course to some extent. This suggests if vocationally trained workers experienced the same (smaller) change in levels of routine tasks over their careers as tertiary graduates, the difference in outcome trajectories between the two groups would *widen* (**hypothesis 3**).

Whereas the prevalence of routine tasks should recede with age, we expect that the negative effect of RTI increases over the career. RBTC literature suggests that the decreasing price of computer technology over time reinforces displacement risk and complicates wage negations causing downward pressure on wages for workers at a given level of routine task intensity. Simultaneously, the benefits of nonroutine tasks that are complemented by technological innovation may spread and increase incomes and employment stability for workers performing nonroutine tasks.

If, on average, vocationally trained workers perform more routine intense tasks than university graduates, increasing negative returns for routine tasks over the life course should partially account for the growing income gap and diverging rates of unemployment risk. The size of this effect additionally depends on whether the change in returns to routine tasks over the career is more pronounced for one of the two groups. We expect that negative returns to routine tasks increase more strongly for vocational graduates than for tertiary graduates. Vocationally trained workers usually hold highly specialized skill sets which complicates mobility between occupations and may force vocationally trained workers in routine-intense jobs to accept lower wages but particularly it increases their risk of becoming unemployed. University education equips workers with more general skills which may allow them to move out of routine-intense jobs more easily. Earlier research shows that occupational mobility rates for university graduates in Germany are low, particularly in their late careers (Decker et al. 2023) which may be linked to them performing less routine tasks to begin with. We therefore hypothesize, that if returns to routine tasks for vocationally trained workers decreased at the same (lower) rates over their careers as for tertiary graduates, the difference in outcome trajectories between the two groups would *narrow* (**hypothesis 4**).

3 Method

3.1 Data

In the empirical part of this study, we use two different data sets. To measure educational groups, labor market outcomes, and age we use 38 waves of panel data from the German Socio-Economic Panel (GSOEP) collected between 1984 and 2021 (Goebel et al. 2019). The GSOEP is an annual representative panel survey of private households in Germany and covers various topics such as income, employment, and education. It currently encompasses information on approximately 105,000 individuals. The analytic sample is restricted to cases with either vocational or tertiary education observed between ages 25 and 65 who are employed. Limiting the sample to observations in employment is necessary because occupations that allow the identification of workers' task content are only recorded for observations in employment. Workers who reenter employment after a spell of unemployment also reenter the analytic sample. After observations with missing information on occupation or income were excluded, the analytic sample comprises 318,830 person-year observations nested within 48,444 individuals. Table A1 in the supplementary material reports on sample reduction associated with each inclusion criterion.

We merge information on routine-task content to the GSOEP data using ISCO88 three-digit occupational codes as the key variable. Task content is measured using three waves from the BIBB/BAuA Employment Survey (Hall et al. 2020a, 2020b, Hall and Tiemann 2021). The data is collected over telephone interviews with about 20,000 individuals per wave in intervals of six years. It contains detailed information on workers' educational backgrounds, employment circumstances, and task content. We use the latter to construct an index measure for routine tasks which is then aggregated on occupational level. We use all available waves that contain the relevant indicators (2006, 2012, and 2018).

The data approach we use in this study yields two noteworthy advantages. First, by measuring task content at the level of three-digit occupational codes, we can pick up subtle differences in task content between seemingly similar occupations and produce a finer-grained picture than prior studies that had to rely on broader occupational categorizations. In Table A2 in the supplementary material, we report case numbers and average RTI for all three-digit ISCO categories. Second, using multiple survey waves to measure task content enables us to account for changes in task content within occupations over time (Haslberger 2022). Studies that use other ways of assessing task content (e.g., expert coding of occupational databases) obtain time-constant measures by design that do not reflect change in the labor market. With our approach, we can assess whether the routine task content of each occupation has increased or decreased over the last two decades and whether that has impacted changes in labor market outcomes over individual careers.

3.2 Variables

We examine two outcome variables: income and unemployment risk. To measure *income*, we use real gross income per month in Euro. To obtain real income, we offset the nominal income against the consumer price index with 2015 as the reference year. The original distribution of the income variable is right-skewed with a long tail of high-income outliers. To compress the distribution and reduce the effect of outliers on the arithmetic mean, we recode the top 0.5% share to the 99.5 percentile value. Real income distributions before and after recoding are displayed in Figure B1 in the supplementary material.

To analyze differences in *unemployment risk*, we use a binary variable that indicates whether a person in a given year will remain employed (=0) or become unemployed (=1) in the year that follows. This means, that a person who is employed in 2019 and 2020, but unemployed in 2021 is coded 0 in 2019, 1 in 2020, and is not part of the analytic sample in 2021 as observations in unemployment are excluded. The indicator allows us to link transitions into unemployment to the task content of workers' previous occupations.

The key explanatory variable in this study is *task routineness.* We measure it using four survey items from the BiBB/BAuA Employment surveys. The items are displayed in Table 1. In line with Acemoglu and Autor (2011), we use standardized versions of these items to build a simple index by, averaging, first, across individual respondents and, second, across three-digit ISCO categories. The resulting scale is 0 for occupations with average routine scores and uses standard deviations as the unit of measurement. Following Haslberger (2022), we refrain from using principal component analysis based on the limited number of items available to build this index. We generate the respective scores for each available survey wave. When merging the occupational scores with the GSOEP data, we assign the score that is closest to the respective survey year. In the decomposition analysis, we use a categorical measure of task routineness as this yields certain advantages that are explained further below. The variable distinguishes eight categories: *less than* -0.6, -0.6 *to* -0.4, -0.4 *to* -0.2, -0.2 *to* 0, 0 *to* 0.2, 0.2 *to* 0.4, 0.4 *to* 0.6, and *greater than* 0.6.

Items	Scale
How often is the execution of the work prescribed to you in every detail?	1-4
How often is one and the same operation repeated in every detail?	1-4
How often do you find yourself confronted with new tasks in your work, which you first have to think about and familiarize yourself with? (reverse coded)	1-4
How often do you have to recognize and close your own gaps in knowledge? (reverse coded)	1-3

Table 1: Items from the BIBB/BAuA Employment Survey (waves 2006, 2012, and 2018) used to measure task routineness.

Lastly, we distinguish two *educational groups*: workers with vocational or tertiary education. Individuals are categorized based on their highest educational degree obtained at age 25 when most people in Germany have completed their full-time education. For individuals who enter the panel at age 26 or older, the highest degree at first observation is used. We define education as vocational if individuals graduate from a vocational school, hold a vocational master's degree, have completed an apprenticeship, or similar. Any educational qualification from a university or university of applied sciences is coded as tertiary education. By comparing vocational and tertiary graduates we follow Schulz et al. (2023) and deviate from earlier studies that compare vocational to *general* education (see e.g. Forster et al. 2016, Hanushek et al. 2017). The latter category is problematic as it usually pools workers with upper-secondary school diplomas and tertiary academic degrees—two groups with very distinct levels of education and different careers. Findings for this category are poised to inadequately represent either of the two groups. Further, using vocational and tertiary education as comparison groups connects this study to a real decision most students in Germany must take in their educational trajectories since workers without vocational or tertiary education are seen as unskilled in the German labor market (Giesecke et al. 2010).

3.3 Analytic strategy

3.3.1 Estimating the overall role of routine tasks

The analysis involves two steps. First, we apply Kitagawa-Oaxaca-Blinder (KOB) decomposition (Blinder 1973, Kitagawa 1955, Oaxaca 1973) while pooling all panel waves to study the overall role of routine tasks for differences in labor market outcomes between vocationally trained workers and workers with tertiary educational qualifications. For each outcome, two regression models are estimated—one for each educational group. For income, we use a person-level fixed effects regression estimator based on within transformation. Using only within-person variance eliminates confounder bias of time-constant individual characteristics. For unemployment risk, we use linear probability models (LPM) with person-level fixed effects. The indicator is binary and transitions into unemployment are relatively rare—we observe them with a probability of 4.2%. Research indicates that LPMs with fixed effects outperform comparable models when applied to rare events panel data (Timoneda 2021).

