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The Role of Within-Occupation Task Change in Wage Development

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Abstract

There have been dramatic shifts in task mixes of jobs over the past decades. Existing research shows that this leads to substantial welfare losses amongst the most affected groups, workers in routine task jobs. Often reflecting data limitations, existing research typically fixes task mixes of occupations at some initial period. We return to this issue using large administrative data for Germany over a 25-year period, and match this to survey data that allows us to track how occupational task mixes change over time. We document substantial within occupational changes in tasks which are consequential for our understanding of the effects of the routinisation process. We demonstrate important heterogeneity in wage penalties according to the type of task changes amongst initially routine intensive jobs. We explore a range of reasons for these differences in occupational-task evolution. Our results indicate that accounting for within-occupation task change is crucial for understanding the wage effects of technological change.

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1. Introduction

The dramatic 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 losses. 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.

This paper returns to this issue using long-run individual-level data for Germany. Our focus is whether routine workers face worse labour market prospects, and in particular, suffer greater losses in terms of wages when compared to other workers. Our main point of departure from the existing literature is how we treat task mixes of jobs over time. A standard approach when estimating the evolution of task wages has been to use the initial task content of jobs to define a job as being routine-intensive. This has advantages in terms of data requirements, ease of estimation, and interpretation. Yet, it misses an important component of the process of routinisation, i.e. within-occupation changes in task mixes. As we demonstrate, within-occupation task changes are particularly important when examining longer periods of time, confirming previous evidence (Spitz-Oener et al, 2006; Bachmann et al., 2019). These changes over time are likely to have important important implications for wage development. Using detailed task data for Germany, we therefore investigate how jobs change task mix over time, and examine the implications of this for understanding task mix effects on wages premia.

We estimate the effect of exposure to different task mixes on wages for Germany over a long time period, 1985 to 2010. Using combined social security data and survey data on occupational task mixes we are able to 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 demonstrate dramatic changes in within occupation task mix changes, the magnitude of these changes for initial routine jobs dwarf average across occupation task changes. This, we argue, is consequential. While previous work for the US demonstrates marked wage penalties associated with routine work and research for Germany has demonstrated no routinisation wage penalty (Cortes, 2016; Wang, 2020), we present large heterogeneity in wage premia that reflects changes in within occupation task mix. Those occupations that remain (relatively) routine intensive over the time period indeed generate substantial wage penalties. Yet, as we show, a range of initially routine occupations that changed task mix over time, are instead associated with substantial wage increases, comparable in magnitude to

those experienced by workers who mainly perform non-routine cognitive tasks. This evidence has not been documented in the previous literature.

This novel fact raises a range of additional questions regarding the source of differences. As an initial step, we rule out a range of potential explanations. For instance, we demonstrate that it does not reflect the occupation specific changes in worker composition and worker flows that have been shown to be important features of the routinisation process (Cortes et al, 2014; Böhm et al., 2020). We also demonstrate that it does not simply reflect differences in the types of workers that do these jobs, or the types of jobs that are characterised by these changes in task mix.

2. Data

2.1 The Sample of Integrated Labour Market Biographies (SIAB) 1975-2019

To address our research questions requires detailed data that contains workers' employment biographies. Furthermore, we require information on workers' wages, occupation, and workplace characteristics. An ideal dataset for our purposes is the Sample of Integrated Labour Market Biographies (SIAB) for 1975-2010. We combine this data with the Establishment History Panel (BHP). A detailed description of the Sample of Integrated Labor Market Biographies is provided in Frodermann et al. (2021).

The SIAB is a representative 2 percent random sample of the population of the Integrated Employment Biographies (IEB). The IEB includes the universe of individuals in Germany with either employment subject to social security, marginal part-time employment (mini-job), registered unemployment benefits, job-seeker status at the Federal Employment Agency, participation in active labor market policy measures or other training measures. Civil servants and self-employed workers are not included in the data.¹ The information on the corresponding labor market spells is exact to the day.

