The Role of Within-Occupation Task Changes in Wage Development

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Abstract

This paper examines how changes in task content condition occupational wage development over time, particularly the effects of working in routine-intensive jobs. Based on survey data from Germany, we document substantial heterogeneity in within-occupational changes in task content. Combining this evidence with administrative data on individual employment outcomes over a 25-year period, we find important heterogeneity in wage penalties amongst initially routine intensive jobs. While occupations that remain (relatively) routine intensive generate substantial wage penalties, occupations with a decreasing routine intensity experience stable or even increasing wages. These findings cannot be explained by composition or cohort effects. Our results imply that the intensive margin of employment plays an important role for the adjustment process to technological change.

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1. Introduction

The shift away from middle skill, routine intensive, jobs is a pervasive feature of structural change in the labour market over the past four decades. A large reduction in the employment shares of these jobs has been documented across a range of developed economies (Autor et al., 1998; Goos and Manning, 2007; Goos et al., 2009; Bachmann et al., 2019). These losses of routine work have implications for individual welfare. Routine task workers who lose jobs face welfare losses through the loss of firm specific human capital along with reductions in overall industry and economy wide demand for their skills. Along these lines, Cortes (2016) uses the PSID and demonstrates that the US wage premium associated with routine intensive occupations reduced by 17% over the period between 1972 and the mid-2000s. However, the existing literature does not consider the fact that occupations may evolve over time, enabling individual workers to adapt to technological change.

In this paper, we re-examine whether routine workers face worse labour market prospects, and in particular, suffer greater wage losses when compared to other workers. Our main contribution to the existing literature is that we explicitly take into account that task mixes within occupations are likely to change over time. The standard approach has been to use the initial task content of occupations to define a job as routine-intensive. This has advantages in terms of data requirements, ease of estimation, and interpretation. Yet, it misses an important component of the adaptation process to the de-routinization of work - within-occupation changes in task mixes. Our research builds on previous work which demonstrates large changes in task mixes within occupations over time in Germany and the US (Spitz-Oener, 2006; Bachmann et al., 2019; Atalay et al, 2020). Our main contribution is to demonstrate the consequences of these task changes for wage development. We do so using detailed task data for Germany matched with administrative wage data spanning 3 decades.

Specifically, we estimate the effect of exposure to different task mixes on wages for Germany for 1985 to 2010. Using combined social security data and survey data on occupational task mixes we go beyond estimates of, for instance, the effect of exposure to routinisation on wages, and decompose this according to within and across occupational changes in task mixes. We document large heterogeneity in within occupation task mix changes. For those jobs that are initially routine task intensive the magnitude of these within changes dwarf across-occupation task changes.

Our empirical strategy is based on the estimation of wage equations with person-occupation fixed effects. This approach controls for workers' time constant unobserved heterogeneity, which is allowed to vary across different types of occupations. We are mainly interested in the estimation of the time varying occupation specific wage components. If unobserved skills and their occupation specific returns are constant over time, this approach identifies yearly occupation-specific wage premia which are common to all workers in a specific occupation group (Cortes, 2016). However, a change in workers' unobserved skills and a changing task mix within an occupation might violate the assumption of time constant skills and their occupation specific returns. In this case, the estimated occupation specific wage component reflects both, the wage premia common to all workers, and the impact of the change in skills and their potentially changing return in an occupation group.

While previous work demonstrates marked wage penalties associated with routine work for the US and no routinisation penalty for Germany (Cortes, 2016; Wang, 2020), we present large heterogeneity in the development of wages of initially routine jobs that reflects changes in within-occupation task mix. Occupations that remain (relatively) routine intensive over time generate substantial wage penalties. Yet, as we show, a range of initially routine occupations that changed task mix over time and became more intensive in non-routine cognitive tasks, are instead associated with substantial wage increases. These increases are comparable in magnitude to those experienced by workers who perform primarily non-routine cognitive tasks, and lead to sizeable differences in wage growth amongst initially routine task-intensive occupations. If task changes within occupations are not taken into account, the growth in occupation-specific wage components would be understated by up to 16 percentage points for those routine occupations with a growing importance of non-routine cognitive tasks and overstate the growth in occupation-specific wage components by up to 10.9 percentage points for routine occupations with relatively constant non-routine cognitive task intensity. This heterogeneity in wage development amongst routine workers has not been documented in the previous literature. It is, however, consistent with evidence for the US by Deming and Noray (2020) who show for the time period 2007-2019 that faster-changing occupations display lower returns to experience.

This novel fact raises a range of additional questions regarding the source of these differences. As an initial step, we rule out a range of potential explanations. For instance, we demonstrate that this does not reflect the occupation specific changes in worker composition that have been shown to be important features of the routinisation process (Böhm et al., 2019). We also demonstrate that it does not simply reflect cohort effects.

This leaves the question of which factors, in addition to changes in task mix, have changed in these specific jobs in a way that increases worker productivity, and through this, wages. We explore one likely factor, receipt of training. It seems probable that worker skills must evolve along with the changing nature of the job. We demonstrate that those initially routine intensive jobs that changed in task mix to become more demanding of cognitive tasks are associated with greater training receipt. This paints a picture of a group of occupations that changed markedly in nature, and where workers through training were able to avoid wage penalties associated with routinisation.

Finally, we provide descriptive evidence based on those workers who change their task group. First, we find that workers who switch from routine occupations to occupations with non-routine cognitive tasks experience a higher wage growth than those who stay in routine occupations, and we observe a similar pattern for workers switching from routine occupations to initially routine occupations experiencing an increase in non-routine cognitive tasks. Second, we observe that workers in initially routine occupations who experience an increase in non-routine cognitive tasks have a relatively high probability to switch to occupations with non-routine cognitive tasks, and vice versa. This suggests that these occupations are relatively close to each other in terms of human capital transferability.

Taken together our results provide a more nuanced view of the wage and welfare consequences of exposure to routinisation than has been presented before, stressing the role of changing occupations and worker adaptability to technological change. Our results also offer a potential explanation for conflicting results from the literature that during the last decades, routine workers have experienced declining wage premia in the US but not in Germany.

The paper proceeds as follows. Section 2 introduces the datasets that allow us to follow workers over time as well as to capture the changing task content of occupations and presents approach to measuring task content along with the definition of the sample. Section 3 describes the econometric approach. Section 4 presents the main results, provides robustness checks and evidence on mechanisms, and analyses the role of job training. Section 5 concludes.

2. Data

Our analysis is based on the Sample of Integrated Labour Market Biographies (SIAB). The SIAB is a representative 2 percent random sample from the Integrated Employment Biographies (IEB) which covers the universe of individuals in Germany in employment subject to social security contributions or with registered unemployment spells (Dauth and Eppelsheimer, 2020 and Frodermann et al., 2021). Civil servants and self-employed workers are not included in the data. The data contain individual information such as age, gender, nationality, education, and place of residence, as well as job information such as the daily wage and the occupation. We combine these worker-level data with the Establishment History Panel (BHP) containing information on the industry of the establishment.

We match the SIAB to survey data that provides information on occupational task intensities. Specifically, we use the BIBB/IAB and BIBB/BAuA Employment Surveys (herein BIBB data) that provide a representative sample of German employees working at least 10 hours per week (BIBB 2021). The BIBB data consists of repeated cross-sections on approximately 20,000 to 30,000 employees in Germany for each survey wave that we use in this paper (1985-6, 1991-2, 1998-9, 2006).

We use the information on the job tasks performed by a worker to compute individual level task intensities, imposing the same sample restrictions as for the SIAB data. We follow the approach of Antonczyk, Fitzenberger and Leuschner (2009) and categorize the activities employees perform at the workplace into routine (R), non-routine manual (NRM) and non-routine cognitive (NRC). These individual level task intensities are calculated as follows

$$Task_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in cross section } t}{\text{total number of activities performed by } i \text{ over all categories at time } t} \qquad (1)$$

where t= 1985-6, 1991-2, 1998-9 and 2006 and j indicates routine (R), non-routine manual (NRM), and non-routine cognitive (NRC) tasks, respectively. Using the occupation field classification in Tiemann et al. (2008), we aggregate these individual task intensities for 53 occupation fields. The shares of task intensities for each occupation-time period combination sum to 100 percent. As a result, these measures provide a continuous measure of routine task intensity (RTI), non-routine manual task intensity (NRMTI), and non-routine cognitive task intensity (NRCTI) over time for a given occupational group. We merge the task intensity measures to the worker-level SIAB data based on occupation and year combinations. Together this allows us to create time-varying task intensities by occupational group.

Before 1985 the wage variable in the SIAB does not include bonus payments but does so afterwards. This results in large inconsistencies in measured wages across these periods and as a result we restrict our observation period to start from 1985. While the occupational classification data in the SIAB is consistent until 2010, as highlighted by Böhm et al. (2019), there is a change in occupational classifications from 2011 onwards. Critically for our purposes, there is no approach available that allows for consistent classification of occupations before and after this change. Consequently, we only use data until 2010. The SIAB data includes no information on working hours, however it allows us to distinguish between full-time and part-time workers. We focus on full-time workers as this increases the comparability of daily wage rates. Wages are top-coded at the social security contribution limit. We deal with this issue by imputing censored wages following the imputation procedures outlined in Gartner (2005), Dustmann et al. (2009) and Card et al. (2013). We convert gross daily wages into real daily wages by using the consumer price index of the Federal Statistical Office. We create a yearly panel and select all employment spells that include June 30th as the cutoff date.

We exclude observations for East German workers who were registered in the data only from 1992 onwards. We further exclude apprentices, trainees, homeworkers, and individuals older than 65. Additionally, we restrict our analysis to male workers to avoid selectivity issues regarding female labour force participation and corresponding changes over time.[1]

We use, and contrast, two approaches to estimating the effect of job tasks on occupation specific wage components over time. First, we use a *fixed group definition* of task groups. Specifically, we define occupation fields as routine if the RTI of that occupation field is in the highest tercile of the employment weighted RTI distribution in 1985. We classify the remaining occupation fields as NRM (NRC) occupations if the NRMTI (NRCTI) of an occupation field in 1985 is higher than its NRCTI (NRMTI) in 1985.[2]

Next, we exploit the time variation in task intensities in the BIBB data to generate our *dynamic group definition* of task groups. Specifically, we use the routine task category from the *fixed group definition* and split it into three subcategories by using the time variation in NRCTI. To do so, for each occupation field in the routine task category we calculate the difference in NRCTI from the first to the last BIBB wave that we use ($NRCTI_{2006-1985} = NRCTI_{2006} - NRCTI_{1985}$). The routine occupation fields which are in the highest tercile of the 1985 employment weighted $NRCTI_{2006-1985}$ distribution are then classified as routine – Δ NRC high, those in the middle tercile as routine – Δ NRC middle and those in the lowest tercile as routine – Δ NRC low.

Table A 1 presents descriptive statistics using the *fixed group definition* of task groups. The NRM task group has the highest share in our sample. The routine and NRC task groups have similar shares. In line with other studies examining task and labour market polarization (see e.g., Autor and Dorn, 2013), NRC workers are at the top, routine workers in the middle and NRM workers at the end of the wage and skill distribution. The average job tenure is highest for routine workers and much lower for NRM workers who also have on average lower full-time labour market experience compared to the other task groups. Routine workers are more likely to work in the manufacturing industry compared to the other task groups. Table A 2 uses the *dynamic group definition* of task groups in which we split the routine task group into three subgroups: routine – Δ NRC high, routine – Δ NRC middle and routine – Δ NRC low. For the whole observation period, workers in the routine – Δ NRC high task category earn on average more and are better educated compared to the other routine subgroups. Workers in routine – Δ NRC middle and routine – Δ NRC low are more likely to work in the manufacturing industry.

[1] Individuals can hold more than one job in the data. We keep the main job, defined as the job with the highest daily wage or, in case of a tie, the spell with the longest tenure.

[2] As an alternative version of this approach, we classify 3-digit occupations into three task groups based on the approach in Acemoglu and Autor (2011) and Cortes (2016): (1) Routine: administrative support, operatives, maintenance and repair occupations, production and transportation occupations (among others); (2) Non-Routine Cognitive (NRC): professional, technical management, business and financial occupations; (3) Non-Routine Manual (NRM): service workers. These task groups are rather broad and fixed over time. However, this classification allows comparisons with the US literature on the evolution of wage premia over time (Cortes 2016).

3. Estimation Approach

Our starting point follows the empirical approach outlined in Cortes (2016) which in turn builds on the theoretical model of Jung and Mercenier (2014). The main aim of this approach is to retrieve occupational wage premia over time.

Consider 3 occupations: routine (R), nonroutine manual (NRM) and nonroutine cognitive (NRC). Workers receive a potential wage which is equal to:

$$w_j(z) = \lambda_j \varphi_j(z)\ , j\ \epsilon\ \{R.NRM, NRC\} \tag{2}$$

Where λ_j is the wage per efficiency unit in that occupation and $\varphi_j(z)$ is the productivity of a worker of skill *z* performing task $j\ \epsilon\ \{R, NRM, NRC\}$.