Next, the estimated coefficients are normalized using the averaging method introduced by Yun (2005). Decomposition effects of categorical explanatory variables suffer from identification problems as they vary depending on the chosen reference category (Oaxaca and Ransom 1999). Yun's averaging method produces normalized coefficients by averaging over all coefficients with different reference categories. Effects are then expressed as deviations from the mean. Identification problems also arise with continuous variables. Redefining the starting point on a continuous scale—for instance by mean centering the variable—does not change the estimated regression coefficients but the constant which, in turn, alters some decomposition components (Kim 2010). To circumvent this problem, we use a categorical measure for RTI which is then normalized as mentioned above.

Using a categorical measure of RTI yields another advantage. KOB decomposition can suffer from functional-form misspecification (Hamjediers and Sprengholz 2023). For instance, assuming that the relationship between RTI and income is linear may lead to bias in the estimated decomposition components if linearity is a poor representation of the true relationship form. We mitigate that type of bias with a categorical measure.

The resulting KOB decomposition model decomposes the mean differences in income or unemployment risk between workers with vocational and tertiary education into four components as displayed in Equation 1. Each term is calculated by summing across the eight categories of RTI denoted by $k = \{1, 2, 3, 4, 5, 6, 7, 8\}$.

$$
\begin{array}{cc}
\bar{Y}^T - \bar{Y}^V = & \\
\sum_{k=1}^{8} \breve{\beta}_k^V \left(\overline{RTI}_k^T - \overline{RTI}_k^V\right) + & \mathrm{E} \\
 & + \\
\sum_{k=1}^{8} \overline{RTI}_k^V \left(\breve{\beta}_k^T - \breve{\beta}_k^V\right) + & \mathrm{C} \\
 & + \\
\sum_{k=1}^{8} \left(\overline{RTI}_k^T - \overline{RTI}_k^V\right)\left(\breve{\beta}_k^T - \breve{\beta}_k^V\right) + & \mathrm{I} \\
 & + \\
\left(u^T - u^V\right) & \mathrm{U}
\end{array}
\tag{1}
$$

$\bar{Y}^T$ and $\bar{Y}^V$ are the average outcomes for tertiary and vocational graduates. $\overline{RTI}_k^T$ and $\overline{RTI}_k^V$ are the group-specific means of routine task intensity for the kth category of

RTI—equivalent to the share of workers in that category. $\breve{\beta}_k^T$ and $\breve{\beta}_k^V$ are the group-specific normalized regression coefficients, and u^T and u^V group-specific constants.

The first component of the decomposition—the endowment effect E —captures the portion of the outcome gap that is attributed to group differences in average routine-task intensity. The endowment effect tells us how much vocational graduates' average income/unemployment risk would change if they had the same mean RTI as tertiary graduates (while returns remain unchanged). We use this information to test hypothesis 1. The second component—the coefficient effect C—measures the contribution of differences in group-specific effects of RTI on the outcome variables. It yields how vocational graduates' labor market outcomes would change if they received the same returns as tertiary graduates (while levels remain unchanged). We use it to test hypothesis 2. The third component I is an interaction effect which accounts for the simultaneous occurrence of group differences in endowments and coefficients. It can either intensify or dampen the joint effect but has no substantial interpretation on its own (Skopek and Leopold 2018). The last component U captures differences in characteristics that are unobserved or unaccounted for by the other decomposition components.

The decomposition in Equation 1 is formulated from the perspective of vocational graduates with tertiary graduates as the reference category. We use group-specific arithmetic means while pooling observations across survey waves as measures of average income, average unemployment risk, and average RTI.

KOB decomposition may be undermined by certain methodological issues, for instance, the pervasiveness of group comparisons may be limited if the groups are structurally noncomparable—often referred to as *lack of common support*

(Hamjediers and Sprengholz 2023). That may be the case if members of a group with particular features have no comparable counterparts in the other group. In our case that would apply, for instance, if vocational and tertiary graduates were located on different ends of the RTI spectrum. If few individuals with vocational education engage in work as (non)routine as the average tertiary graduate, estimating an effect based on that average would largely rely on extrapolation. Figure B2 in the supplementary material displays group-specific distributions of RTI. The distributions largely overlap indicating comparability over most of the RTI value range. However, at the lowest levels of RTI (<-0.6) vocationally trained workers are scarce whereas tertiary graduates rarely work in occupations with the highest levels of RTI (>0.6). It should be noted that with the chosen decomposition approach we solely examine group differences in average effects disregarding the actual distributions.

3.3.2 Estimating the effect of routine tasks over the life course

As a second step in the analysis, we study differences in labor outcomes over the life course. We do so by, first, showing how income and unemployment risk trajectories evolve and diverge for workers with vocational and tertiary educational qualifications. Next, we examine how average routine-task intensity and returns to RTI evolve over the career for both educational groups. Average RTI trajectories are studied based on marginal effects from group-specific OLS regression with age dummies. To study returns to RTI, we rely on marginal effects from group-specific person fixed effects models that include interactions between RTI and age dummies. Results are presented graphically. They should provide an initial indication of how the impact of routine tasks for education-based differences in labor market outcomes may develop over the career.

To conclude our analysis, we decompose the difference in the *change* over the career between vocational and tertiary graduates for both outcomes using the decomposition-of-change approach proposed by Kröger and Hartmann (2021). We again sum over RTI categories k and use normalized regression coefficients ($\breve{\beta}$). The model decomposes the group difference in outcome change between age 25 and age s into four components as denoted in Equation 2.

$$
\begin{aligned}
D = \Delta Y^T_{25-s} - \Delta Y^V_{25-s} = \qquad & & (2)\\
\sum_{k=1}^{8} \breve{\beta}^T_{k,25}\left(\overline{RTI}^T_{k,s} - \overline{RTI}^T_{k,25}\right) - \breve{\beta}^V_{k,25}\left(\overline{RTI}^V_{k,s} - \overline{RTI}^V_{k,25}\right) + & \quad E \\
& \quad + \\
\sum_{k=1}^{8} \overline{RTI}^T_{k,25}\left(\breve{\beta}^T_{k,s} - \breve{\beta}^T_{k,25}\right) - \overline{RTI}^V_{k,25}\left(\breve{\beta}^V_{k,s} - \breve{\beta}^V_{k,25}\right) + & \quad C \\
& \quad + \\
\sum_{k=1}^{8} \left(\overline{RTI}^T_{k,s} - \overline{RTI}^T_{k,25}\right)\left(\breve{\beta}^T_{k,s} - \breve{\beta}^T_{k,25}\right) - \left(\overline{RTI}^V_{k,s} - \overline{RTI}^V_{k,25}\right)\left(\breve{\beta}^V_{k,s} - \breve{\beta}^V_{k,25}\right) & \quad I \\
& \quad + \\
+\left(\alpha^T_{k,s} - \alpha^T_{k,25}\right) - \left(\alpha^V_{k,s} - \alpha^V_{k,25}\right) & \quad U
\end{aligned}
$$

The endowment effect (E) should be interpreted as the portion of the change in the outcome gap between age 25 and age s that is accounted for by life-course changes in group-specific RTI between age 25 and age s while coefficients are held constant at their initial group-specific levels (Kröger and Hartmann 2021:372). Similarly, the coefficient effect (C) reflects the portion of change attributable to a change in coefficients over the defined period given the group-specific distribution of RTI at age 25. The interpretation of the interaction (I) and the intercept components (U) are analogous to before. We apply this decomposition repeatedly for different age brackets by varying s. We report results in tabular form for $s = \{30, 35, 40, 45, 50, 55, 60, 65\}$.