The administrative individual data of the IEB contains data from a variety of sources. For our purposes, the Employee History (BeH) is the most important source. The BeH is based on the integrated notification procedure for health, pension, and unemployment insurances. Employers have the legal obligation to notify the responsible social security agencies about all of their employees covered by social security at the beginning and at the end of an employment spell, and to update the information at least once a year. Misreporting is a legal offense (for more information on the notification procedure see Bender et al. 1996). The data provides us with personal information such as age, gender,

¹ Caliendo and Uhlendorff (2008) find that only 3% of all non-employed workers and only 1% of all wage-employed workers in Germany enter the state of self-employment annually. This implies that transitions into and out of this state only play a minor role for our analyses.

nationality, education, and place of residence, as well as job information such as the daily wage and the occupation. The information on the daily wage is censored at the yearly varying social security contribution ceiling. In Section 2.3 we describe how we deal with this issue.

Establishment-level information comes from the Establishment History Panel (BHP). The BHP data consists of BeH data which is aggregated at the establishment-year level on the 30th June every year. The BHP provides information on the industry of the establishment and other establishment characteristics such as worker group shares with respect to skill, gender, part-time employment, and nationality, as well as the establishment size and the average age of its workforce. Using the establishment identifier that is included in the data, we can link the individual-level data with the Establishment History Panel (BHP).

2.2 BIBB/IAB and BIBB/BAuA Employment Surveys

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 workers (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). The BIBB data are representative of the core labor force in Germany, that is, for persons who are at least 15 years old and work at least 10 hours per week. For our purposes, important information come from questions regarding the job tasks of a worker.

We use the information of job tasks of a worker to compute individual level task intensities. To do this, 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

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

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.² The shares of task intensities for each occupation-time period combination sum to 100 percent. As a result, these

² Using a finer occupational classification is not possible given the relatively small sample size of the BIBB data.

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 TI measures to the worker-level SIAB data based on occupation and year combinations.

Occupations evolve and their task content changes over time (see e.g. Autor et al. 2003; Spitz-Oener 2006). However, most analyses of task groups ignore changes in the composition of tasks within occupations. This mainly reflects reasons of data availability. An important advantage of this study is the usage of the BIBB data and its survey that were conducted at regular six- to seven-year intervals throughout our period of analysis. This allows us to have time-varying task intensities by occupational groups. Our analysis therefore reflects the actual task composition of an occupation at the time of observation. In other words, computing task intensities with the usage of additional data sources contrasts with the more parsimonious approach, which assigns workers to routine, non-routine manual, and non-routine cognitive categories at one point in time based on groups of standardized occupational codes (see for example Goos and Manning 2007; Goos, Manning, and Salomons 2009; Cortes 2016). A cost of relying on the time-varying task measures computed from the BIBB data consists in discontinuities in these measures from one survey wave to the next. However, as shown by Bachmann, Cim, and Green (2019), these discontinuities are not large.

2.3 Sample Construction

To analyze wage premia over time requires a consistent measure of wages in our sample. 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, it is well known that there is a dramatic change in occupational classifications from 2011 onwards (e.g., Böhm et al. 2022). Critically, there is no approach available that allows for consistent treatment of occupations before and after this change. Consequently, as with other related research 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. As mentioned in Section 2.1, 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.³ We create a yearly panel and select all employment spells that include the June 30th as the cutoff date.

Our analysis also requires a long-time horizon to properly answer our research questions. Therefore, we circumvent additional restrictions of our analysis period by excluding observations for East German workers who were registered in the data only from 1992 onwards. We further focus on the core labour force in dependent employment and therefore 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. Individuals can hold more than one job in the data. We keep his main job, defined as the job with the highest daily wage or, in case of a tie, the spell with the longest tenure.

We analyze how different tasks at the job influence the wage premia over time. To do this, we need to operationalize job tasks in our estimations. We proceed use the following two approaches. First, we use a *fixed group definition* of task groups. To do this we use the BIBB data to classify occupation fields into 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 1985.⁴

We next exploit the time variation in the 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, in the middle tercile as routine – Δ NRC middle and in the lowest tercile as routine – Δ NRC low.

Table A1 presents descriptive statistics using the *fixed group definition* of task groups. The NRM task group has the highest employment share in our sample. The routine and NRC task groups have similar employment shares. In line with other studies examining task and labor market polarization (see e.g.,

³ See Dauth and Eppelsheimer (2020) for a recent guide for preparing the SIAB.

⁴ 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).

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. NRM workers also work with fewer and worse paid coworkers compared to routine and NRC workers. 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 A3 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, work in establishments with better paid coworkers and are much better educated compared to the other routine subgroups. Workers in routine – Δ NRC middle and routine – Δ NRC low who are much more likely to work in the manufacturing industry.