Workers sort into tasks in the following way: High skilled workers are more productive at all tasks but have a comparative advantage in more complex tasks. Nonroutine cognitive tasks are assumed to be the most complex and nonroutine manual tasks the least complex. More formally:

$$0 < \frac{d\varphi_{NRM}(z)}{dz} < \frac{d\varphi_R(z)}{dz} < \frac{d\varphi_{NRC}(z)}{dz}$$

Consider, as an example $\lambda_{NRC} = \lambda_R = \lambda_{NRM}$, meaning that the wages per efficiency unit are the same for all three tasks. In this case, all workers would sort into the nonroutine cognitive occupation where they are most productive and receive the highest wage. However, in equilibrium, λ_{NRC} is relatively low, while λ_{NRM} is relatively high, with λ_R in the middle. The low λ_{NRC} makes it optimal only for the most skilled workers to select into the nonroutine cognitive occupation, while the high λ_{NRM} attracts the least skilled workers to the nonroutine manual occupation, as their productivity in the other tasks is relatively small.

In logs the wage can be expressed as:

$$\ln w_j(z) = \ln \lambda_j + \ln \varphi_j(z)\,. \tag{3}$$

An intuitive way to think about the productivity term is:

$$\ln \varphi_j(z_i) = z_i a_j. \tag{4}$$

Hence, the individual's occupation-specific productivity $\varphi_j(z_i)$ consists of individual's ability or skill z_i and occupation-specific return to skills a_j. Assuming that z_i and a_j are time constant while the wage premia might change, we can express the log wage of individual *i* in period *t* in the following way:

$$\ln w_{ijt} = \theta_{jt} + z_i a_j, \tag{5}$$

where $\theta_{jt} \equiv \ln \lambda_{jt}$ is the occupation wage premium in occupation *j* in year *t*. Intuitively, NRC occupations have a relatively low level of occupation wage premium, but a high level of occupation-specific return to skills. Therefore, workers with a high skill level are better off in NRC occupations, as their high skills have a higher reward in those occupations. On the other hand, nonroutine manual occupations have a relatively high level of occupation wage premium, but low occupation-specific returns to skills ($a_{NRM} < a_{NRM} < a_{NRM}$). Thus, for highly skilled workers, it is not rational to sort into nonroutine manual occupations, because the returns to skills are low there.

With routine-biased technical change (RBTC), and a skill level such that it is not optimal for a worker to switch, wages will fall for routine workers as θ_{jt} declines due to RBTC. Automation technology substitutes routine workers and complements NRC workers. Due to demand factors, routine workers loose wages and NRC workers gain. Thus, while $z_i a_j$ stays fixed over time, θ_{jt} does not. The prediction is that θ_{jt} will fall for routine jobs once we account for the selection mechanisms described above.

The assumption that z_i and a_j are time constant may not hold. For example, z_i might change over time if workers invest in their human capital through training. While a_j may change if the task mix in occupation *j* changes over time. An increase in the occupation-specific return to skills a_j for initially routine jobs – for example due to a change in the task mix to more non-routine cognitive tasks – would imply a less negative or even a positive impact of RBTC on the evolvement of θ_{jt} over time.

We use the following empirical specification as in Cortes (2016):

$$\ln w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}\gamma_{ij} + Z_{it}\zeta + u_{it} \,. \tag{6}$$

The dependent variable is the log wage of worker *i* at year *t*. θ_{jt} is the occupation specific wage component in occupation *j* in year *t*. We capture the occupation specific wage component by using occupation-year dummies. The reference task group is non-routine manual (NRM). D_{ijt} is an occupation indicator that equals one if individual *i* works in occupation *j* at year *t* and is zero otherwise. γ_{ij} is composed of an individual's time-invariant skills and the occupation-specific returns to those skills. It varies for an individual across occupations, but it stays constant whenever the individual stays in the same occupation. We estimate γ_{ij} by using person-occupation fixed effects. Z_{it} includes the region type, federal state dummies, sector dummies, a dummy for nationality and year dummies.

In our empirical specification, we control for occupation-individual fixed effects, which capture time constant unobserved heterogeneity. This implies that a change in occupation-specific skill returns or individual human capital over the time being employed in a specific occupation, for example due to technological changes or work-orientated training, will contribute to our estimate of θ_{jt}. In other words, estimates $\hat{\theta}_{jt}$ based on this approach will reflect occupation wage premia *and* changes in individuals' occupation-specific productivity over time if occupation-specific productivity is not constant over time. We therefore interpret our results as reflecting occupation-specific wage changes which go beyond occupation-specific wage premia in the strict sense.

As discussed above, workers sort into occupations based on their skills and the occupation-specific returns to those skills. By using person-occupation fixed effects, we aim to eliminate a bias that arises from different types of workers selecting into occupations that benefit them (positive selection). Specifically, occupation specific wage components are identified from variation in wages for workers who have stayed within specific occupation groups over time. Any bias that arises from time-constant unobserved variation across persons, occupations or person-occupation combinations is eliminated with this approach. Therefore, this approach explicitly exploits the shocks to which workers who have stayed in their occupation group are exposed to. We use 1985 as our base year and the NRM task group as the reference category. Hence, the occupation-year dummies identify the changes over time relative to the base year and relative to the analogous change experienced by the NRM task group.

We estimate several variants of Equation 6 to explore potential heterogeneity in the development of occupations over time. To achieve this, we use the different classifications described in Section 2. First, we estimate Equation 6 by using our *fixed group definition*. This approach classifies occupations into routine, NRM and NRC task groups according to their initial task intensities.

Second, we estimate Equation 6 by using our *dynamic group definition*. This approach aims to capture changes in the task composition of occupations over time. Intuitively, we follow Acemoglu and Autor (2011) and Acemoglu and Restrepo (2020) in understanding occupations as a bundle of tasks. Thus, each occupation consists of a share of tasks that is routine, NRM and NRC. The composition of tasks within occupations can change and adapt to changes in technology. For example, occupations in finance and accounting have experienced a strong decrease in their RTI between 1985 and 2006, which was mostly compensated by an increase in their NRCTI (see Table A 3). While workers in this occupation field mostly performed routine tasks initially, such as measuring, calculating and operating, this has changed to more NRC tasks such as investigating, consulting and organizing. We expect that routine occupations which experience an increase in their NRC task content over time also experience an increase in their occupation specific wage components. The reasoning goes as follows. As more automating technologies are used in these occupations which substitute for routine tasks, for some occupations the share of NRC tasks increases. This also has implications for the type of worker, or the skill level required for this job. Hence, next to a potential change in the return to skills a_j, the wage per efficiency unit λ_j increases for those occupations as the relative demand for NRC tasks increases.

A change in the task mix will change the occupation specific returns to skills, a_j, meaning that more skilled workers select and stay in those occupations over time. For occupations that continue to use a relatively high share of routine tasks, such as occupations in metal production and processing, the λ_j decreases as the relative demand for routine tasks decreases over time due to technological change. Specifically, we estimate the wage changes for the 5 task categories routine – Δ NRC high, routine – Δ NRC middle, routine – Δ NRC low, NRM and NRC. Again, we use the year 1985 and the NRM task category as base categories in our estimation.

4. Results

4.1 The Evolution of Task Wages

Figure 1 plots the annual evolution of occupation-specific wage components relative to non-routine manual jobs associated with working in a routine and non-routine cognitive job, respectively (see Table A 5 for details). It does so by fixing initial task mixes at 1985 such that NRC and routine jobs reflect those occupations that in 1985 were most intensive in those tasks. This displays the development of a much larger wage growth for non-routine cognitive work that by the late 2000s leads to a wage difference to non-routine manual work of 20%. This is consistent in general pattern and magnitude to that reported, for instance, for the US (Cortes 2016). This pattern, however, takes longer to develop, with substantial wage differences between task groups only becoming apparent in the mid to late 1990s. This is some 10 years after similar patterns for the US and fits with the suggestion in previous research that routinisation occurred later in continental Europe (Goos and Manning 2007).

One striking feature of Figure 1 is the complete absence of the deterioration in wages for German routine workers. While this contrasts with the quite marked wage penalties for these groups that have been demonstrated elsewhere, this pattern has been noted in other research for Germany using other data sources across shorter time periods (Wang 2020). Nonetheless, the lack of a wage penalty for routine workers in Germany, relative to non-routine manual jobs, remains a puzzle and runs against the general view of the impact of technological change on workers.[3]

INSERT FIGURE 1

An issue with fixing occupational tasks content at initial values is that it may miss important changes in task content within occupations over time that increasingly make the occupations within given task groups heterogeneous. For example, consider auxiliary office occupations such as secretaries and typists. These are jobs impacted strongly by routine biased technological change as they involved a set of tasks that were largely replaceable by algorithm. However, these occupations still exist, albeit with markedly different task mixes (see Table A 3 for examples of occupational groups with a strong change in task content over time). To explore this process, our next step is to utilise the strength of our task data to examine within occupational changes in task mix, and the implications of accounting for this on our understanding of the evolution of occupational wages over time.

Using the BIBB data, our initial descriptive step is to use our two end points in this data, 1985 and 2006, and decompose occupational changes in routine task intensity across this period. We perform a simple shift-share analysis of changes (decline in RTI) over time into that component explained by changes in employment shares of given occupations (between differences) and changes in the routine task intensity of given occupations (within differences). As shown in Table 1, within occupational changes in task mix dominate the overall decline in RTI over this period, comprising some 75% of total reductions in RTI. This highlights a key point, holding occupational employment shares constant at 1985 values, RTI of given occupations have changed substantially over this 21-year period. This suggests that technological change induced large shifts in the task content of occupations.

INSERT TABLE 1

Using this information, we return to estimating task group-wages over time where we now allow task content to vary over time. Our first step is to re-estimate Equation 6 separately for occupations which were intensive in routine tasks in 1985, but then evolved differently in terms of their task content over time. We thus use our dynamic group definition of task groups, in which we create sub-categories within the initially routine task jobs, those with very high increases in NRC, those with only small increases in NRC and those with very low increases or even decreases in NRC over the 21-year period. Figure 2 plots the evolution of wages for these disaggregated categories (see Table A 6 for details).

INSERT FIGURE 2

What is immediately clear is how dramatically the evolution of wages for routine task intensive workers is contingent on subsequent changes in within-job task content. In particular, the lack of any wage growth of routine task intensive workers relative to non-routine manual workers demonstrated earlier reflects two very different patterns. For those initially routine intensive occupations that do not experience increases in non-routine cognitive task content, we observe relative wage stagnation, and small wage increases or decreases contingent on the period. This broadly fits with previous evidence

[3] As a robustness check, we use a similar classification of task groups as in the US literature (see e.g. Cortes 2016, Acemoglu and Autor 2011) in Figure A 1 and find similar results as for our baseline specification.

across a range of settings, routine task intensive jobs are associated with wage stagnation and/or losses. However, this is simply not true for those jobs that increased in NRC content, and in fact these jobs are associated with marked increases in wages over time. These are only slightly smaller than those present for non-routine cognitive occupations over this period and often overlap.

The small difference in wage trends between R - Δ NRC middle and R - Δ NRC low occupations and the large gap with R - Δ NRC high occupations can most likely be attributed to the non-monotonic difference in the change in NRCTI between these task groups, as reported in Table A 3. While we observe a very large increase in NRCTI for R - Δ NRC high occupations, the change in NRCTI was similar for R - Δ NRC middle and R - Δ NRC low.

These findings indicate very different wage effects across jobs that initially had similar routine intensity, and it is quantitatively sizeable: over the time period under consideration, the wage growth of routine occupations with a growing importance of NRC tasks amounts to 10.3% (relative to NRM occupations) when using the fixed task group definition (Table A 5), but to 26.3% when using the dynamic task group definition, i.e. taking into account within-occupation changes in task intensity Table A 6). Not taking into account task changes within occupations, we would therefore understate the growth in the occupation-specific wage component by up to 16 percentage points. By contrast, we would overstate the wage growth for routine occupations with relatively constant non-routine cognitive task intensity by 10.9 percentage points, as a similar comparison makes clear.

4.2 Robustness

Naturally, these results raise questions regarding their robustness. First, is the observed change in task content likely to be driven by changes in worker composition? Second, can worker composition explain wage growth within task groups? Third, do workers with different occupational tenure, who are otherwise observationally equivalent, perform different job tasks, and do we therefore observe cohort effects for wages?

Regarding the first question, we analyze whether the change in task content of our task groups over time is driven by changing worker composition in terms of education or by changing task content within education groups. Specifically, using the BIBB data, we perform two decompositions of the change in mean NRC task content over time with education as the explanatory variable. The first decomposition compares the R - Δ NRC high and R - Δ NRC middle task groups, the second decomposition compares the R - Δ NRC high and R - Δ NRC low task groups.

We use the decomposition method of Smith and Welch (1989). This method allows us to decompose the difference in the change in mean NRCTI between two task groups over time. For example, the mean NRCTI of R - Δ NRC high workers increased by 0.133 more than the mean NRCTI of R - Δ NRC middle workers from 1985 to 2006 (see Table A 7). We can decompose this total change into four components: the main effect, i.e. the change in education groups within the task groups valued at base year 1985 in R - Δ NRC middle (or R - Δ NRC low); the group interaction, i.e. the change in education groups within R - Δ NRC high that is valued differently between task groups in base year 1985; the time interaction, i.e. the returns to education in R - Δ NRC middle (or R - Δ NRC low) given the education difference in 2006 between R - Δ NRC high vs. R - Δ NRC middle (or R - Δ NRC low); and the group-time interaction, i.e. the returns to education over time given the 2006 level in education of group R - Δ NRC high. If changing composition in terms of education within task groups explains the relative increase in mean NRCTI for R - Δ NRC high, we would find that the main effect of the decomposition dominates the total change.

The decomposition results show, however, that almost all the change in mean NRCTI for R - Δ NRC high can be explained by a change in returns to education. In other words, the increase in mean NRCTI within the R - Δ NRC high task group cannot be explained by an inflow of highly educated workers. Instead, highly educated workers do more NRC tasks within the R - Δ NRC high task group. In Section 4.4, we present suggestive evidence that more job training for R - Δ NRC high is a likely driver of increasing NRC task content over time.