4 Results

4.1 KOB decomposition

4.1.1 Income

In Table 2 we report the results from the decomposition of both outcomes together with means and effects across categories of RTI. We find that the average real monthly income for vocational graduates is €2,507 while it is €4,011 for workers with tertiary educational qualifications. That means, vocational graduates, on average, earn €1,504 or 37% less per month than tertiary graduates.

In line with our expectations, vocational graduates perform more routine tasks than tertiary graduates. 75% of the workers with vocational training work in occupations with above-average routine scores (RTI>0). RTI scores between 0.0 and 0.2 are the most common category. It contains a broad range of occupations including administrative associate professionals (16%), building finishers (9%), office clerks (9%), and nursing associate professionals (9%). Only 4% of workers with vocational training work in low routine jobs (RTI<-0.4) whereas 35% of workers with tertiary education do so. 77% of workers with tertiary education work in occupations with below-average routine scores. The largest group has RTI scores of -0.6 to -0.4. This group largely consists of engineers (40%), secondary school teachers (13%), computing professionals (13%), and social science professionals (11%). Only 3% of university graduates in the sample work in high-routine occupations (RTI > 0.4) such as motor-vehicle drivers, domestic helpers and cleaners, or cashiers.

	Income		Unemployment risk	
	Estimate	SE	Estimate	SE
Mean outcome – Tertiary educ.	4,010.53	3.835	0.032	0.001
Mean outcome – Vocational educ.	2,506.77	1.600	0.046	0.000
Outcome difference	**1,503.76**	**4.154**	**-0.013**	**0.001**
$\overline{RTI}$ per category – Tertiary educ.				
< -0.6	0.053	0.001	0.053	0.001
-0.6 to -0.4	0.292	0.002	0.292	0.002
-0.4 to -0.2	0.274	0.002	0.274	0.002
-0.2 to 0.0	0.158	0.001	0.158	0.001
0.0 to 0.2	0.131	0.001	0.131	0.001
0.2 to 0.4	0.061	0.001	0.061	0.001
0.4 to 0.6	0.021	0.000	0.021	0.000
> 0.6	0.010	0.000	0.010	0.000
$\overline{RTI}$ per category– Vocational educ.				
< -0.6	0.002	0.000	0.002	0.000
-0.6 to -0.4	0.036	0.000	0.036	0.000
-0.4 to -0.2	0.069	0.001	0.069	0.001
-0.2 to 0.0	0.148	0.001	0.148	0.001
0.0 to 0.2	0.353	0.001	0.353	0.001
0.2 to 0.4	0.231	0.001	0.231	0.001
0.4 to 0.6	0.114	0.001	0.114	0.001
> 0.6	0.046	0.000	0.046	0.000
Endowment effect	**165.302**	**5.762**	**-0.000**	**0.001**
$\breve{\beta}$ per category – Tertiary educ.				
< -0.6	-142.432	35.385	0.006	0.005
-0.6 to -0.4	150.616	17.716	0.003	0.003
-0.4 to -0.2	263.624	17.049	0.003	0.002
-0.2 to 0.0	277.209	19.662	-0.006	0.003
0.0 to 0.2	87.652	18.405	-0.005	0.003
0.2 to 0.4	-128.216	23.560	-0.002	0.003
0.4 to 0.6	-180.255	39.880	-0.002	0.006
> 0.6	-328.199	56.147	0.003	0.008
$\breve{\beta}$ per category – Vocational educ.				
< -0.6	187.571	49.966	0.012	0.013
-0.6 to -0.4	197.509	13.722	-0.003	0.003
-0.4 to -0.2	190.546	11.014	-0.002	0.003
-0.2 to 0.0	64.753	9.568	-0.003	0.002
0.0 to 0.2	-65.761	8.835	-0.001	0.002
0.2 to 0.4	-161.159	9.265	0.002	0.002
0.4 to 0.6	-149.590	10.764	-0.004	0.003
> 0.6	-263.869	13.392	-0.001	0.003
Coefficient effect	**89.548**	**11.303**	**-0.002**	**0.002**
Interaction	-46.533	12.157	0.003	0.002
Intercept difference	1,295.443	13.659	-0.015	0.003

Table 2: KOB decompositions of differences in income and unemployment risk between vocational and tertiary graduates.

Notes: From the perspective of vocationally trained workers with tertiary graduates as the reference category. $\overline{RTI}$ is mean routine task intensity. $\breve{\beta}$ is the normalized regression coefficient obtained from person fixed effects models.

These differences in average routine task intensity moderately contribute to the real income gap between both groups. The endowment effect suggests that, in a counterfactual scenario where vocational graduates performed the same amount of routine tasks as tertiary graduates, the real income gap would be €165 or 11% smaller. The standard error for the endowment effect is small (€5.76), with a confidence interval (CI) of [€154, €177]. This finding supports H1 for income. Predicted real income under different counterfactual scenarios is displayed in the top panel of Figure 1.

Further, our findings indicate that RTI is negatively associated with income. The normalized coefficients for vocationally trained workers reported in Table 2 show that above-average RTI categories (RTI > 0) are linked to growing income losses while below-average RTI (RTI < 0) yields incomes above the group-level mean when adjusting for time-constant individual characteristics. For tertiary graduates, we find similar tendencies whereas the relationship follows a right-skewed inverse u-shape. We find the largest positive coefficients for observations with routine scores slightly above average. Higher categories yield smaller income gains while RTI scores above 0.6 are even linked to income losses. The coefficient effect of the decomposition suggests that in a counterfactual scenario where vocational graduates received the same returns to routine tasks as tertiary graduates, the real income gap would be €90 or 6% smaller (CI=[€66,€115]). This finding contradicts H2 where we expected that a flatter RTI-income slope for vocational graduates would naturally attenuate income disparities to some extent. Our findings show that although vocationally trained workers indeed face smaller penalties for within-person gains in RTI, returns are still higher for tertiary graduates at RTI levels slightly above 0, where most vocational graduates are located.

Lastly, examining both, endowment and coefficient effects jointly yields a combined effect that is only slightly larger than the endowment effect alone (see top panel of Figure 2). That is the case because the negative interaction effect mitigates the joint effect. The estimate suggests that if vocationally trained workers performed as many routine tasks as tertiary graduates and received the same returns, the real income gap would be €208 or 14% smaller. This also indicates that accounting for differences in routine tasks leaves 86% of the income gap unexplained.

4.1.2 Unemployment risk

We find that the risk of becoming unemployed in the next year is 1.3 percentage points or 28% larger for vocationally trained workers than for tertiary graduates. Surprisingly, the endowment effect of 0.000 suggests that differences in mean RTI between vocational and tertiary graduates play a negligible role in the risk difference. As displayed in the right two columns of Table 2, within-change in RTI across most RTI categories is not meaningfully associated with changes in unemployment risk for vocationally trained workers when adjusting for individual time constant characteristics. Consequently, differences in mean RTI do not matter for differences in unemployment risk as we measure it in this study. These findings do not support H1 for unemployment risk.