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 aims of this approach are to retrieve occupational premia over time.

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

$$w_j(z) = \lambda_j \varphi_j(z), j \in \{M, R, C\} \quad (2)$$

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 $j \in \{R, M, C\}$.

Workers sort into tasks in the following way. Workers of higher skill levels are assumed to be more productive at all tasks but have 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:

$$0 < \frac{d \ln \varphi_m(z)}{dz} < \frac{d \ln \varphi_R(z)}{dz} < \frac{d \ln \varphi_C(z)}{dz}$$

Consider, as an example $\lambda_C = \lambda_R = \lambda_M$, 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_C is relatively low, while λ_M is relatively high, with λ_R in the middle. The low λ_C makes it optimal only for the most skilled workers to select into the nonroutine cognitive occupation, while the high λ_M 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:

$$\ln w_j(z) = \ln \lambda_j + \ln \varphi_j(z). \quad (3)$$

An intuitive way to think about the productivity term is:

$$\ln \varphi_j(z_i) = z_i a_j. \quad (4)$$

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 . We can reformulate Equation 3 in the following way:

$$\ln w_{ijt} = \theta_{jt} + z_i a_j, \quad (5)$$

where $\theta_{jt} \equiv \ln \lambda_{jt}$ is the occupation wage premium in occupation j at time 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. 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 worker 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 once we account for the selection mechanisms described above. Household income increases, which further increases demand in service goods, leading to a slight increase in the wage premia for NRM workers.

We use the following empirical specification to estimate the occupation premia of different occupations over time:

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

The dependent variable is the log wage of employment spell i at time t . θ_{jt} is the occupation wage premium in occupation j at time t . We capture the occupation wage premium by using occupation-year dummies. The reference task group is non-routine manual (NRM). D_{ijt} is an occupation selection

indicator that equals one if employment spell i selects into an occupation j at time t and is zero otherwise. We assume that, conditional on our covariates, occupational mobility will be driven exclusively by changes in θ_{jt} over time. 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 occupation spells, but it stays constant whenever the individual stays in the same occupation. We estimate γ_{ij} by using person \times occupation fixed effects. Z_{it} includes the region type, federal state dummies, sector dummies, an immigrant dummy and year dummies.

This approach purges the estimates of the occupation wage premium from selection effects into those occupations. As described in more detail above, workers sort into occupations based on their own skills and the occupation-specific returns to those skills. By using person \times occupation fixed effects, we eliminate any bias that arises from different types of workers selecting into occupations that benefit them (positive selection). Specifically, the occupation wage premia are identified from variation in wages for workers who have stayed within specific occupation groups over time. Any bias that arises from variation across person, occupation 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 base occupation (NRM).

We use several variants of Equation 6 to pick up explore potential heterogeneity in the development of occupations over time. To achieve this, we use the different classifications described in Section 2.3.

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. We estimate the occupation wage premia by using the year 1985 and the task group NRM as reference categories.⁵

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 dramatic decrease in their RTI between 1985 and 2006 which was mostly compensated by an increase in their NRCTI. So, while workers in this occupation field mostly performed routine tasks initially, such as e.g. measuring, calculating and operating, this has

⁵ As a robustness check, we estimate the wage premia by using a similar classification of task groups as in the US literature (see e.g. Cortes 2016, Acemoglu and Autor 2011).

changed to more NRC tasks such as investigating, consulting and organizing. Staying within the framework outlined in Equations 2 to 5, we expect that routine occupations which experience an increase in their NRC task content over time also experience an increase in their wage premia. 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, using the notation in Equations 2 to 5, λ_j , the wage per efficiency unit, increases for those occupations as the relative demand for NRC tasks increases. However, a_j , the occupation specific returns to skills increases as well, meaning that more skilled workers select and stay in those occupations over time. For occupations that still use a relatively high share of routine tasks over time the λ_j decreases as the relative demand for routine tasks decreases over time due to technological change. Specifically, we estimate the wage premia for the 5 task categories routine – Δ NRC high, routine – Δ NRC middle, routine – Δ NRC low, NRM and NRC. Again, as in the first approach, we use the year 1985 and the NRM task category as base categories in our estimation.

4. Results

4.1 Task Wage Premia

As an initial step, Figure 1 plots annual wage premia relative to non-routine manual jobs associated with working in a routine and non-routine cognitive job, respectively. 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 large wage premium for non-routine cognitive work that by the late 2000s is as high as 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 premia 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). The other striking pattern from 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.