Regarding the second question on whether worker composition can explain wage growth within task groups, it is worth recalling that our estimates come from variation within person *x* occupation cells such that they should not reflect returns to an individuals' time-invariant skill level or occupation-specific returns to skill. However, as reported in Table A 4, there are initial differences in both the composition of these jobs and the workers in these occupations. Most notably, there are differences in terms of industry structure (those occupations where NRC did not increase are disproportionately in the manufacturing industry), and differences in terms of the educational profiles of the workers (those occupations where NRC did increase have a markedly larger share of workers with university level education). There are few if any other differences. Our approach to exploring this uses more homogeneous workers groups (in terms of observables) while maintaining sufficient sample sizes. We do this by re-estimating our main models first (a) only including manufacturing industry workers and then separately (b) excluding all workers with university education.

The resultant estimates are reported in two panels as Figure A 2. As can be seen, the reported patterns of occupation-specific wage growth essentially match those for our main results. This provides supportive evidence that the differential patterns in the evolution of routine worker wages we present do not simply reflect observable differences across these occupations.

As noted in Section 3, we assume that changes in occupation-specific skill returns stay constant over time or that any changes in occupation-specific skill returns do not affect our estimates. One approach to relaxing this assumption is to allow changes in *observable* occupation-specific skills to vary over time. To do so, we follow Cortes (2016) in assuming that the time variation in the return to education is the same for all occupations and additionally include education *x* year fixed effects in our baseline estimation Equation (6). We report the results in Figure A 3 and find very similar results compared to our baseline estimation in Figure 2. Thus, these results provide supportive evidence that observable returns to skills are not driving our results.

The third question is whether workers with low occupational tenure do not, in practice, conduct the same average task mix as workers with higher tenure they are joining or replacing, and whether this is an important determinant of wage growth. Examining this is equivalent to asking whether our main result that task change within occupations is a key determinant of wage growth is driven by age and/or cohort effects. For example, one may suspect that young workers are best able to reap the benefits of technological change, whereas older workers have difficulties adapting and are therefore particularly vulnerable to technological change. In this case, one would observe strongly differing wage growth of task groups between young and older workers, with young NRC workers displaying the highest, older R–NRC low workers the lowest wage growth. Furthermore, looking at different cohorts allows us to examine whether our results are driven by specific time periods where technological change may have had a particularly strong effect on workers.

We therefore analyse the wage growth of workers in different task groups by age group and start year. We separately estimate the wage growth for young workers (age 25-34) and older workers (age 35-50) who in a specific year t (1985, 1990, 1995, 2000) were in one of the task groups R- Δ NRC high, R - Δ NRC middle, R - Δ NRC low or NRC occupations.[4] We estimate a regression with wage growth from t to t+1, t+2, t+4 or t+10 as the dependent variable and dummies for being in one of the task groups as independent variables with NRM as the reference category.

The results of our wage growth regressions by age and start year are displayed in Figure 3. Two features become apparent. First, for young and older workers, we observe two task groups with increasing wage growth over time (R- Δ NRC high and NRC), and two task groups with decreasing wage growth over time (R- Δ NRC low and R- Δ NRC middle), where the reference group are NRM workers. Second, this first feature is observable for all start years, and it is quantitatively similar across start years.

Thus, in line with Figure 2, wages grow over time for occupations with higher NRC task content. Most importantly, wage growth in these occupations is not driven by young workers who start those jobs and do something different than older workers, but rather by higher wage growth in R – Δ NRC high and NRC occupations for all workers across all years. This result is in line with the additional observation that average task intensities for young and older workers are very similar (Table A 8), i.e. that young and older workers perform roughly the same tasks within any given task group. Therefore, the higher wage growth of younger workers in Figure 3 is unlikely to reflect differences in job task between young and older workers. Instead, job ladder effects, which are more important early in the life cycle, are a more likely explanation.

INSERT FIGURE 3

4.3 Wage changes and selection of workers who switch task groups

Our main results come from regressions in which we control for selection into task groups using worker x occupation fixed effects (see Equation (6)). Here, we provide descriptive evidence on the consequences on wage growth of switching between task groups. Our working hypothesis is that switching out of occupations with falling labour demand, R- Δ NRC low and R- Δ NRC middle, to occupations with growing labour demand, NRC or R- Δ NRC high is associated with subsequent positive wage growth. By contrast, switching out of R- Δ NRC high or NRC is expected to be associated with subsequent negative wage growth unless workers switch to either NRC or R-NRC high.

This leads us to analyse the wage growth of workers who in year t were in one of these five task groups and switched to another task group in year t+1. To do so, we regress wage growth from year t to year t+1, t+2, t+4 and t+10 on dummy variables which indicate whether a worker has switched out of his original task group to another specific task group. The regression therefore yields the wage growth in year t+1, t+2, t+4 or t+10, conditional on switching from one task group to another, and relative to staying in the original task group. In the regression, we include as control variables dummies for the year, region type, federal state, 1-digit industry, nationality (German vs. non-German), age group (18-25, 26-35, 36-45, 46-55, 56-65) and three skill group dummies (no vocational training, vocational training, university, or university of applied sciences).

[4] Note that „start year“ denotes the year where we start analysing these workers, not the year where they start a job or enter a task group.

The analysis of task group switches yields several insights (Figure 4). First, in line with our working hypothesis, switching out of one's task group to NRC occupations is always associated with positive subsequent wage growth. Second, switching out of ones' task group to R- Δ NRC high is also associated with positive wage growth. This effect even increases over time and is therefore most pronounced for long periods (t+10). Third, switching out of R- Δ NRC high to the other routine occupations is associated with negative wage growth over the long time horizon for the time period 1985-1995 and immediate wage decline even in the short time horizon (t+1) for the later time period 1996-2010. A similar pattern is observable for the NRC task group. Thus, over time it becomes more and more profitable to stay in the R- Δ NRC high (NRC) occupations rather than switching out of it, unless a switch to NRC (R- Δ NRC high) occupations occurs.

INSERT FIGURE 4

Switching between task groups does not occur at random. Instead, workers purposefully select into task groups (Böhm et al. 2019), and this has important consequences for wage development (Gathmann and Schönberg, 2010). We therefore investigate in more detail which workers switch to which task group, and whether this selection into task groups has changed over time. We are particularly interested which workers switch to NRC or R- Δ NRC high and therefore experience wage gains.

In our analysis, we focus on unobservable skills which we proxy with workers' ability quintile. More specifically, we follow Cortes (2016) and use the predicted occupation spell fixed effects ($\hat{\gamma}_{ij}$) from Equation 6, i.e. the estimation equation for Figure 2. As γ_{ij} in Equation 6 is monotonically increasing in underlying ability z, we refer to the quintiles of the estimated occupation spell fixed effects as ability quintiles (see Section 3). To construct ability quintiles, we rank workers according to their position in the ability distribution of the estimated occupation spell fixed effects for a given task group and for each year separately. To capture changes over time, we perform the estimation of switching probabilities for two time periods, 1985-98 and 1999-2010.

The results of this exercise are displayed in Figure 5 and can be summarized as follows. First, workers with higher ability have a higher likelihood of switching to NRC, workers with lower ability have a higher likelihood of switching to NRM. Second, workers in R- Δ NRC high across all ability quintiles have a relatively high probability of switching to NRC occupations, this likelihood becomes higher with higher ability. In the initial time period (1985-98) workers in the lowest ability quintiles of R- Δ NRC high workers have the highest likelihood of switching to NRM. This changes over time as even R- Δ NRC high workers with lower ability in 1999-2010 have a higher likelihood of switching to NRC and lower likelihood of switching to NRM. Third, the probability that R- Δ NRC middle and R- Δ NRC low stay within their task group increases over time (only implicit in the graph). Other than this, the switching patterns do not change much over time for R- Δ NRC middle and R- Δ NRC low occupations. Fourth, there is a high likelihood of switching into NRM occupations, which likely reflects the large size of this task group (see Table A 3). Fifth, despite the small size of the R- Δ NRC high task group, NRC workers have a relatively high probability of moving into this task group.

INSERT FIGURE 5

Our results imply that R- Δ NRC high and NRC occupations are relatively close in terms of human capital transferability. If workers in R- Δ NRC high occupations switch, they are more likely to switch to NRC, and vice-versa for NRC workers. This pattern is stronger for workers with higher ability. R- Δ NRC middle, R- Δ NRC low and NRM occupations are also relatively close to each other in terms of human capital transferability. Thus, these results are in line with our other findings: NRC and R- Δ NRC high occupations feature high wage growth and attract workers with better skills and ability; workers in R- Δ NRC middle, R- Δ NRC low and NRM occupations feature relatively low wage growth and attract workers with lower skills and ability.

4.4 The role of training

To this point, we have demonstrated robust differences in the occupation-specific wage component attached to initially routine intensive occupations that are a function of the evolution of the task mix of these occupations over time. If, as we contend, there is wage growth in routine jobs that increased markedly in their NRC content, a natural question is what happened to the skills of workers in these jobs. To examine this, we explore the role of job training in occupation task mix changes over time.[5] Specifically, if the change in task mixes for initially routine intensive occupations is a process of individual adaptation to the new task environment rather than a change in the workforce composition, this should also be reflected in the likelihood of on-the-job training over time. In terms of our task groups, we hypothesize that the share of workers participating in job training has distinctively increased over time for R-NRC high occupations relative to the other routine occupations.

To test this hypothesis, we use an additional data source, the German Socio-Economic Panel (SOEP). The SOEP is a representative longitudinal data set of private households in Germany which includes information regarding on-the-job training over time.[6] In Figure 6, we illustrate the shares of workers in training courses financed by the employer over time and for each task group. The following features become apparent.[7] First, NRC workers have relatively high shares of training participation which remains relatively stable over time. Second, the share of training participation for R- Δ NRC high workers increased strongly from 1989 to 2000 and decreases in 2004 and 2008. In particular, the share of R – Δ NRC high workers in training financed by the employer increased abruptly from 1989 to 1993 (from 9.5 percent to 23.4 percent). Third, training participation for the other two routine task groups (R – Δ NRC middle and R – Δ NRC low) increased steadily over time, however not as strongly and abruptly as for the R – Δ NRC high task group. Fourth, training participation of the NRM task group also increased steadily over time with a stronger increase from 2004 to 2008. Together, these results suggest that employers and workers adapted to changing tasks by increasing training participation in a manner that was particularly pronounced for workers in R – Δ NRC high occupations. In particular, we observe a sharp increase in training participation for the R – Δ NRC high occupation in the 1990s, when the decline in routine tasks and the increase in more complex tasks were most pronounced (see Table 1).

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[5] Other papers studying the relation of job tasks and job training include e.g. Görlitz and Tamm (2016a), Görlitz and Tamm (2016b), Mohr et al. (2016), Tamm (2018), Feng and Graetz (2020), and Lukowski et al. (2021).

[6] Specifically, the SOEP asked in the years 1989, 1993, 2000, 2004 and 2008: „How many professional development courses or classes have you taken in the last three years?" The SOEP also asks respondents when these courses started, how long they took, whether the courses took place during working time, who organized these courses and who financed these courses. We only focus on courses which took place in the interview year or the year before. We classify courses as "financed by employer" if the course took place during working time or was organized by the employer or financed by the employer. More information on the SOEP can be found in Goebel et al. (2019).

[7] In Figure A 4, we illustrate the shares in any type of training course. In general, most training course, conditional on employment, are in some way financed by the employer.

INSERT FIGURE 6

The raw changes in training participation in Figure 6 could be driven by compositional changes within the task groups over time. To check whether these results still hold once we control for observable characteristics, we estimated, by pooled linear probability models, the relationship between our task group dummies and training financed by the employer, respectively. In doing so we control for age, education, marital status, migration background, federal state, industry, firm size, and year dummies.

Table A 9 illustrates the results using the NRM task group as reference category. We find a statistically insignificant positive coefficient for R – Δ NRC high workers and negative statistically significant coefficients for R – NRC middle and R – Δ NRC low workers. Furthermore, we find that the coefficients between R – NRC high workers vs. R – Δ NRC middle and R – Δ NRC high vs. R – Δ NRC low are statistically different from each other.[8] NRC workers have a statistically significant positive coefficient on training participation. Overall, we conclude that our main results in Figure 6 still hold once we control for observable characteristics. Specifically, R – Δ NRC high workers participate significantly more in training compared to the other routine task groups which experienced smaller changes in their task intensities.

5. Conclusion

There have been dramatic changes in the nature of job tasks over the past decades. A focus has been on how the workers in routine jobs, most readily replaced by computing, have suffered wage losses over this period. We provide evidence on the importance of an adaptation process at the intensive margin of employment: changes of within-occupational task mixes over time, which we are able to analyse using unique data for Germany. Looking at a 25-year period, we show that many initially routine intensive occupations have changed markedly in terms of their task mix. This has substantive implications for our understanding of the effect of routinisation on the welfare outcomes of workers.

We demonstrate that how these occupations changed over time has important consequences for the evolution of wages, and that only those jobs that remain routine task intensive over this period are associated with wage losses or stagnation. By contrast, jobs that increase the content of non-routine cognitive tasks feature significant wage gains. These effects are quantitatively sizeable. For example, initially routine occupations with a strong increase in non-routine cognitive task content over our 25-year observation period experience wage growth nearly 27 percentage points higher than initially routine occupations with relatively constant non-routine cognitive task content. These results do not appear to reflect factors such as worker composition or cohort effects within occupations. We also provide evidence that on-the-job training is a likely driver of these wage effects.