Differences in the coefficients between both groups may matter for the gap in unemployment risk. Whereas there is no clear association between RTI and unemployment risk for vocational graduates, we observe a u-shaped link for tertiary graduates with negative effects on unemployment risk for RTI scores around 0. Transitions into higher or lower regions of RTI yield smaller negative or positive effects. The coefficient component of the decomposition suggests that in a counter-factual scenario where the association between RTI and unemployment risk was the same for vocationally trained workers as for workers with tertiary education, the gap in unemployment risk would decrease by about 0.2 percentage points or 15%. However, with a standard error of 0.002, the estimated coefficient effect is relatively imprecise. The associated 95%-confidence interval covers values between -0.006 (45% reduction of the gap) and 0.003 (19% increase of the gap). This finding does not support H2.

Ultimately, a joint effect of 0.001 suggests that in a scenario where mean levels *and* effects of RTI for vocationally trained workers matched those of tertiary graduates the gap between both groups would be slightly larger due to the positive interaction between levels and returns. The different counterfactual scenarios are visualized in the bottom panel of Figure 1.

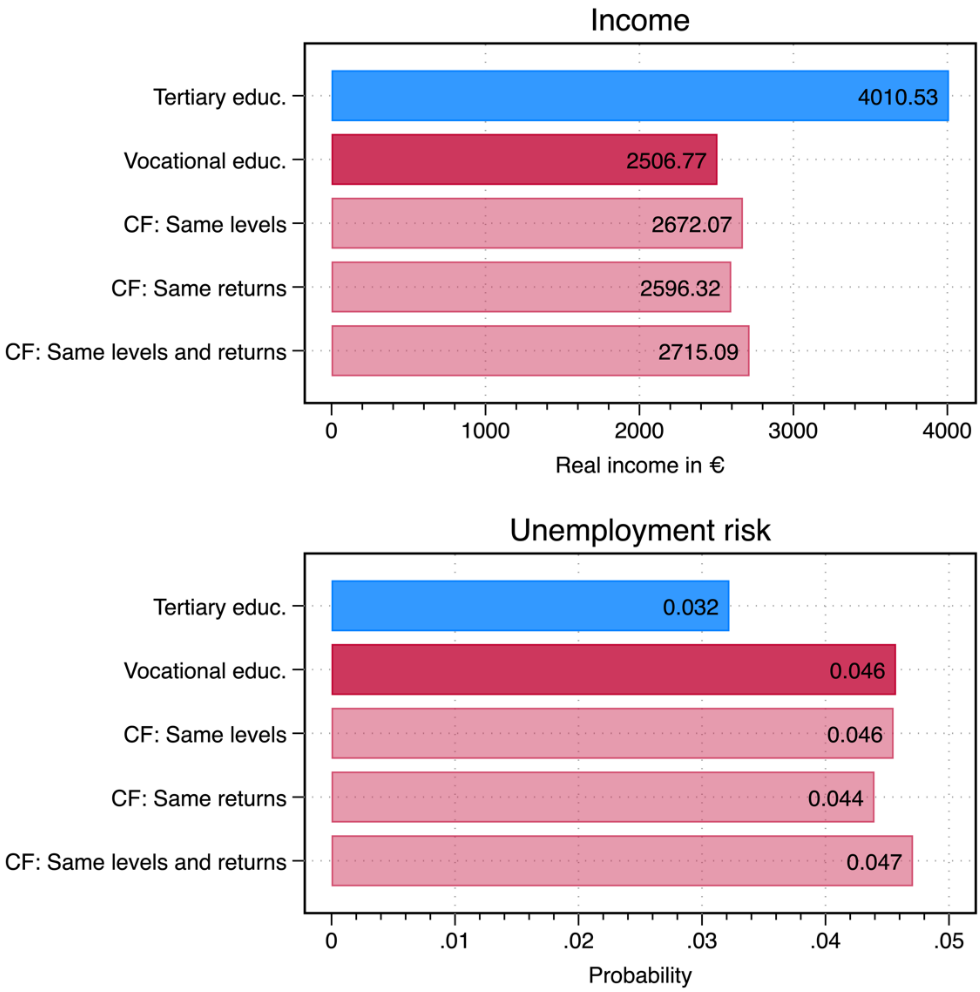

Figure 1: Labor market outcomes under different counterfactual scenarios.

Notes: Based on the decomposition results displayed in Table 2. CF abbreviates counterfactual.

4.1.3 Auxiliary analyses

To support our main analysis in the prior section, we performed two auxiliary examinations. First, we analyze whether routine task intensity is linked positively to *occupational mobility*. Earlier findings suggest that technological change may have neutral effects on employment but increase occupational mobility within sectors (Autor et al. 2015). Figure B3 in the supplementary material displays marginal probabilities of occupational mobility for categories of RTI. It implies that RTI is indeed positively linked to the risk of changing occupations. Above we assumed that this may impact income. Results from person fixed effects regression suggest that occupational change is on average linked to a €158 decrease in real monthly income. Consequently, the income gradient between vocational and tertiary graduates that is attributable to differences in mean levels of RTI may indeed be partially accounted for by differences in occupational mobility.

Second, we address the potential impact of *task complexity.* A KOB decomposition with a measure of task complexity as an additional explanatory variable suggests that group differences in task complexity likely contribute to the gap in labor market outcomes and may even be more relevant than differences in routine tasks (see Table A3 in the supplementary material). However, we also find a correlation of -0.84 between routineness and complexity which is higher than in prior studies (see e.g. Haslberger 2022). Collinearity of predictors may produce unreliable coefficient estimates hence we cannot confidently disentangle the respective effects of routineness and complexity in this study.

4.2 Life course decomposition

Figure 2 displays how average levels of income and unemployment risk change between ages 25 and 65 for vocational and tertiary graduates. The figure suggests that a decomposition of change is only warranted for income. The left panel shows that income grows more strongly for tertiary graduates leading to a widening income gap between both groups—this difference in change can be decomposed. For unemployment risk, we find that decreases over the career are relatively uniform for both groups, with no systematic advantage of one group over the other. Since a decomposition of the difference in change is uninformative in the absence of a distinguishable time trend, we focus on income in the following analysis.

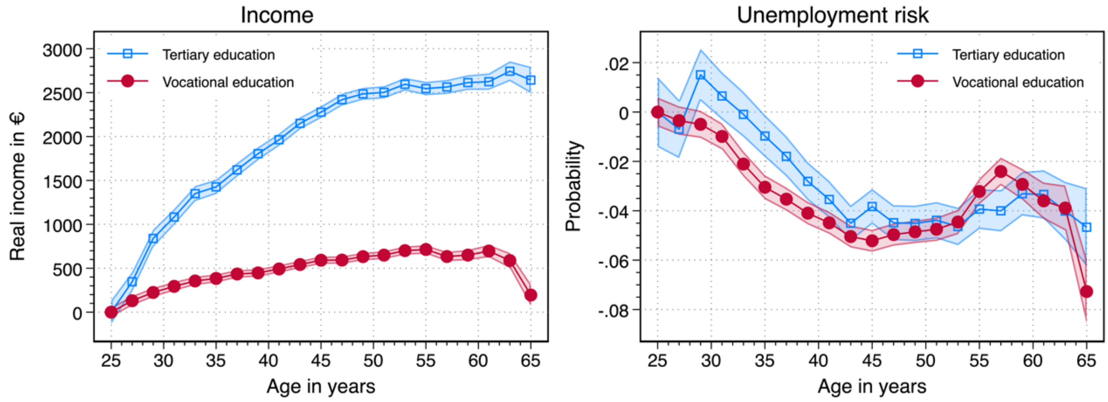

Figure 2: Change in labor market outcomes for vocational and tertiary graduates over the career.

Notes: Estimates obtained from group-specific OLS regression with age dummies. Colored areas represent 95% confidence intervals.