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 occupations such as secretaries or bank tellers. These are jobs impacted strongly by routine biased technological change as they involved a set of tasks that were largely replaceable by algorithm. However, to differing extents these occupations still exist, albeit with markedly different task mixes. 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 occupational wage premia/penalties over time.

Using the BIBB data, our initial descriptive step is to use our two end points in this data, 1985 and 2006⁶, and decompose occupational changes in routine task intensive 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 Figure 2, within occupational changes in task mix dominate the overall decline in RTI over this period, comprising some 80% 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 FIGURE 2

Using this information, we return to estimating task group-wage premia over time where now we allow task content to vary over time. Our first step is to re-estimate Equation 6 but decompose initially routine occupations in terms of their task content by 2006. Specifically, we focus on how the non-routine cognitive content changed over this time-period. We use our dynamic group definition of task groups, in which we create exhaustive sub-categories of 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 3 plots the resulting wage premia using these disaggregated categories.

INSERT FIGURE 3

What is immediately clear is how dramatically the evolution of wage premia for routine task intensive workers is contingent on subsequent changes in within job task content. In particular, the lack of any wage premia/penalty demonstrated earlier for routine task intensive workers reflects two very different patterns. For those initially routine intensive occupations, but which do not experience

⁶ The following wave of the BIBB data for 2021 set suffers from the change in occupational classification described previously.

increases in non-routine cognitive task content, we observe wage stagnation, and small wage penalties / premia contingent on the period. This is most marked for routine jobs which experienced a (further) decrease in NRC content. This broadly fits with previous evidence across a range of settings, routine task intensive jobs are associated with wage stagnation and / or losses. However, this is simply not true of 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. This is an important finding as it indicates dramatically different wage effects across jobs that initially had similar routine intensity.

4.2 Robustness and Mechanisms

Naturally, these results raise a range of questions. A first obvious concern is that these initially routine task jobs are simply different in some way and that this is predictive of wage growth over the period. It is worth recalling that these 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, and as reported in Table A3, there exist 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 reflects attempts to make comparisons across task groups more comparable (in terms of observables) jobs and workers 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 or higher.

The resultant estimates are reported in two panels as Figure A2. As can be seen, the reported patterns of wage premia 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.

A further concern is that there are patterns of entry and exit into these occupations that may explain the differential wage premia. For instance, and related to the point above, perhaps patterns of entry and exit of workers differ across occupations in ways that affect the evolution of wages. For instance, initially routine task jobs that increased in NRC may have replaced older, lower skilled workers, with younger higher skilled workers. These workers would not only be more productive, but more likely to become increasingly productive on the job and hence experience wage growth as they learn on the job.

A related issue is that entrants to occupations may not, in practice, conduct the same average task mix as the older workers they are joining or replacing. To examine 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 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 years) and older workers (age 35-50 years) who in a specific year t (1985, 1990, 1995, 2000) were in one of the task groups R- NRC high, R-NRC middle, R-NRC low or NRC occupations.⁷ 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 4. Two features become apparent. First, for young and older workers, we observe two task groups with increasing wage growth over time (R- NRC high and NRC), and two task groups with decreasing wage growth over time (R-NRC low and R- 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 3, 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 old workers in those jobs, but rather by higher wage growth in R – NRC high and NRC occupations for all workers across all years. This result is in line with the additional observation that mean task intensities for young and old workers are very similar (Table A5), i.e. that young and old workers are doing roughly the same tasks. The higher wage growth of younger workers in Figure 4 is likely to be the result of job ladder effects which are more important early on in the life cycle, rather than differences in job task between young and older workers.

INSERT FIGURE 4

⁷ 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.

Another important determinant of wage growth, in addition to within-occupation task change, is job mobility between task groups. Our working hypothesis is that switching out of the “declining” occupations R-NRC low and R-NRC middle to NRC or R-NRC high is associated with positive subsequent wage growth. By contrast, switching out of R-NRC high or NRC can be expected to be associated with negative subsequent wage growth unless workers switch to either NRC or R-NRC high.

We therefore analyse the wage growth of workers who in year t were in one of the five task groups considered, 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).

The analysis of task group switches yields several insights (Figure 5). 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-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-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-NRC high (NRC) occupations rather than switching out of it, unless you switch to NRC (R-NRC high) occupations.