Our results have a number of implications. First, some occupations that are considered initially rather inefficient can adapt over time by changing their production technology. This means that the intensive margin of employment plays an important role for the adaptation process to technological change: workers may be better off staying in an occupation rather than switching to another one, even as technological progress continues or becomes more intensive, e.g. with the growing importance of artificial intelligence. Second, the importance of adaptability within a given occupation highlights the

[8] The coefficients of R – Δ NRC middle and R – Δ NRC low are also statistically different from each other. This difference is entirely driven by two occupation fields within the R – NRC low task group: "Occupations in mechanics and tool making" and "Precision engineering and related occupations".

relevance of a good education system, and particularly the relevance of lifelong learning and on-the-job training. This means that workers, firms, and policy makers should devote even more attention to this part of the education system. Third, our results indicate that accounting for within-occupation task change is crucial for understanding the wage effects of technological change. In particular, differences in the evolution of the task content of occupations could explain why during the last decades, routine workers have experienced a relative decline in wages in the US but not in Germany. This conjecture is left for further research.

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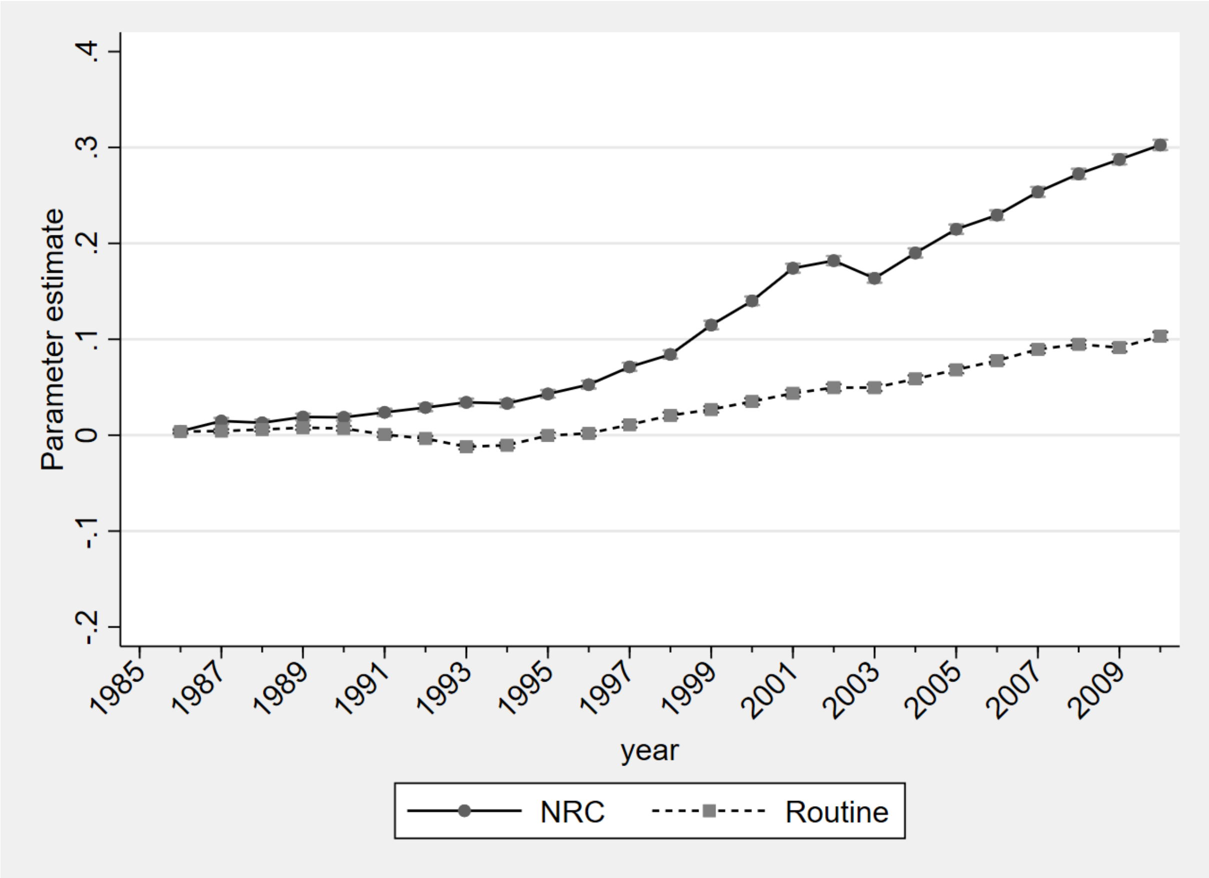
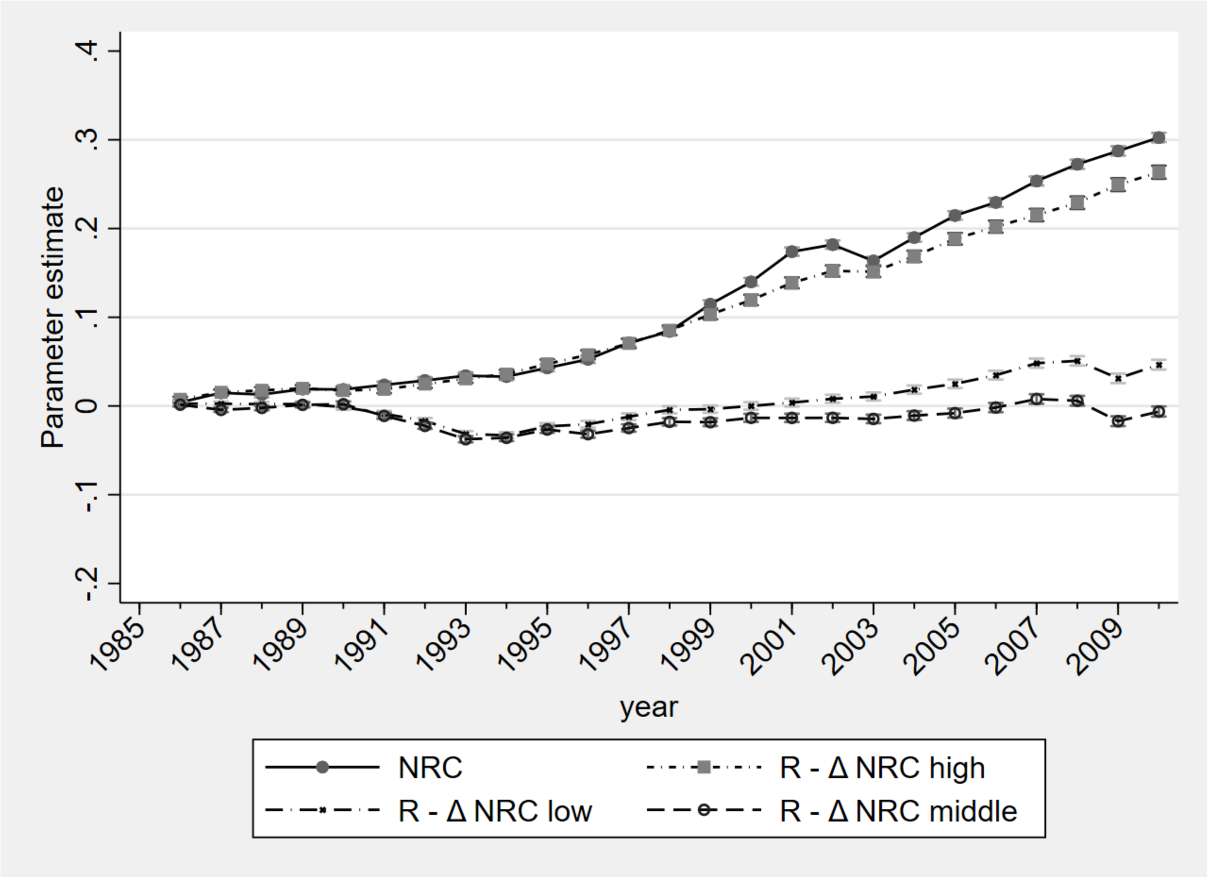
Figures and Tables

Figure 1 Task-group specific wages over time (fixed task groups using BIBB 1985 data)



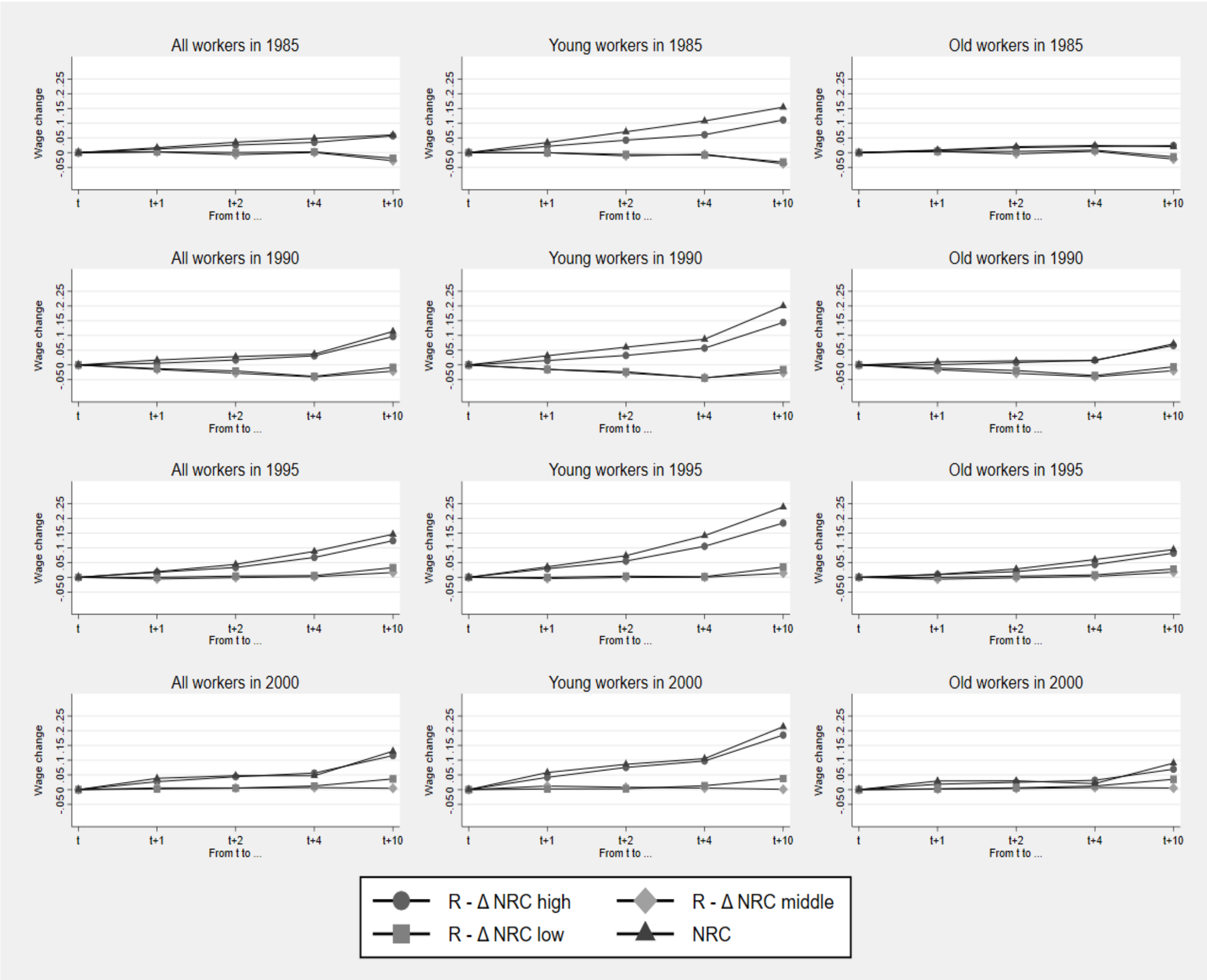
Notes: NRC: non-routine cognitive occupations. Reference category: NRM = non-routine manual occupations.