In Figure 3 we display how mean levels of RTI (left panel) and age-specific effects of RTI on income (right panel) evolve over the life course. We find that average RTI remains remarkably steady over the career. For vocationally trained workers we observe a subtle U-shape with the lowest levels of RTI during workers mid careers and slightly higher levels in their later careers. For tertiary graduates, RTI decreases by about 0.06 standard deviations between ages 25 and 65. Consequently, differences in RTI between the two groups increase only slightly over the career. The absence of a more substantial and sustained decrease in the mean levels of RTI over the life course is surprising and indicates that—in contrast to our expectation in hypothesis 3—these changes do not contribute substantially to the widening income gap.

The right panel of Figure 3 shows that for both educational groups RTI coefficients decrease substantially over workers' careers. In the early career, routine tasks are associated with income gains. The association turns negative at age 31 for vocational graduates and at age 34 for tertiary graduates. Between 32 and 52 we find slightly larger negative coefficients for vocationally trained workers and slightly smaller ones in their sixties relative to university graduates. Growing negative returns to routine tasks over the career are in line with our initial expectations, however, we don't observe a notably more pronounced decline in returns for vocationally trained workers than for university graduates.

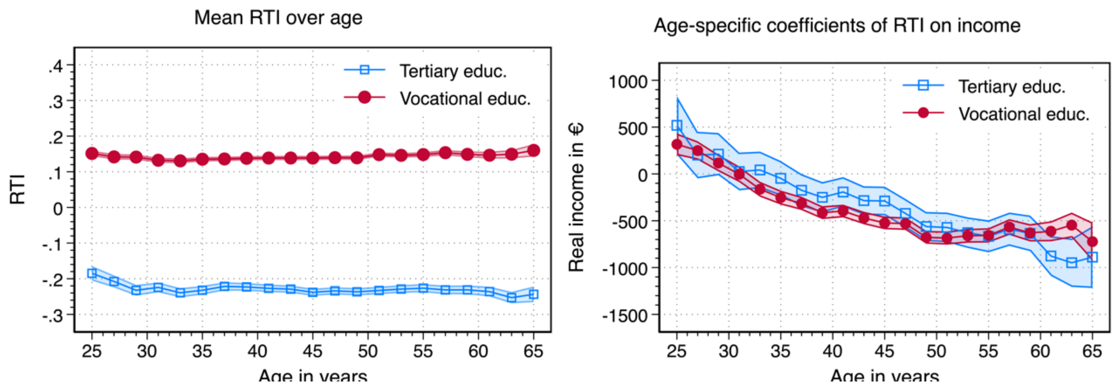

Figure 3: Mean levels of RTI and coefficients of RTI on income for vocational and tertiary graduates over the career.

Notes: Coefficients in the left panel are obtained from group-specific OLS regression with age dummies. Coefficients in the right panel are marginal RTI effects from group-specific person fixed-effects models with age dummies. Colored areas represent 95% confidence intervals.

Next, Table 3 presents the decomposition of differences in income change. The top two rows display the average income of vocational and tertiary graduates from age 25 to 65. The third row indicates the difference in income change from age 25 to the age specified in the column's head, which is equivalent to the gap between the lines of Figure 2 at that age. The decomposition suggests, first, that changes in mean levels of RTI over the career (endowment effect) contribute only marginally to the growing income gap. Given the initial difference in RTI coefficients, changes in mean levels of RTI over the career account for a maximum of €36 or 2% of the change in the income gap (at age 60). This reflects our earlier finding that average RTI remains largely constant over the career for both educational groups. This finding does not support hypothesis 3 which assumed that existing differences in RTI trajectories between vocational and tertiary graduates would partially mitigate growth of the income gap.

Second, we find that life-course changes in the *returns* to RTI have a more substantial impact. Considering the initial difference in average RTI, the decomposition suggests that changes in coefficients over the career account for €600 or 25% of the change in the income gap that accumulated from age 25 to 65 between vocational and tertiary graduates. Although the coefficient effects reported in Table 3 grow with age, this does not imply that RTI returns become more relevant for the income gap over the life course. The relative contribution to the income gap remains stable at around 25% reflecting the uniform development of RTI returns over the career for both educational groups identified in the right panel of Figure 3. This finding does not support hypothesis 4 where we expected that *differences* in how RTI returns develop between groups over the career would drive the growing income gap. Instead, our results imply that the overall decline in RTI returns over the career matters for diverging income trajectories because vocationally trained workers are more likely to perform routine tasks and are therefore affected disproportionally.

This finding is further illustrated in Figure 4 which displays factual and counterfactual trajectories of income change differentials based on the decomposition analysis. The dashed line with hollow circle markers shows the counterfactual income trajectory for vocationally trained workers if returns to RTI had not declined over the career. The dashed line with triangular markers visualizes the negligible impact of change in mean levels of RTI whereas the joint effect (diamond markers) is predicted to be initially similar and then slightly larger than the coefficient effect alone driven by positive interactions between change in averages and coefficients of RTI.

Income	25	30	35	40	45	50	55	60	65
Average – Tertiary educ. (ref.)	1946.153	2935.654	3373.764	3848.802	4223.945	4457.605	4493.133	4565.073	4589.529
	(68.932)	(48.363)	(41.503)	(36.492)	(34.540)	(34.998)	(39.119)	(44.652)	(76.917)
Average – Vocational educ.	2010.382	2287.302	2394.494	2476.166	2601.795	2655.224	2724.185	2634.893	2205.389
	(28.634)	(26.164)	(23.675)	(21.966)	(21.643)	(22.619)	(25.255)	(32.270)	(63.927)
Diff. in change since age 25	0.000	712.581	1,043.499	1,436.865	1,686.379	1,866.610	1,833.177	1,994.409	2,448.369
	(0.000)	(56.888)	(63.257)	(67.909)	(69.072)	(69.169)	(77.946)	(85.613)	(166.307)
Endowment effect	0.000	-2.997	22.748	26.394	25.141	33.746	27.303	36.215	0.603
	(0.000)	(17.265)	(19.737)	(18.567)	(19.259)	(21.423)	(20.063)	(21.432)	(30.748)
Coefficient effect	0.000	172.406	398.29	354.035	449.547	474.502	542.408	551.206	600.192
	(0.000)	(119.405)	(106.579)	(104.911)	(114.167)	(115.721)	(111.567)	(134.128)	(146.299)
Interaction	0.000	-1.854	-21.419	-22.744	-6.926	3.363	16.582	23.242	95.329
	(0.000)	(15.121)	(20.607)	(20.354)	(21.276)	(24.396)	(25.381)	(28.800)	(49.778)
Intercept difference	0.000	545.027	643.88	1079.179	1218.616	1354.999	1246.884	1383.746	1752.245
	(0.000)	(132.586)	(121.320)	(122.358)	(132.714)	(134.565)	(135.184)	(161.945)	(216.804)

Table 3: Decomposition of change in real income for different age brackets

Notes: The Decomposition is based on Kröger and Hartmann (2021). Estimates are from the perspective of vocationally trained workers with tertiary graduates as the reference category. Coefficients were obtained from person fixed effects regression models with categorical RTI and age dummies. They were normalized as suggested in Yun (2005). We report averages over RTI categories. Standard errors are reported in parentheses. They are obtained via bootstrapping with 500 repetitions.