INSERT FIGURE 5

Switching between task groups does not occur at random. Instead, workers purposefully select into task groups (Böhm et al. 2022). 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 into to NRC or R-NRC increase 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 3. 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. In order 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 6 and can be summarized as follows. First, in general there is a high likelihood of switching into NRM occupations, this likely reflects the large size of this task group (see Table A3). Second, workers with higher ability have a higher likelihood of switching to NRC, workers with lower ability have a higher likelihood of switching to NRM. Third, workers in R-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-NRC high workers have the highest likelihood of switching to NRM. This changes over time as even R-NRC high workers with lower ability in 1999-2010 have a higher likelihood of switching to NRC and lower likelihood of switching to NRM. Fourth, the probability that R-NRC middle and R-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-NRC middle and R-NRC low occupations. Fifth, despite the small size of the R-NRC high task group, NRC workers have a relatively high probability of moving into this task group.

INSERT FIGURE 6

Our results imply that R-NRC high and NRC occupations are relatively close in terms of human capital transferability. If workers in R-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-NRC middle, R-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-NRC high occupations feature high wage growth and attract workers with better skills and ability; workers in R-NRC middle, R-NRC low and NRM occupations feature relatively low wage growth and attract workers with lower skills and ability. This suggests that the positive selection of workers with higher ability who switch to NRC and/or R-NRC high occupations is an important driver of the high wage gains in these task groups.

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 return to this issue with novel data for German that allows us to explore how these jobs have changed particularly in terms of within occupational task mixes. Over a 25 year period

we demonstrate 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 conditions resultant wage premia, and that only those jobs that remain routine task intensive over this period are associated with wage losses or stagnation. These results do not appear to reflect factors such as demographic shifts in workers within occupations, but rather more fundamental changes in the nature of these jobs.

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 workers may be better off staying in an occupation rather than switching to another one, even as technological progress continues or even becomes more intensive, e.g. with the growing importance of artificial intelligence. Second, the importance of adaptability within a given occupation highlights the 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, and more generally, our results indicate that accounting for within-occupation task change is crucial for understanding the wage effects of technological change.