Figure 2 **Task-group specific wages over time (routine subgroups by change in NRCTI between 1985 and 2006)**



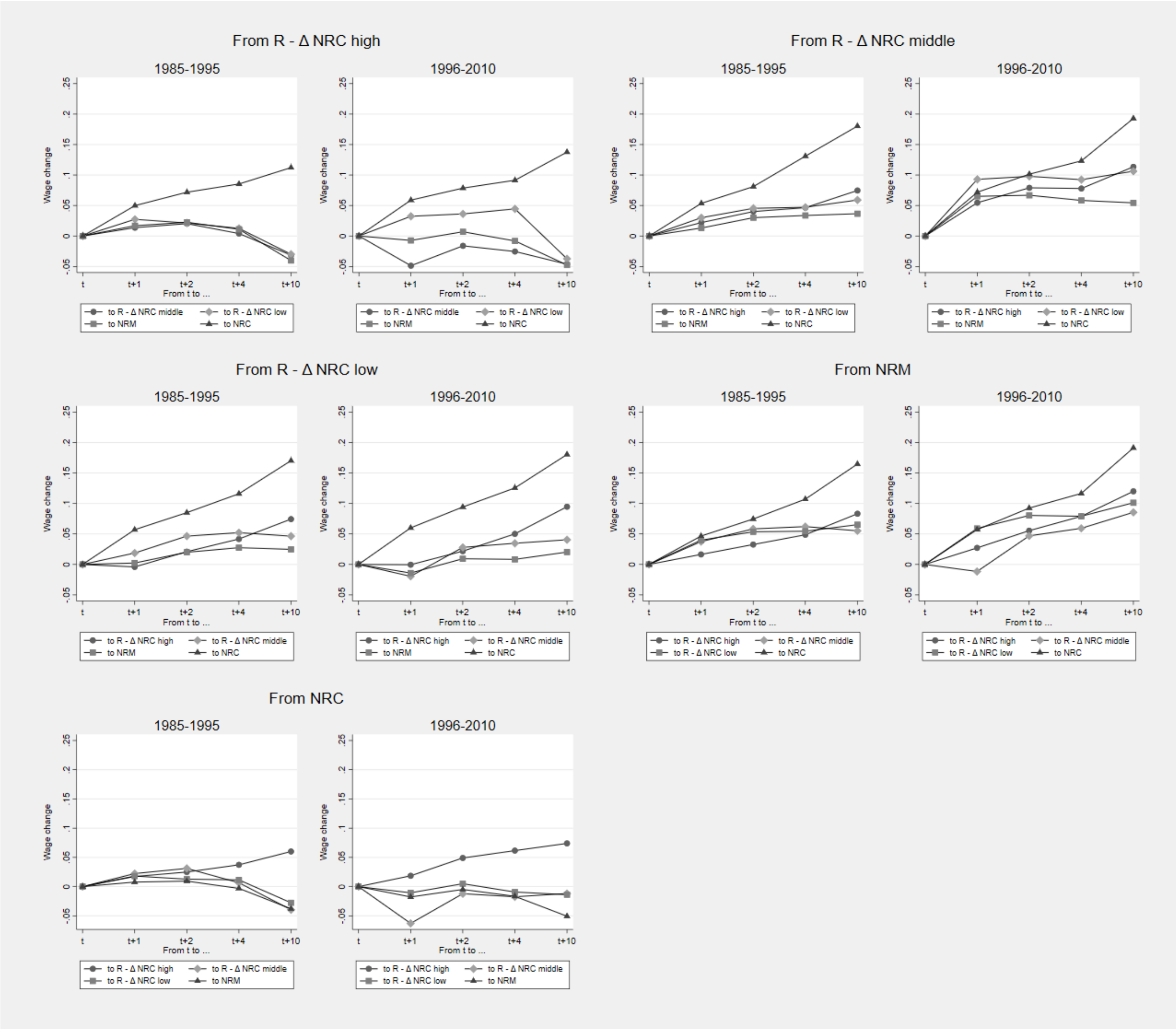
Notes: This figure shows the task-group specific wage component over time for occupations which were routine or non-routine cognitive in 1985 (according to the BIBB data). Additionally, the routine task group is divided into three further subgroups by change in NRCTI over time: Routine – Δ NRC high, Routine – Δ NRC middle and Routine – Δ NRC low. Reference category= NRM.

Figure 3 Wage Growth by Age and Cohort



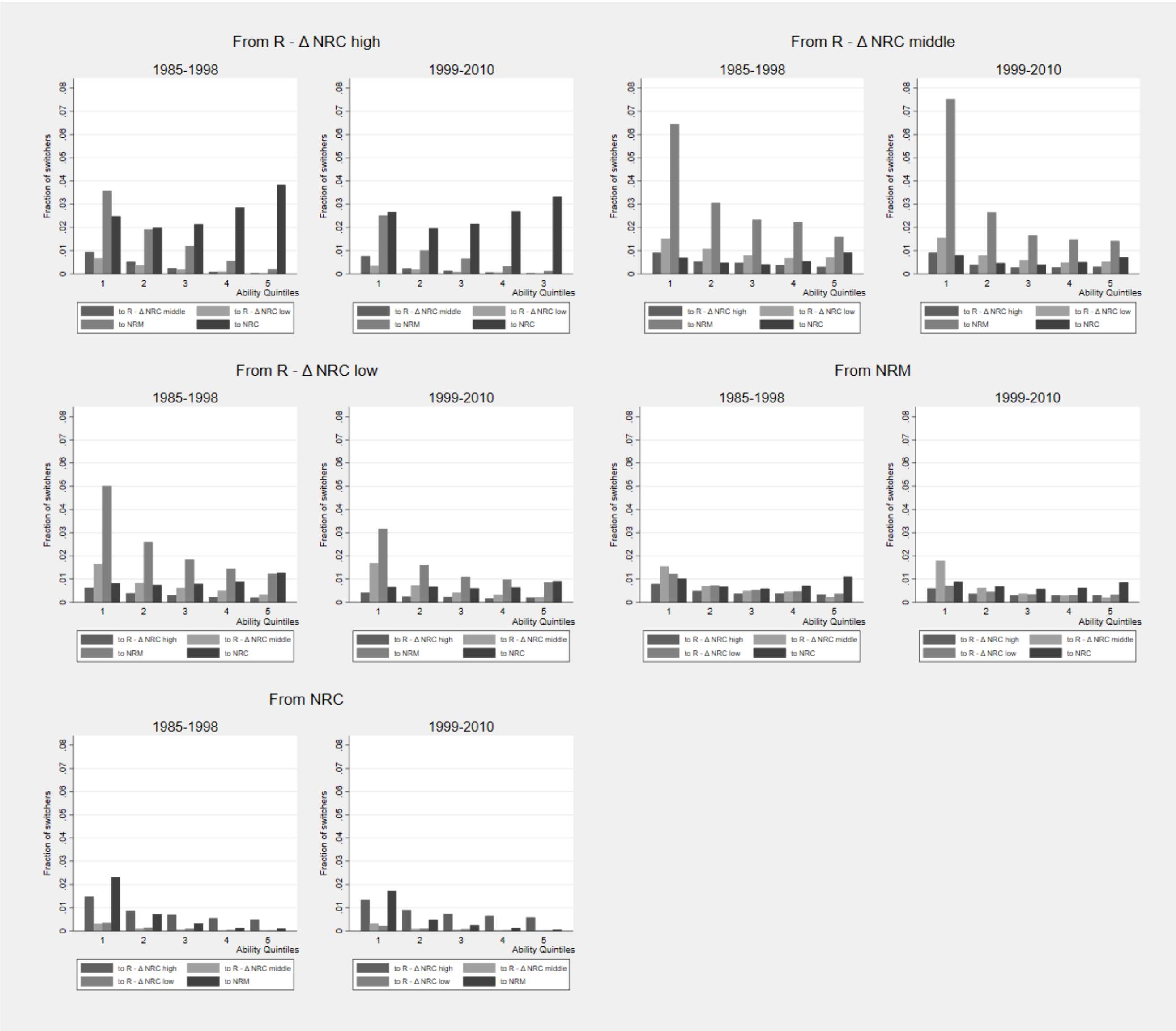
Notes: This figure shows the wage growth for different task groups over time and for young workers (25-34 years) vs. older workers (35-50 years). We subsample different years and regress wage growth on workers who in starting year t were in one of the task groups. Reference category: NRM.

Figure 4 Wage Growth by Task Group Switchers



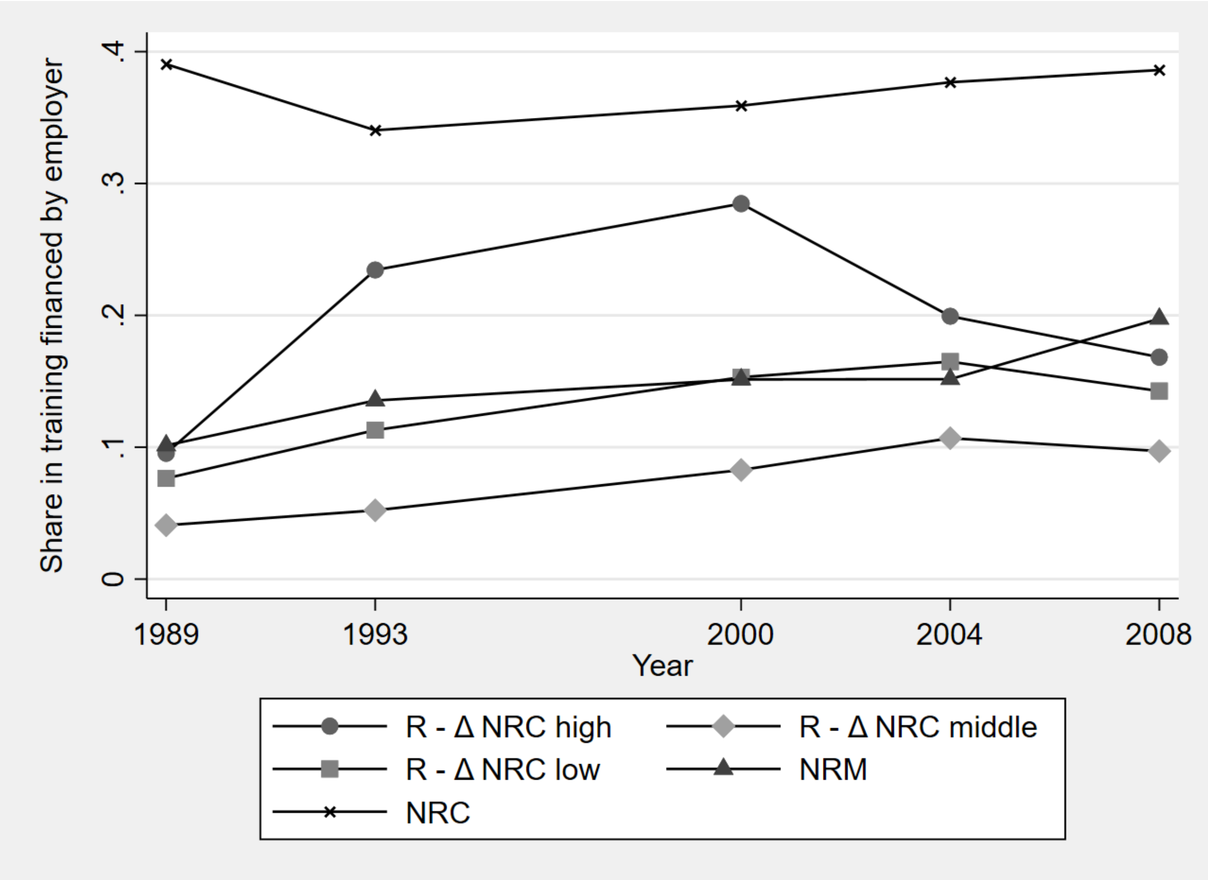
Notes: This figure shows the wage growth over time for workers who switch out of their task group from t to t+1. Workers who stay in their respective task group are the omitted category. The wage changes are taken over the horizons 1985-1995 and 1996-2010. All regressions include dummies for year, region type, federal state, 1-digit industry, nationality (German vs. non-German), age group (18-25, 26-35, 36-45, 46-55, 56-65) and three skill group dummies (no vocational training, vocational training, university, or university of applied sciences).

Figure 5 Fraction of Switchers by Ability Quintiles



Notes: This figure illustrates the probability of switching out of a task group between years t and t+1, according to a workers' ability quintile.

Figure 6 **Shares in Training Course Financed by Employer**



Notes: This figure illustrates the shares of workers in training courses financed by the employer by task group and year. Source: SOEP

Table 1 **Shift-share analysis of RTI, different time periods**

	Total	Between	Within
1985-1992	-0.87	-1.01	0.14
1992-1999	-3.73	-1.54	-2.20
1999-2006	-3.17	-0.58	-2.59
1985-2006	-7.78	-1.97	-5.81

Notes: This table shows the change in overall RTI as well as the importance for this overall change of the composition of occupations in total employment holding RTI within occupations constant (Composition Change) and of the RTI change within occupations holding composition constant (Change in RTI). Results are 100 x annual changes in task measures.

Appendix

Table A 1 Sample descriptives, task classification according to task intensity (BIBB data)

	Routine		Nonroutine Manual		Nonroutine Cognitive	
No. of observations	1,589,127		2,079,037		1,534,333	
Share	30.55		39.96		29.49	
No. of individuals	188,821		228,073		154,875	
Averages:						
Log (daily) wage	4.65	(0.31)	4.58	(0.28)	4.92	(0.30)
Log (daily) imputed wage	4.68	(0.36)	4.59	(0.31)	5.07	(0.50)
Age	39.70	(10.98)	39.70	(11.17)	41.74	(10.15)
Job tenure (in years)	8.19	(7.12)	7.25	(6.77)	7.68	(6.96)
Labour market experience (in years)	13.23	(7.93)	12.85	(7.88)	13.77	(7.78)
Task measures:						
RTI	0.52	(0.18)	0.35	(0.08)	0.24	(0.09)
NRM	0.22	(0.10)	0.48	(0.10)	0.12	(0.06)
NRC	0.26	(0.23)	0.16	(0.09)	0.64	(0.11)
Fractions within the task group:						
No vocational training	14.96		13.10		2.55	
Vocational training	79.43		83.35		63.60	
University or university of applied science	4.61		2.55		33.31	
Missing	0.99		1.01		0.55	
Mining industry	2.66		0.68		0.64	
Manufacturing industry	63.87		30.97		35.04	
Energy and water supply industry	1.43		1.66		1.52	
Construction industry	1.78		23.02		2.71	
Trade and repair industry	8.69		13.36		18.26	
Catering industry	2.39		1.50		0.37	
Transport and news industry	2.54		11.38		2.99	
Finance and insurance industry	0.79		0.24		10.89	
Real estate and housing, renting of movable property, business service industry	6.79		5.35		14.03	
Public services industry	5.41		4.13		4.36	
Education industry	0.52		0.54		2.67	
Health industry	1.54		4.78		2.73	
Other services industry	1.57		2.40		3.79	
Missing	0.01		0.01		0.01	
Foreign workers	12.10		11.21		3.86	
Censored wages	7.04		3.16		37.40	

Notes: Standard deviation in parentheses. Tasks groups are defined by using the fixed group definition described in Section 2.