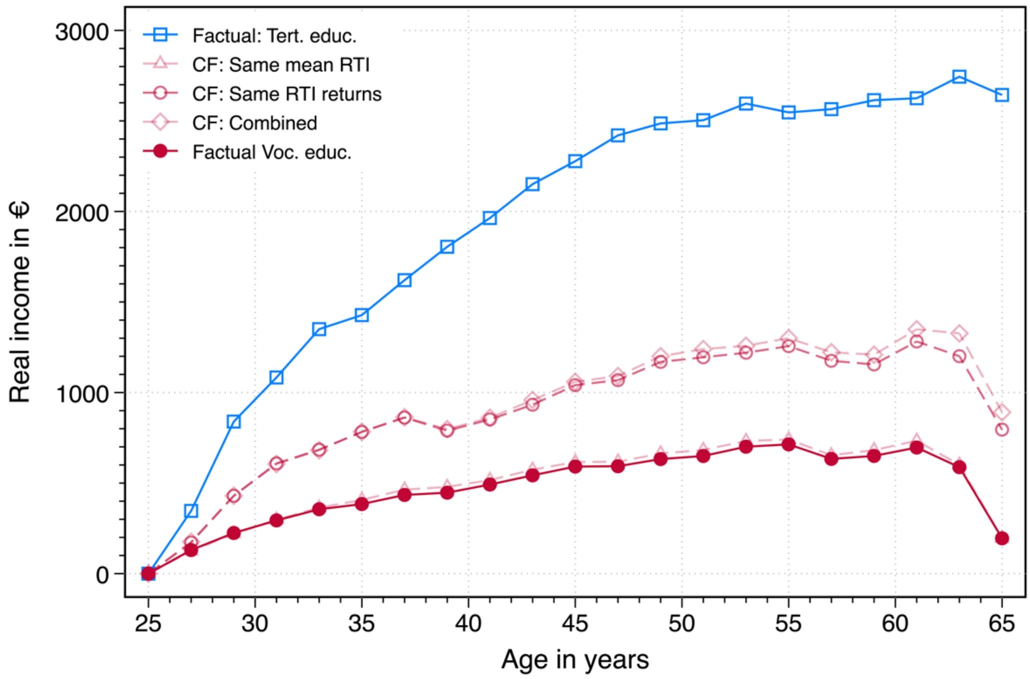

Figure 4: Factual and counterfactual change in the income gap over the career.

Notes: Factual trajectories are based on group-specific OLS regression with age dummies. Counterfactual trajectories were obtained by adding the decomposition components to the factual trajectories for vocationally trained workers.

5 Discussion and conclusion

To what extent do routine tasks affect labor market inequalities between workers with vocational and tertiary educational qualifications? Our analysis reveals mixed results. We find that routine tasks matter for understanding income differences between the two groups. Routine intense work yields lower incomes and workers with vocational training perform more routine work than workers with university degrees. Kitagawa-Oaxaca-Blinder decomposition implies that this mechanism accounts for 11% of the income gap between both groups.

Second, we find null effects of routine task intensity on workers' risk of becoming unemployed. This finding does align with earlier studies showing that automation mainly leads to occupational mobility rather than sheer unemployment (Autor et al. 2015, Autor and Dorn 2009). We suspected that this type of mobility may be linked to income losses and indeed found that routine work is associated with higher rates of occupational change which, in turn, are linked to notable decreases in monthly income. A different potential explanation for this finding is found in our estimation approach. We assessed whether changes in routine work within individuals in a given year increase their likelihood of becoming unemployed in the following year and thereby focus on the short-term impact of routine work. However, the effects of routine work may develop over the medium to long term and thus remain undetected in our study.

Earlier studies on the career disadvantages of vocationally trained workers have emphasized how occupation-specific skills yield limited capabilities to switch occupations and thereby adapt to changes in the labor market. Our study indicates that differences in the distribution of tasks may also expose vocationally trained workers to a greater risk of downward job mobility. This suggests that measures such as retraining and life-long learning that address adaptability gaps should be complemented by regulations that protect workers from wage reduction and displacement. Particularly in vulnerable industries this is crucial to reduce disadvantages for vocationally trained workers.

Third, we find that disparities in the returns to routine tasks account for 6% of the income gap between vocational and tertiary graduates. This suggests that the incomes of tertiary graduates are more robust toward a moderate level of routine work than we expected. Tertiary graduates still obtain incomes above their group average in occupations with slightly above-average RTI while vocationally trained workers in that group already earn below their group average. Zooming in on the occupations with moderate RTI scores shows that tertiary graduates more often work as administrative associate professionals and numerical clerks. In contrast, vocationally graduates more often work as building finishers, welders, or machinery mechanics. This indicates that differences in the returns to routine tasks may be linked to auxiliary task dimensions such as cognitive and manual routine work and points to the limits of what we can explain by examining routine tasks in isolation.

Fourth, our study shows that routine work also matters for income inequality over the career. Income returns to routine tasks decrease substantially over time. This process accounts for 25% of the gap in income growth between vocational and tertiary graduates. In line with RBTC, this may indicate that diminishing prices for automation technology have increased pressure on wages in routine-heavy occupations whereas complementing technology has boosted wages for non-routine work. Surprisingly, we don't find notable differences in returns between both groups. Accordingly, the explained part of the income gap is solely based on the disproportionate prevalence of routine tasks among workers with vocational training.

Finally, we do not find substantial shifts in the prevalence of routine tasks over the career, particularly for vocationally trained workers. That finding is difficult to align with the implications of RBTC which suggests that routine work should decrease over time as automation develops. It is also at odds with the finding that routine work in Germany has decreased across occupational groups (Helmrich et al.

2016). Other studies however found that the RBTC hypothesis may not hold for Germany and other countries with strong vocational systems (Seegers and Ehmann in print). The discrepancy may also point towards a contradictory effect of computer technology. Evidence from European data suggests that computers may replace routine tasks while simultaneously increasing the routinization and standardization of the remaining tasks (Fernández-Macías et al. 2023, Shestakofsky 2017).

The findings of this study face some limitations. Most crucially, our theoretical considerations largely focus on technological change as a key driver of task-based differences in labor market outcomes. That perspective is motivated by the fact that the disadvantages of workers with vocational training are usually discussed in the context of labor market change brought by technological development. However, we do not directly measure technological change in this study. Consequently, how routine work affects labor market outcomes could also be explained by other factors. One that is often addressed in the literature is offshoring (Autor et al. 2015, Baumgarten 2015, Grossman and Rossi-Hansberg 2008, Reijnders and de Vries 2018). Offshoring jobs to other economies is indeed expected to decrease the demand for routine tasks and affect labor market outcomes between general and vocational graduates similarly to technological change. While our analytic strategy does not allow us to model technological change and offshoring as two distinct mechanisms, we see this as a promising avenue for further research.

A second limitation is that the present study focuses on a single task dimension. Which tasks or task dimensions are most affected by fundamental structural changes in the labor market and under what conditions they have implications for individual workers is an ongoing debate (Haslberger 2022). To better capture the economic value of jobs' task profiles, their transferability, and how those factors manifest in distinct career trajectories, future research should examine the role of alternative task dimensions, such as complexity, manuality, creativity, or interactivity, and investigate their interplay with task routineness.

Third, in our life course analysis, we theorized that the effects of work experience and the associated change in job task content manifest jointly with the effects of technological change, which alter the demand for task inputs over workers' careers. In doing so, we mix an age-related mechanism with a period effect that develops over calendar years. Therefore the relevant temporal dynamics remain partially unclear in our study. Future research should use data that allows disentangling those dimensions to better understand the extent to which labor market disparities between educational groups are produced and reproduced by how careers are structured vs. how macro-level phenomena tip the scales for those groups.

Nevertheless, this study takes a first step in integrating the notion of work tasks into the literature on education-based inequality, assessing the relevance of one of the most prominent task dimensions in the current literature. Considering the large unexplained differences in labor market outcomes between vocational and tertiary graduates, further research is needed to identify the precise mechanisms that drive these unequal patterns and how they are interrelated.