Table A 2 Sample descriptives, task classification according to task intensity (BIBB data) for task subgroups

	Routine - Δ NRC high		Routine - Δ NRC middle		Routine - Δ NRC low		Nonroutine Manual		Nonroutine Cognitive	
No. of observations	549,951		503,845		535,331		2,079,037		1,534,333	
Share	10.57		9.68		10.29		39.96		29.49	
No. of individuals	74,297		75,356		63,548		228,073		154,875	
Averages										
Log (daily) wage	4.74	(0.33)	4.56	(0.31)	4.66	(0.25)	4.58	(0.28)	4.92	(0.30)
Log (daily) imputed wage	4.79	(0.43)	4.56	(0.32)	4.67	(0.27)	4.59	(0.31)	5.07	(0.50)
Age	40.71	(10.75)	39.07	(11.12)	39.25	(10.99)	39.70	(11.17)	41.74	(10.15)
Job tenure (in years)	8.13	(7.18)	7.78	(7.04)	8.64	(7.11)	7.25	(6.77)	7.68	(6.96)
Labour market experience (in years)	13.56	(7.94)	12.55	(7.92)	13.53	(7.88)	12.85	(7.88)	13.77	(7.78)
Task measures										
RTI	0.34	(0.18)	0.65	(0.10)	0.57	(0.07)	0.35	(0.08)	0.24	(0.09)
NRM	0.15	(0.10)	0.22	(0.07)	0.29	(0.07)	0.48	(0.10)	0.12	(0.06)
NRC	0.51	(0.22)	0.13	(0.08)	0.14	(0.05)	0.16	(0.09)	0.64	(0.11)
Fractions within the task group										
No vocational training	8.92		23.01		13.59		13.10		2.55	
Vocational training	78.38		74.64		85.03		83.35		63.60	
University or university of applied science	11.96		0.69		0.76		2.55		33.31	
Missing	0.74		1.67		0.62		1.01		0.55	
Mining industry	0.56		0.46		6.89		0.68		0.64	
Manufacturing industry	38.70		77.24		77.15		30.97		35.04	
Energy and water supply industry	1.77		0.25		2.19		1.66		1.52	
Construction industry	2.32		1.37		1.62		23.02		2.71	
Trade and repair industry	17.40		2.75		5.32		13.36		18.26	
Catering industry	0.35		6.91		0.22		1.50		0.37	
Transport and news industry	5.14		0.66		1.64		11.38		2.99	
Finance and insurance industry	2.11		0.15		0.05		0.24		10.89	
Real estate and housing, renting of movable property, business service industry	12.01		5.95		2.22		5.35		14.03	
Public services industry	13.44		1.38		0.96		4.13		4.36	
Education industry	0.82		0.39		0.35		0.54		2.67	
Health industry	2.03		1.70		0.88		4.78		2.73	
Other services industry	3.34		0.78		0.50		2.40		3.79	
Missing	0.01		0.01		0.01		0.01		0.01	
Foreign workers	6.06		20.07		10.80		11.21		3.86	
Censored wages	15.90		1.61		3.04		3.16		37.40	

Notes: Standard deviation in parentheses. Tasks groups are defined by using the dynamic group definition described in Section 2.

Table A 3 RTI and NRCTI of Occupation Fields in 1985 and 2006

Occupational Field	Classified as	RTI in 1985	RTI in 2006	NRCTI in 1985	NRCTI in 2006
Occupations in spinning and rope-making	R - Δ NRC high	0.63	0.57	0.11	0.29
Textile processing, leather manufacture	R - Δ NRC high	0.49	0.32	0.15	0.38
Goods examiners, Packagers, despatchers	R - Δ NRC high	0.47	0.43	0.13	0.26
Occupations in finance and accounting	R - Δ NRC high	0.68	0.14	0.32	0.76
Commercial office occupations	R - Δ NRC high	0.45	0.14	0.48	0.74
Auxiliary office occupations, telephone operators	R - Δ NRC high	0.53	0.19	0.15	0.64
Occupations in production and processing of glass- and ceramic	R - Δ NRC middle	0.70	0.59	0.06	0.13
Paper manufacture, paper processing, printing	R - Δ NRC middle	0.69	0.55	0.14	0.22
Metal productions and processing	R - Δ NRC middle	0.65	0.63	0.07	0.15
Bakers, pastry cooks, production of confectionary goods	R - Δ NRC middle	0.82	0.51	0.08	0.19
Cooks	R - Δ NRC middle	0.51	0.35	0.24	0.34
unskilled workers	R - Δ NRC middle	0.54	0.55	0.03	0.16
Miners and mineral extraction workers	R - Δ NRC low	0.56	0.46	0.15	0.07
Occupations in plastic and chemistry - making and –processing	R - Δ NRC low	0.64	0.58	0.13	0.14
Occupations in mechanics and tool making	R - Δ NRC low	0.57	0.51	0.11	0.18
Precision engineering and related occupations	R - Δ NRC low	0.46	0.55	0.25	0.27
Butchers	R - Δ NRC low	0.71	0.51	0.14	0.19
Production of beverages, foods and tobacco, other nutrition occupations	R - Δ NRC low	0.53	0.50	0.25	0.21
Metal, plant, and sheet metal construction, installation, fitters	NRM	0.34	0.45	0.09	0.23
Vehicle and aircraft construction, maintenance occupations	NRM	0.24	0.33	0.15	0.29
Occupations in mechatronics, energy electronics and electrical engineering	NRM	0.26	0.39	0.17	0.28
Construction occupations, wood and plastics manufacture and processing occupations	NRM	0.27	0.41	0.08	0.25
Transport occupations	NRM	0.41	0.38	0.09	0.18
Occupations in aircraft and ship operation	NRM	0.40	0.45	0.25	0.18
Packers, warehouse operatives, transport processors	NRM	0.42	0.34	0.13	0.24
Personal protection, guards	NRM	0.15	0.21	0.17	0.31
Building caretakers	NRM	0.29	0.26	0.06	0.22
Medical and health care occupations with medical licence	NRM	0.11	0.19	0.42	0.54

Medical and health care occupations without medical medical licence	NRM	0.15	0.17	0.28	0.43
Body care occupations	NRM	0.07	0.06	0.33	0.47
Hotel and restaurant occupations, housekeeping	NRM	0.15	0.20	0.32	0.48
Cleaning and disposal occupations	NRM	0.22	0.24	0.03	0.27
Engineers	NRC	0.21	0.18	0.70	0.74
Chemists, physicists, scientists	NRC	0.17	0.21	0.79	0.73
Technicians	NRC	0.32	0.29	0.48	0.54
Technical draughtsmen/draughtswomen, related occupations	NRC	0.32	0.10	0.66	0.90
Surveying and mapping	NRC	0.26	0.45	0.59	0.50
Specialist skilled technicians	NRC	0.40	0.41	0.49	0.45
Sales occupations (retail)	NRC	0.31	0.16	0.48	0.66
Occupations in wholesale and retail	NRC	0.36	0.13	0.57	0.77
Occupations in insurance and financial services	NRC	0.36	0.14	0.62	0.82
Other commercial occupations (not including wholesale, retail, banking)	NRC	0.34	0.09	0.55	0.80
Advertising specialists	NRC	0.21	0.21	0.61	0.77
Managing directors, auditors, management consultants	NRC	0.25	0.14	0.69	0.77
Administrative occupations in the public sector	NRC	0.27	0.12	0.70	0.82
IT professions	NRC	0.41	0.21	0.53	0.67
Occupations in security	NRC	0.26	0.14	0.43	0.56
Legal occupations	NRC	0.24	0.09	0.58	0.78
Artists and musicians	NRC	0.41	0.25	0.33	0.52
Designers, photographers, advertising creators	NRC	0.24	0.31	0.50	0.56
Social occupations	NRC	0.20	0.09	0.62	0.68
Teachers	NRC	0.21	0.15	0.75	0.75
Journalists, librarians, translators, related academic research occupations	NRC	0.31	0.18	0.59	0.78

Source: BIBB/IAB and BIBB/BAuA Employment Surveys 1985 and 2006.

Table A 4 **Sample descriptives, task classification according to task intensity (BIBB data) for task subgroups. Only 1985 – 1989**

	Routine - Δ NRC high		Routine - Δ NRC middle		Routine - Δ NRC low		Nonroutine Manual		Nonroutine Cognitive	
No. of observations	104,928		106,623		120,438		427,922		273,238	
Share	10.16		10.32		11.66		41.42		26.45	
No. of individuals	30,270		31,821		34,399		119,305		71,713	
Averages										
Log (daily) wage	4.65	(0.29)	4.56	(0.25)	4.61	(0.23)	4.54	(0.25)	4.84	(0.27)
Log (daily) imputed wage	4.70	(0.38)	4.56	(0.26)	4.62	(0.25)	4.55	(0.28)	5.00	(0.47)
Age	40.52	(11.49)	38.46	(11.82)	38.01	(11.69)	38.87	(11.74)	41.40	(10.44)
Job tenure (in years)	7.26	(4.68)	6.74	(4.74)	6.97	(4.69)	6.16	(4.69)	6.97	(4.73)
Labour market experience (in years)	9.66	(3.92)	9.15	(4.12)	9.29	(4.07)	9.12	(4.05)	9.76	(3.88)
Task measures										
RTI	0.49	(0.07)	0.65	(0.07)	0.58	(0.06)	0.31	(0.08)	0.30	(0.06)
NRM	0.15	(0.15)	0.26	(0.08)	0.28	(0.05)	0.58	(0.08)	0.12	(0.07)
NRC	0.36	(0.16)	0.09	(0.05)	0.13	(0.04)	0.12	(0.06)	0.58	(0.10)
Fractions within the task group										
No vocational training	12.53		27.80		17.19		16.29		2.89	
Vocational training	80.08		69.87		81.53		80.60		70.22	
University or university of applied science	6.33		0.40		0.45		1.86		26.33	
Missing	1.06		1.93		0.83		1.25		0.56	
Mining industry	0.88		0.51		10.72		0.92		1.10	
Manufacturing industry	45.68		84.45		73.53		32.35		38.73	
Energy and water supply industry	1.85		0.29		2.38		1.85		1.72	
Construction industry	2.11		1.20		1.60		25.43		2.84	
Trade and repair industry	16.01		2.39		5.02		12.40		18.55	
Catering industry	0.32		4.94		0.23		1.31		0.33	
Transport and news industry	3.44		0.82		2.07		10.58		2.81	
Finance and insurance industry	2.05		0.21		0.07		0.37		11.20	
Real estate and housing, renting of movable property, business service industry	7.05		1.78		1.57		3.64		9.27	
Public services industry	15.50		1.40		1.21		4.94		5.33	
Education industry	0.69		0.21		0.30		0.49		2.38	
Health industry	1.75		1.23		0.89		3.63		1.91	
Other services industry	2.67		0.57		0.41		2.09		3.83	
Missing	0.00		0.00		0.00		0.00		0.00	
Foreign workers	5.62		19.27		10.52		9.98		3.04	
Censored wages	15.04		2.07		3.41		3.29		40.47	

Notes: Standard deviation in parentheses. Tasks groups are defined by using the dynamic group definition described in Section 2.

Table A 5 Task-group specific wage growth by fixed task group definitions

	Fixed group definition - BIBB data approach		Fixed group definition - Cortes (2016) approach	
Routine x 1986	0.004***	(0.001)	-0.004***	(0.001)
Routine x 1987	0.004***	(0.001)	-0.006***	(0.001)
Routine x 1988	0.006***	(0.001)	-0.002	(0.001)
Routine x 1989	0.008***	(0.001)	0.000	(0.001)
Routine x 1990	0.007***	(0.001)	0.002	(0.002)
Routine x 1991	0.001	(0.001)	0.004**	(0.002)
Routine x 1992	-0.003***	(0.001)	0.005***	(0.002)
Routine x 1993	-0.012***	(0.001)	0.007***	(0.002)
Routine x 1994	-0.010***	(0.001)	0.011***	(0.002)
Routine x 1995	0.000	(0.001)	0.013***	(0.002)
Routine x 1996	0.002	(0.001)	0.013***	(0.002)
Routine x 1997	0.011***	(0.002)	0.011***	(0.002)
Routine x 1998	0.021***	(0.002)	0.009***	(0.002)
Routine x 1999	0.027***	(0.002)	0.011***	(0.002)
Routine x 2000	0.035***	(0.002)	0.012***	(0.002)
Routine x 2001	0.044***	(0.002)	0.016***	(0.002)
Routine x 2002	0.050***	(0.002)	0.016***	(0.002)
Routine x 2003	0.050***	(0.002)	0.013***	(0.002)
Routine x 2004	0.059***	(0.002)	0.017***	(0.002)
Routine x 2005	0.068***	(0.002)	0.019***	(0.002)
Routine x 2006	0.078***	(0.002)	0.024***	(0.003)
Routine x 2007	0.090***	(0.002)	0.028***	(0.003)
Routine x 2008	0.095***	(0.002)	0.028***	(0.003)
Routine x 2009	0.091***	(0.002)	0.027***	(0.003)
Routine x 2010	0.103***	(0.002)	0.027***	(0.003)
NRC x 1986	0.004***	(0.001)	-0.002	(0.002)
NRC x 1987	0.015***	(0.002)	0.008***	(0.002)
NRC x 1988	0.013***	(0.002)	0.010***	(0.002)
NRC x 1989	0.019***	(0.002)	0.012***	(0.002)
NRC x 1990	0.019***	(0.002)	0.015***	(0.002)
NRC x 1991	0.024***	(0.002)	0.027***	(0.002)
NRC x 1992	0.029***	(0.002)	0.033***	(0.002)
NRC x 1993	0.034***	(0.002)	0.044***	(0.002)
NRC x 1994	0.033***	(0.002)	0.046***	(0.003)
NRC x 1995	0.043***	(0.002)	0.052***	(0.003)
NRC x 1996	0.053***	(0.002)	0.062***	(0.003)
NRC x 1997	0.071***	(0.002)	0.074***	(0.003)
NRC x 1998	0.084***	(0.002)	0.080***	(0.003)
NRC x 1999	0.115***	(0.002)	0.108***	(0.003)
NRC x 2000	0.140***	(0.002)	0.131***	(0.003)
NRC x 2001	0.174***	(0.002)	0.164***	(0.003)
NRC x 2002	0.182***	(0.002)	0.169***	(0.003)
NRC x 2003	0.164***	(0.002)	0.148***	(0.003)
NRC x 2004	0.190***	(0.002)	0.174***	(0.003)
NRC x 2005	0.215***	(0.002)	0.196***	(0.003)
NRC x 2006	0.229***	(0.003)	0.210***	(0.003)
NRC x 2007	0.254***	(0.003)	0.233***	(0.003)
NRC x 2008	0.273***	(0.003)	0.250***	(0.003)
NRC x 2009	0.288***	(0.003)	0.266***	(0.003)
NRC x 2010	0.303***	(0.003)	0.276***	(0.003)

	Fixed group definition - BIBB data approach		Fixed group definition - Cortes (2016) approach	
Region type				
Urban districts	-0.009***	(0.001)	-0.010***	(0.001)
Rural districts, some densely populated areas	-0.033***	(0.002)	-0.036***	(0.002)
Rural districts, sparsely populated	-0.052***	(0.003)	-0.056***	(0.003)
Missing	-0.043***	(0.011)	-0.039***	(0.011)
Foreign	0.010***	(0.002)	0.013***	(0.002)
Missing	0.006	(0.011)	0.006	(0.012)
Year dummies	yes		yes	
Federal state dummies	yes		yes	
Industry dummies	yes		yes	
Occupation-person fixed effects	yes		yes	
Observations	5,202,497		5,202,497	

Notes: This table illustrates the results of our estimation of the task-group specific wage component for the fixed group definition in table form. Standard errors (in parentheses) are clustered at the worker level. Significance: *p < 0.10, **p < 0.05, ***p<0.01.

Table A 6 Task-group specific wage growth by dynamic task group definition

	Dynamic group definition - BIBB data approach with Routine subcategories	
Routine - Δ NRC high x 1986	0.008***	(0.001)
Routine - Δ NRC high x 1987	0.015***	(0.002)
Routine - Δ NRC high x 1988	0.018***	(0.002)
Routine - Δ NRC high x 1989	0.020***	(0.002)
Routine - Δ NRC high x 1990	0.017***	(0.002)
Routine - Δ NRC high x 1991	0.019***	(0.002)
Routine - Δ NRC high x 1992	0.025***	(0.002)
Routine - Δ NRC high x 1993	0.031***	(0.002)
Routine - Δ NRC high x 1994	0.036***	(0.002)
Routine - Δ NRC high x 1995	0.047***	(0.003)
Routine - Δ NRC high x 1996	0.058***	(0.003)
Routine - Δ NRC high x 1997	0.071***	(0.003)
Routine - Δ NRC high x 1998	0.085***	(0.003)
Routine - Δ NRC high x 1999	0.103***	(0.003)
Routine - Δ NRC high x 2000	0.119***	(0.003)
Routine - Δ NRC high x 2001	0.139***	(0.003)
Routine - Δ NRC high x 2002	0.152***	(0.003)
Routine - Δ NRC high x 2003	0.151***	(0.003)
Routine - Δ NRC high x 2004	0.169***	(0.003)
Routine - Δ NRC high x 2005	0.188***	(0.003)
Routine - Δ NRC high x 2006	0.202***	(0.003)
Routine - Δ NRC high x 2007	0.215***	(0.004)
Routine - Δ NRC high x 2008	0.229***	(0.004)
Routine - Δ NRC high x 2009	0.249***	(0.004)
Routine - Δ NRC high x 2010	0.263***	(0.004)
Routine - Δ NRC middle x 1986	0.001	(0.001)
Routine - Δ NRC middle x 1987	-0.004***	(0.001)
Routine - Δ NRC middle x 1988	-0.002	(0.001)
Routine - Δ NRC middle x 1989	0.001	(0.001)
Routine - Δ NRC middle x 1990	0.002	(0.002)
Routine - Δ NRC middle x 1991	-0.011***	(0.002)
Routine - Δ NRC middle x 1992	-0.022***	(0.002)
Routine - Δ NRC middle x 1993	-0.037***	(0.002)
Routine - Δ NRC middle x 1994	-0.036***	(0.002)
Routine - Δ NRC middle x 1995	-0.027***	(0.002)
Routine - Δ NRC middle x 1996	-0.032***	(0.002)
Routine - Δ NRC middle x 1997	-0.025***	(0.002)
Routine - Δ NRC middle x 1998	-0.018***	(0.002)
Routine - Δ NRC middle x 1999	-0.018***	(0.002)
Routine - Δ NRC middle x 2000	-0.013***	(0.002)
Routine - Δ NRC middle x 2001	-0.013***	(0.002)
Routine - Δ NRC middle x 2002	-0.013***	(0.002)
Routine - Δ NRC middle x 2003	-0.015***	(0.002)

	Dynamic group definition - BIBB data approach with Routine subcategories	
Routine - Δ NRC middle x 2004	-0.011***	(0.003)
Routine - Δ NRC middle x 2005	-0.008***	(0.003)
Routine - Δ NRC middle x 2006	-0.002	(0.003)
Routine - Δ NRC middle x 2007	0.008***	(0.003)
Routine - Δ NRC middle x 2008	0.006**	(0.003)
Routine - Δ NRC middle x 2009	-0.017***	(0.003)
Routine - Δ NRC middle x 2010	-0.006**	(0.003)
Routine - Δ NRC low x 1986	0.003**	(0.001)
Routine - Δ NRC low x 1987	0.003**	(0.001)
Routine - Δ NRC low x 1988	0.002	(0.001)
Routine - Δ NRC low x 1989	0.002	(0.001)
Routine - Δ NRC low x 1990	-0.001	(0.002)
Routine - Δ NRC low x 1991	-0.009***	(0.002)
Routine - Δ NRC low x 1992	-0.017***	(0.002)
Routine - Δ NRC low x 1993	-0.032***	(0.002)
Routine - Δ NRC low x 1994	-0.033***	(0.002)
Routine - Δ NRC low x 1995	-0.023***	(0.002)
Routine - Δ NRC low x 1996	-0.021***	(0.002)
Routine - Δ NRC low x 1997	-0.012***	(0.002)
Routine - Δ NRC low x 1998	-0.004**	(0.002)
Routine - Δ NRC low x 1999	-0.004*	(0.002)
Routine - Δ NRC low x 2000	0.000	(0.002)
Routine - Δ NRC low x 2001	0.004*	(0.002)
Routine - Δ NRC low x 2002	0.008***	(0.002)
Routine - Δ NRC low x 2003	0.011***	(0.002)
Routine - Δ NRC low x 2004	0.018***	(0.002)
Routine - Δ NRC low x 2005	0.025***	(0.002)
Routine - Δ NRC low x 2006	0.035***	(0.003)
Routine - Δ NRC low x 2007	0.048***	(0.003)
Routine - Δ NRC low x 2008	0.051***	(0.003)
Routine - Δ NRC low x 2009	0.031***	(0.003)
Routine - Δ NRC low x 2010	0.046***	(0.003)
NRC x 1986	0.004***	(0.001)
NRC x 1987	0.015***	(0.002)
NRC x 1988	0.013***	(0.002)
NRC x 1989	0.019***	(0.002)
NRC x 1990	0.019***	(0.002)
NRC x 1991	0.024***	(0.002)
NRC x 1992	0.029***	(0.002)
NRC x 1993	0.034***	(0.002)
NRC x 1994	0.033***	(0.002)
NRC x 1995	0.043***	(0.002)
NRC x 1996	0.053***	(0.002)
NRC x 1997	0.071***	(0.002)

	Dynamic group definition - BIBB data approach with Routine subcategories	
NRC x 1998	0.084***	(0.002)
NRC x 1999	0.115***	(0.002)
NRC x 2000	0.140***	(0.002)
NRC x 2001	0.174***	(0.002)
NRC x 2002	0.182***	(0.002)
NRC x 2003	0.163***	(0.002)
NRC x 2004	0.190***	(0.002)
NRC x 2005	0.215***	(0.002)
NRC x 2006	0.229***	(0.003)
NRC x 2007	0.254***	(0.003)
NRC x 2008	0.272***	(0.003)
NRC x 2009	0.287***	(0.003)
NRC x 2010	0.302***	(0.003)
Region type		
Urban districts	-0.009***	(0.001)
Rural districts, some densely populated areas	-0.033***	(0.002)
Rural districts, sparsely populated	-0.051***	(0.003)
Missing	-0.041***	(0.011)
Foreign	0.006***	(0.002)
Missing	0.005	(0.012)
Year dummies	yes	
Federal state dummies	yes	
Industry dummies	yes	
Occupation-person fixed effects	yes	
Observations	5,202,497	

Notes: This table illustrates the results of our estimation of the task-group specific wage component for the dynamic group definition in table form. Standard errors (in parentheses) are clustered at the worker level. Significance: *p < 0.10, **p < 0.05, ***p<0.01.

Table A 7 Decomposition of the Change in NRC Task Content

	R - Δ NRC high vs. R - Δ NRC middle	R - Δ NRC high vs. R - Δ NRC low
Total Change	0.133***	0.205***
	(0.025)	(0.020)
Main Effect	-0.002	0.014*
	(0.005)	(0.006)
Group Interaction	-0.002	-0.006
	(0.010)	(0.008)
Time Interaction	-0.013	-0.007
	(0.018)	(0.014)
Group-Time Interaction	0.150***	0.205***
	(0.036)	(0.025)
Observations	17,994	17,994

Notes: This table shows the decomposition of the mean NRC task intensity between for the task groups R - Δ NRC high vs. R - Δ NRC middle and R - Δ NRC high vs. R - Δ NRC low using the BIBB waves 1985 and 2006. We use the methodology of Smith and Welch (1989) and the Stata code provided by Kröger and Hartmann (2021). We estimate standard errors via bootstrapping with 100 iterations. Significance: *p < 0.05, **p < 0.01, ***p<0.001. Source: BIBB.

Table A 8 Mean Task Intensities over Time and by Age Groups

	RTI		**NRMTI**		**NRCTI**	
	young	old	young	old	young	old
1985	0.37	0.37	0.32	0.32	0.31	0.31
1992	0.38	0.34	0.30	0.26	0.32	0.40
1999	0.35	0.33	0.28	0.25	0.37	0.42
2006	0.32	0.30	0.23	0.23	0.45	0.47

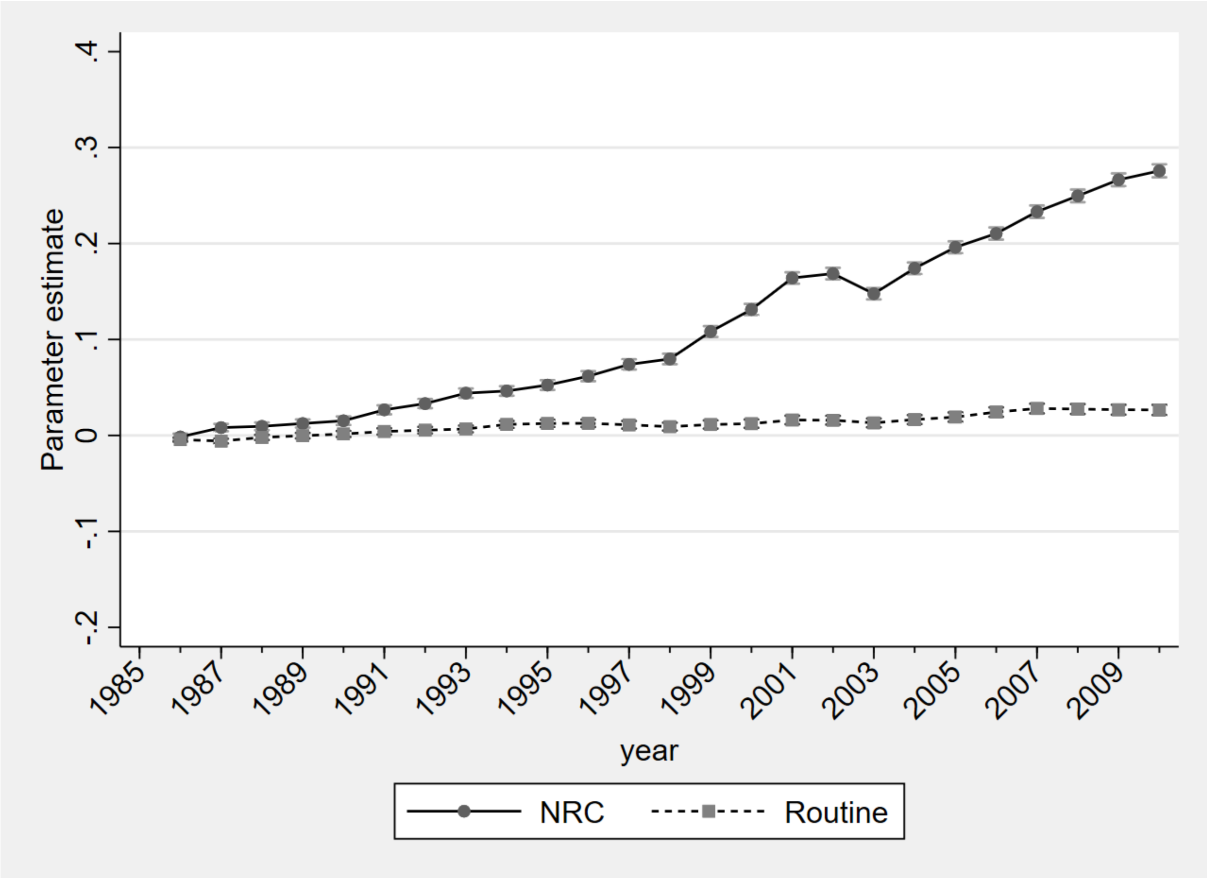
Notes: This table shows the mean routine task intensity (RTI), mean nonroutine manual task intensity (NRMTI) and mean nonroutine cognitive task intensity (NRCTI) for young (age 25-34 years) vs. older (age 35-50 years) workers.