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Supplementary material

How routine tasks affect labor market inequalities between vocational and tertiary graduates over the career

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A. Tables

Table A1: Analytic sample restrictions and the associated changes in case numbers

Criteria	Person-years		Persons	
	N	%	N	%
Initial sample	**761,461**	**100**	**104643**	**100**
Unemployed	314,067	41	30,359	29
Outside age range (25-65)	53,998	7	11,047	11
Missing occupation	16,704	2	3,030	3
No vocational or tertiary degree	57,848	8	11,763	11
Missing income information	14	0	0	0
Analytic sample	**318,844**	**42**	**48,444**	**46**

Table A2: Mean RTI and case numbers for occupational categories

ISCO88com three-digit code	Mean RTI	N
231. College, university and higher education teaching professionals	-0.719	405
242. Legal professionals	-0.661	464
111. Legislators and senior government officials	-0.601	40
240. Other professionals	-0.571	42
246. Religious professionals	-0.545	121
312. Computer associate professionals	-0.541	836
213. Computing professionals	-0.517	1,147
114. Senior officials of special-interest organisations	-0.494	94
234. Special education teaching professionals	-0.448	228
214. Architects, engineers and related professionals	-0.444	2,502
235. Other teaching professionals	-0.43	294
245. Writers and creative or performing artists	-0.429	648
211. Physicists, chemists and related professionals	-0.427	118
244. Social science and related professionals	-0.4	1,377
130. Managers of small enterprises	-0.4	879
232. Secondary education teaching professionals	-0.393	2,005
241. Business professionals	-0.356	1,808
233. Primary and pre-primary education teaching professionals	-0.347	480
212. Mathematicians, statisticians and related professionals	-0.337	31
120. Corporate managers	-0.331	229
123. Other specialist managers	-0.316	793
334. Other teaching associate professionals	-0.314	396
347. Artistic, entertainment and sports associate professionals	-0.298	307
247. Public service administrative professionals	-0.297	1,013
221. Life science professionals	-0.266	79
121. Directors and chief executives	-0.252	293
332. Pre-primary education teaching associate professionals	-0.202	1,126
322. Health associate professionals (except nursing)	-0.197	780
345. Police inspectors and detectives	-0.167	267
122. Production and operations managers	-0.159	619
222. Health professionals (except nursing)	-0.141	842
311. Physical and engineering science technicians	-0.125	2,112
615. Fishery workers, hunters and trappers	-0.102	2
342. Business services agents and trade brokers	-0.078	426
733. Handicraft workers in wood, textile, and related materials	-0.072	5
243. Archivists, librarians and related information professionals	-0.047	99
724. Electrical and electronic equipment mechanics and fitters	-0.036	619
313. Optical and electronic equipment operators	-0.036	200
341. Finance and sales associate professionals	-0.029	2,397

333. Special education teaching associate professionals	-0.028	138
131. Managers of small enterprises	-0.004	650
723. Machinery mechanics and fitters	0.039	1,141
811. Mining and mineral-processing-plant operators	0.039	6
742. Wood treaters, cabinet-makers and related trades workers	0.059	300
816. Power-production and related plant operators	0.082	108
412. Numerical clerks	0.09	1,467
713. Building finishers and related trades workers	0.092	1,324
346. Social work associate professionals	0.098	817
744. Pelt, leather and shoemaking trades workers	0.112	26
343. Administrative associate professionals	0.115	2,942
516. Protective services workers	0.122	529
323. Nursing and midwifery associate professionals	0.13	1,784
610. Skilled agricultural and fishery workers	0.131	243
712. Building frame and related trades workers	0.131	481
315. Safety and quality inspectors	0.136	398
344. Customs, tax and related government associate professionals	0.154	1,407
914. Building caretakers, window and related cleaners	0.161	495
611. Market gardeners and crop growers	0.172	399
419. Other office clerks	0.174	1,947
722. Blacksmiths, tool-makers and related trades workers	0.176	551
721. Metal moulders, welders, and related trades workers	0.18	653
931. Mining and construction labourers	0.185	54
348. Religious associate professionals	0.208	13
411. Secretaries and keyboard-operating clerks	0.217	630
612. Animal producers and related workers	0.224	118
513. Personal care and related workers	0.226	1,434
511. Travel attendants and related workers	0.231	67
731. Precision workers in metal and related materials	0.232	214
413. Material-recording and transport clerks	0.233	925
734. Craft printing and related trades workers	0.234	219
514. Other personal services workers	0.242	402
743. Textile, garment and related trades workers	0.244	166
711. Miners, shotfirers, stone cutters and carvers	0.245	43
314. Ship and aircraft controllers and technicians	0.246	87
321. Life science technicians and related associate professional	0.255	295
614. Forestry and related workers	0.27	51
422. Client information clerks	0.283	516
825. Printing-, binding- and paper-products machine operators	0.347	29
522. Shop, stall and market salespersons and demonstrators	0.348	1,782
512. Housekeeping and restaurant services workers	0.35	1,256

814. Wood-processing- and papermaking-plant operators	0.372	46
823. Rubber- and plastic-products machine operators	0.375	136
741. Food processing and related trades workers	0.378	247
732. Potters, glass-makers and related trades workers	0.384	75
833. Agricultural and other mobile plant operators	0.407	337
714. Painters, building structure cleaners and related workers	0.411	417
829. Other machine operators not elsewhere classified	0.44	284
921. Agricultural, fishery and related labourers	0.441	78
815. Chemical-processing-plant operators	0.444	220
821. Metal- and mineral-products machine operators	0.449	287
911. Street vendors and related workers	0.458	2
832. Motor vehicle drivers	0.463	1,202
812. Metal-processing plant operators	0.476	92
831. Locomotive engine drivers and related workers	0.486	164
414. Library, mail and related clerks	0.488	397
933. Transport labourers and freight handlers	0.504	322
421. Cashiers, tellers and related clerks	0.533	425
826. Textile-, fur- and leather-products machine operators	0.538	104
813. Glass, ceramics and related plant operators	0.558	6
822. Chemical-products machine operators	0.558	83
915. Messengers, porters, doorkeepers and related workers	0.581	210
827. Food and related products machine operators	0.582	137
916. Garbage collectors and related labourers	0.631	44
828. Assemblers	0.647	81
834. Ships' deck crews and related workers	0.673	2
932. Manufacturing labourers	0.691	616
913. Domestic and related helpers, cleaners and launderers	0.729	805
824. Wood-products machine operators	0.993	4
Total	0	59,053

Notes: Observations were pooled from three waves of the BiBB/BAuA Employment survey.

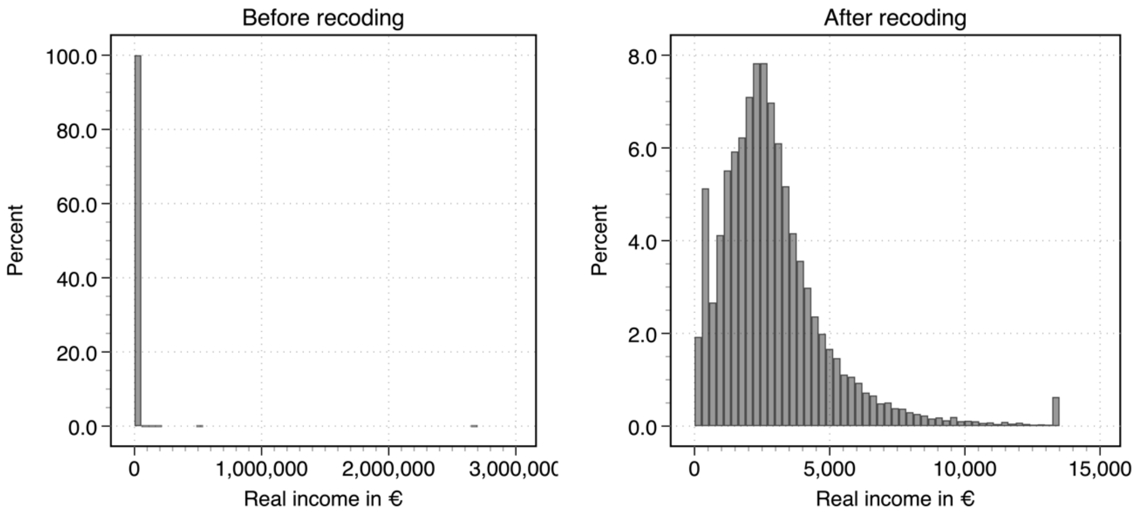
Table A3: KOB decomposition with task complexity as an additional predictor

	Income		Unemployment risk	
	Estimate	SE	Estimate	SE
Mean outcome – Tertiary educ.	4,010.53	3.835	0.032	0.001
Mean outcome – Vocational educ.	2,506.77	1.600	0.046	0.000
Outcome difference	**1,503.76**	**4.154**	**-0.013**	**0.001**
Endowment effects				
RTI	9.935	7.099	0.013	0.002
Task complexity	201.493	5.483	-0.017	0.001
Coefficient effects				
RTI	90.237	11.320	-0.001	0.002
Task complexity	-146.907	9.046	0.004	0.001
Interaction				
RTI	-252.778	18.375	0.008	0.003
Task complexity	323.405	19886	-0.008	0.003
Intercept difference	1278.374	13.827	-0.012	0.003

Notes: From the perspective of vocationally trained workers with tertiary graduates as the reference category. Coefficients were obtained from person-fixed effects regression. RTI is measured categorically and coefficients were normalized as suggested in Yun (2005). Task complexity is measured using three items "How often do these activities occur in your work: working with computers (1-3)", "How often does it occur in your work, that you have to make difficult decisions on your own? (1-3)", "How often does it occur in your work, that you have to react to problems and solve them?". Responses are averaged across respondents and three-digit ISCO88 occupations to build a complexity index included in the decomposition as a continuous variable.

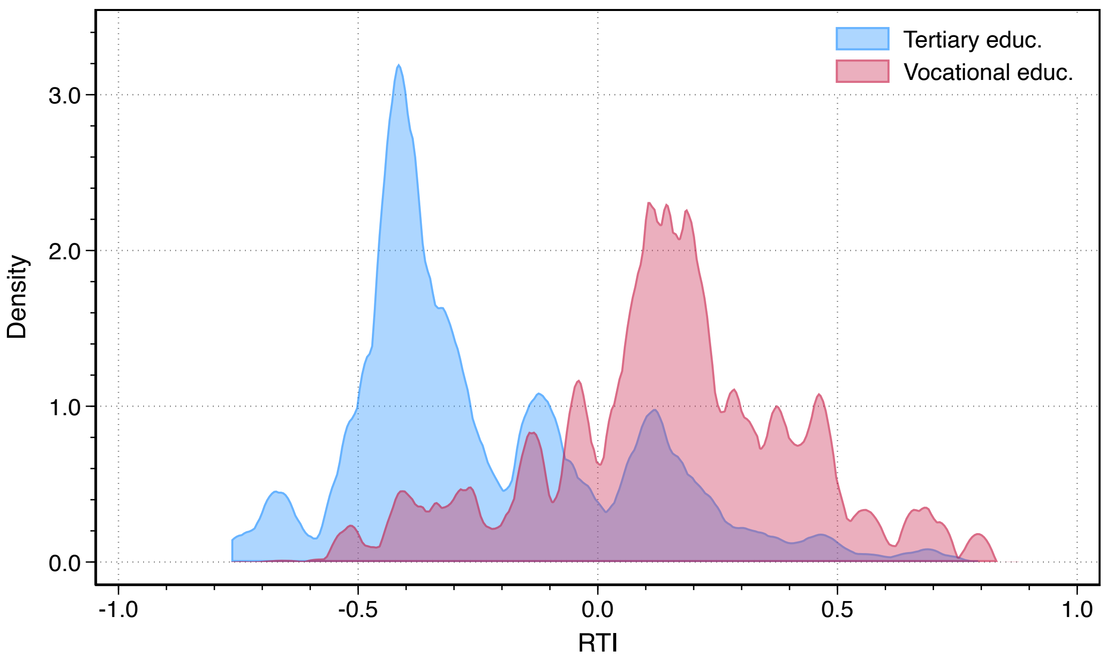
B. Figures

Figure B1: Distributions of real income before and after recoding the top 0.5 percent.



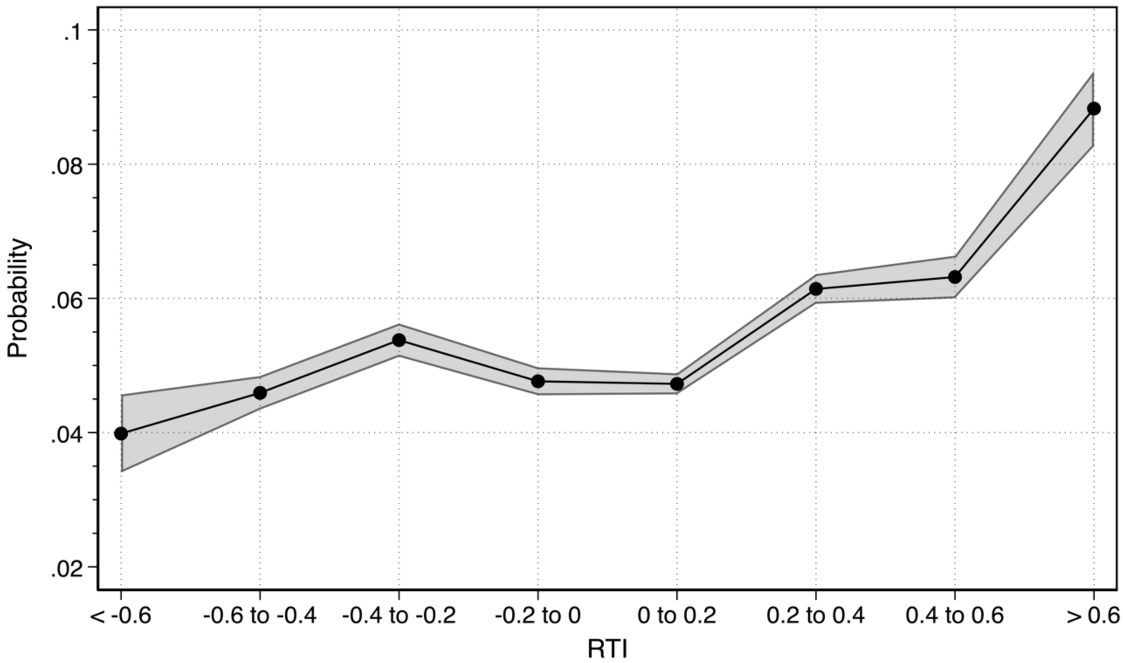
Notes: Bins are set to 50.

Figure B2: Distributions of RTI for vocational and tertiary education



Notes: Kernal density estimates are obtained using the Epanechnikov kernel function. We specify the half-width of the kernel to be 0.02.

Figure B3: Marginal probabilities to change occupation for levels of RTI



Notes: Obtained from linear probability regression. Coefficients are unadjusted. Occupational mobility is measured as a change in three-digit ISCO codes with individuals reporting job change in the respective year as an additional criterion. See Decker et al. (2023) for more information on measurement. Shaded areas represent 95% confidence intervals.