Table A 9 Linear Probability Model of Training Participation Financed by Employer

	Financed by Employer	
R – Δ NRC high	0.015	(0.017)
R – Δ NRC middle	-0.051***	(0.009)
R – Δ NRC low	-0.022**	(0.010)
NRC	0.140***	(0.012)
Controls	yes	
No. of observations	12,429	

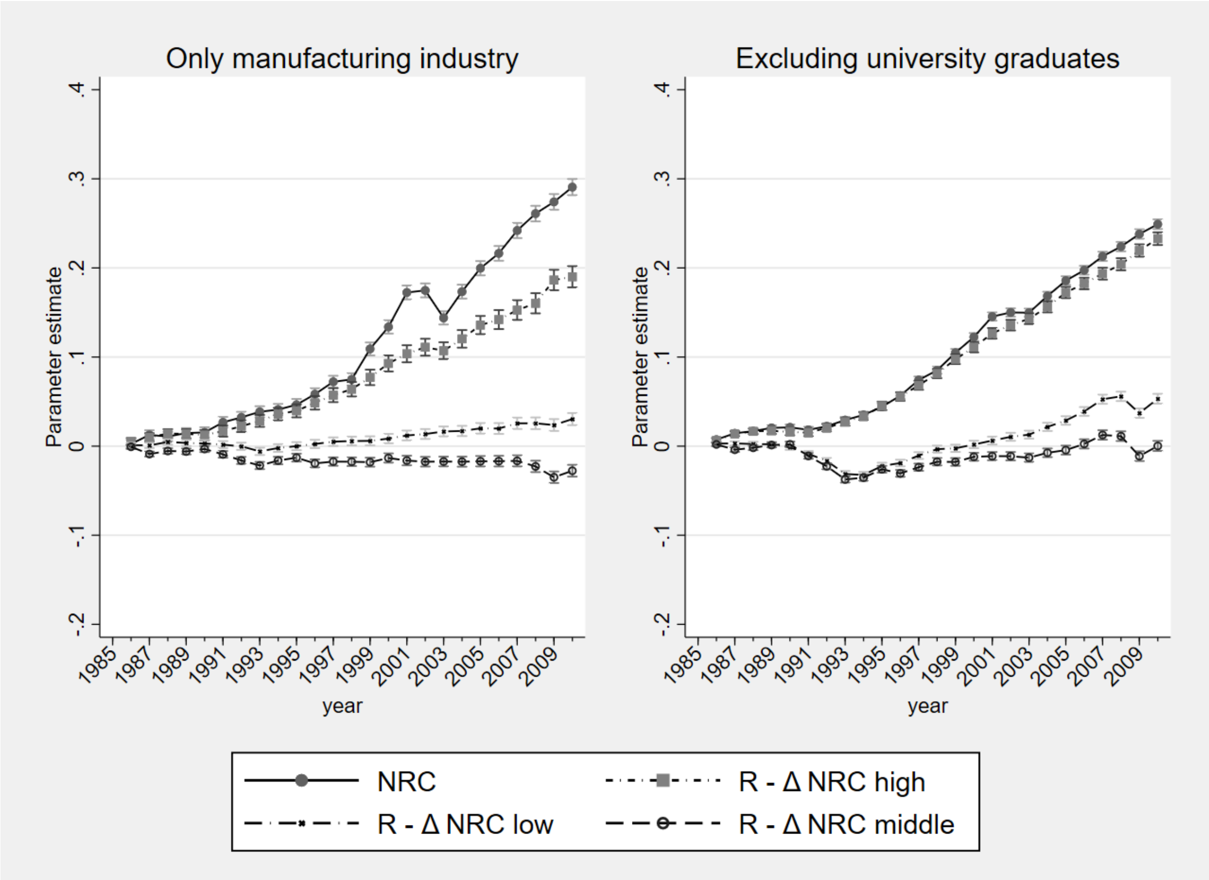
Notes: This table illustrates the results of a linear probability model using the training participation financed by the employer as the outcome variable and task group dummies as the key independent variables. NRM is the reference category. We control for age, education, marital status, migration background, federal state, industry, firm size, and year dummies. Heteroscedasticity-robust standard errors are reported in brackets. Significance: *p < 0.10, **p < 0.05, ***p<0.01. Source: SOEP.

Figure A 1 **Task-group Specific Wages Over Time (Cortes approach)**



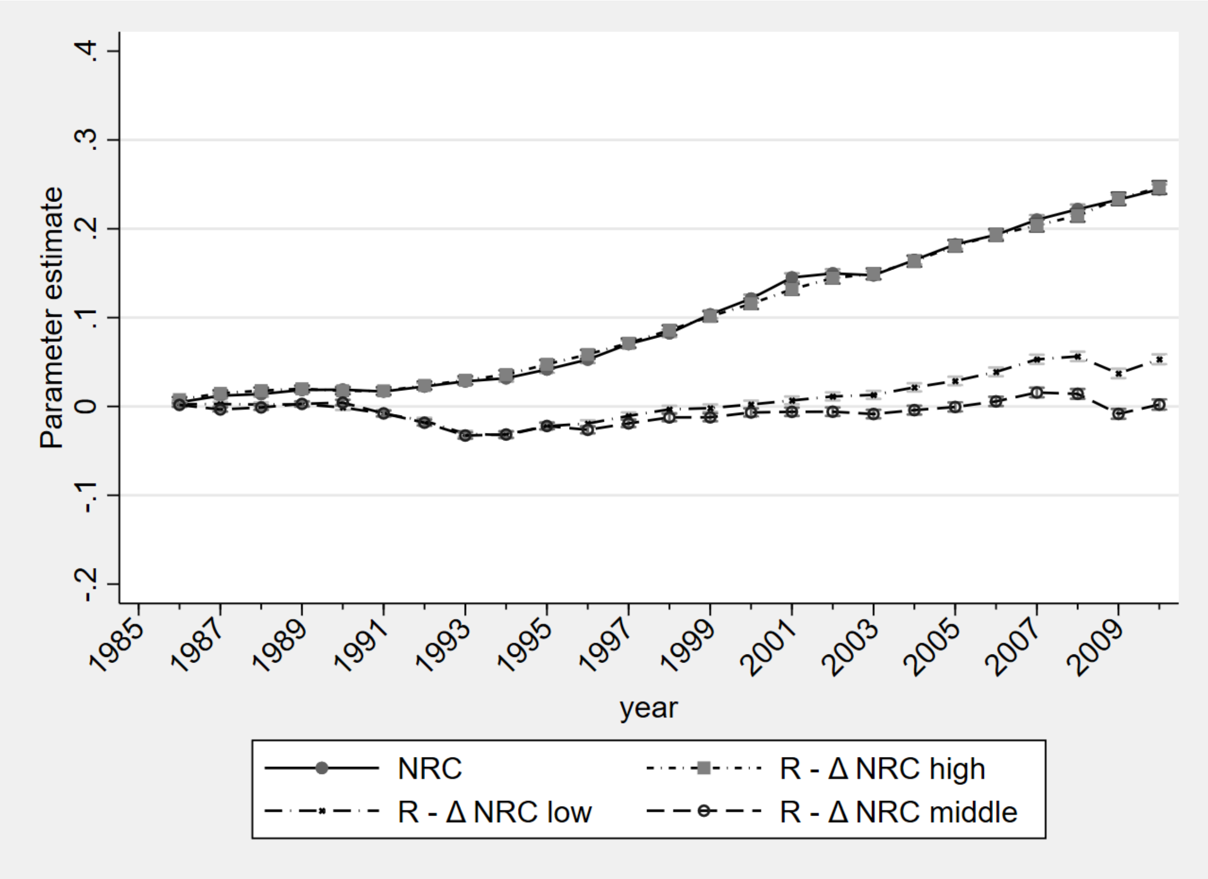
Notes: Evolution of occupation-specific wage growth over time using the task classification of Cortes (2016). NRC: non-routine cognitive occupations. Reference category: NRM = non-routine manual occupations.

Figure A 2 Robustness Checks: Task-group specific wages over time



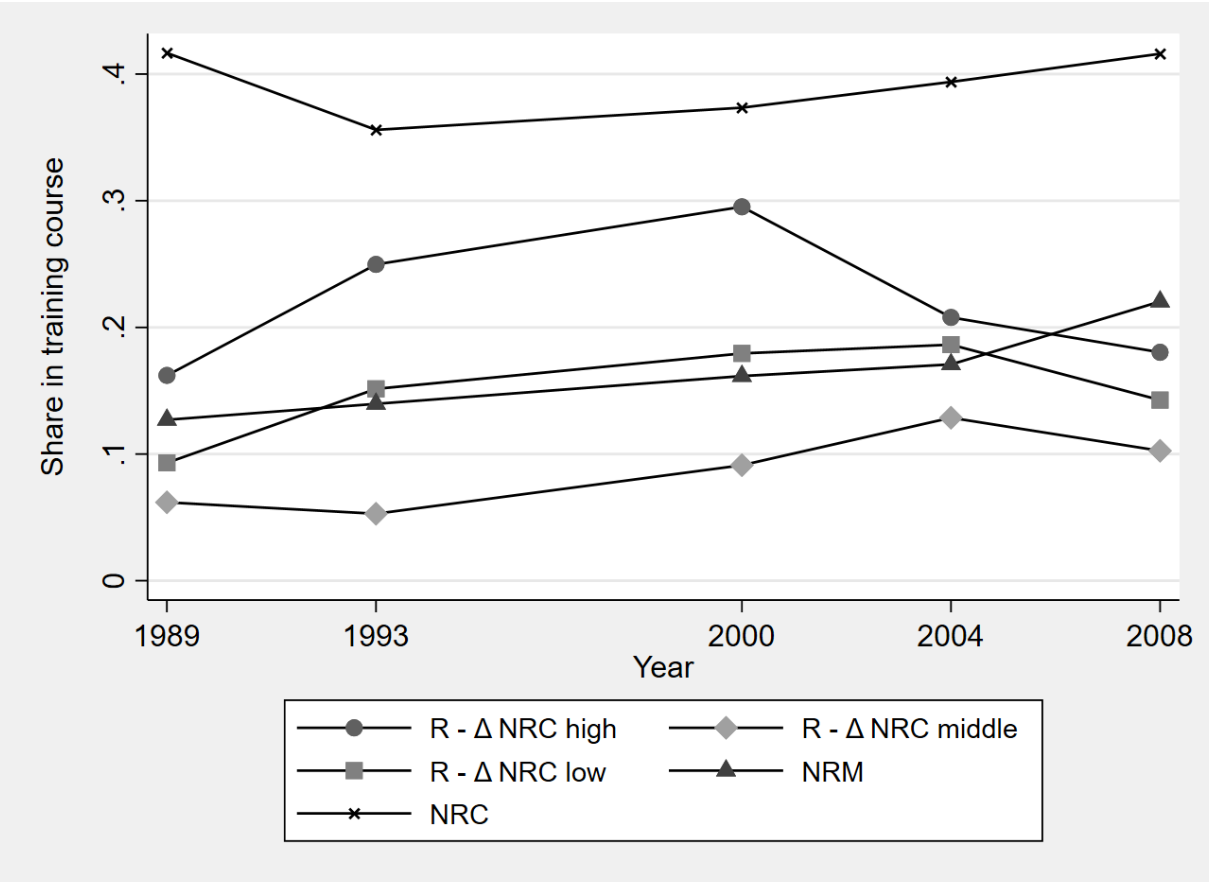
Notes: This figure shows the task-group specific wage component over time for our dynamic group definition separately only for the manufacturing industry and excluding university graduates. Reference category= NRM.

Figure A 3 Robustness Checks: Occupation Wage Growth by Task Groups using Education *x* Year Fixed Effects



Notes: These figures show the occupation-specific wage component over time for our dynamic group definition including education *x* year fixed effects. Reference category= NRM.

Figure A 4 Shares in Any Training Course



Notes: This figure illustrates the shares of workers in any training course by task group and year. Source: SOEP