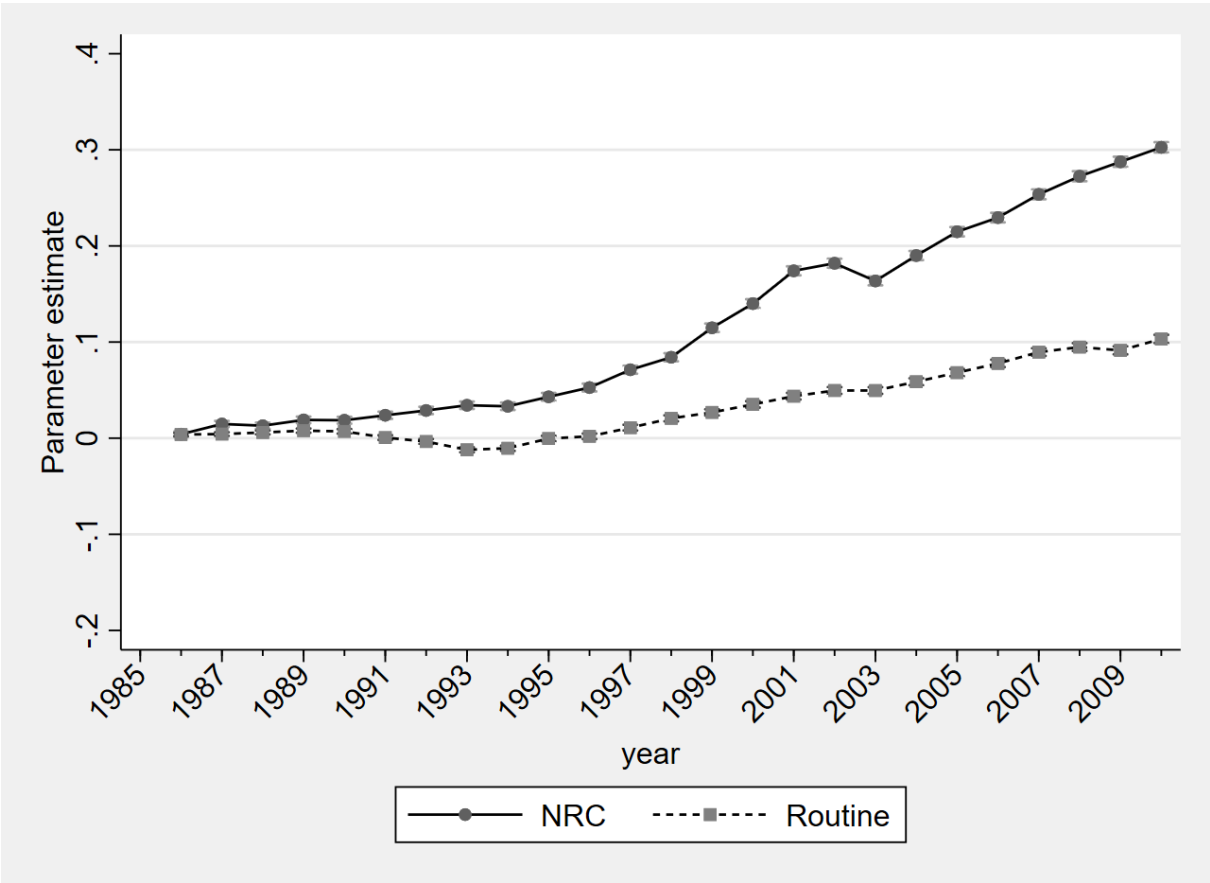
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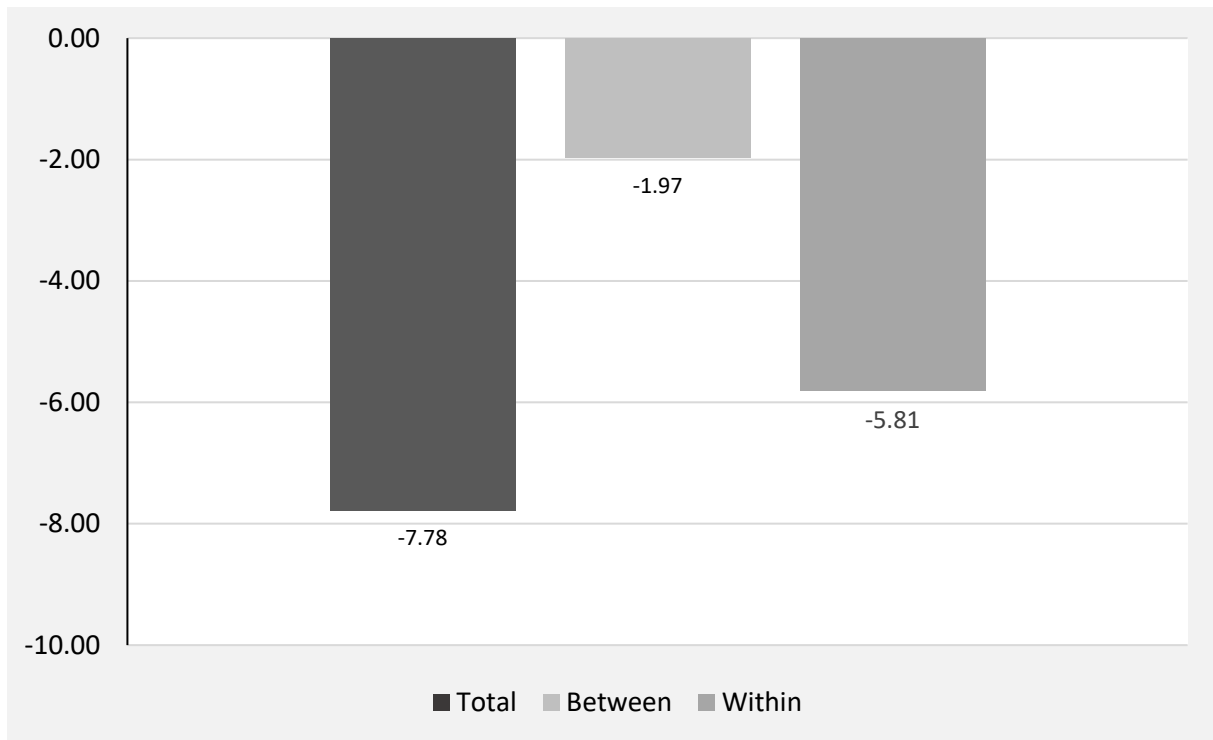
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Figure 1 Occupation premia by task groups (fixed task groups using BIBB 1985 data)



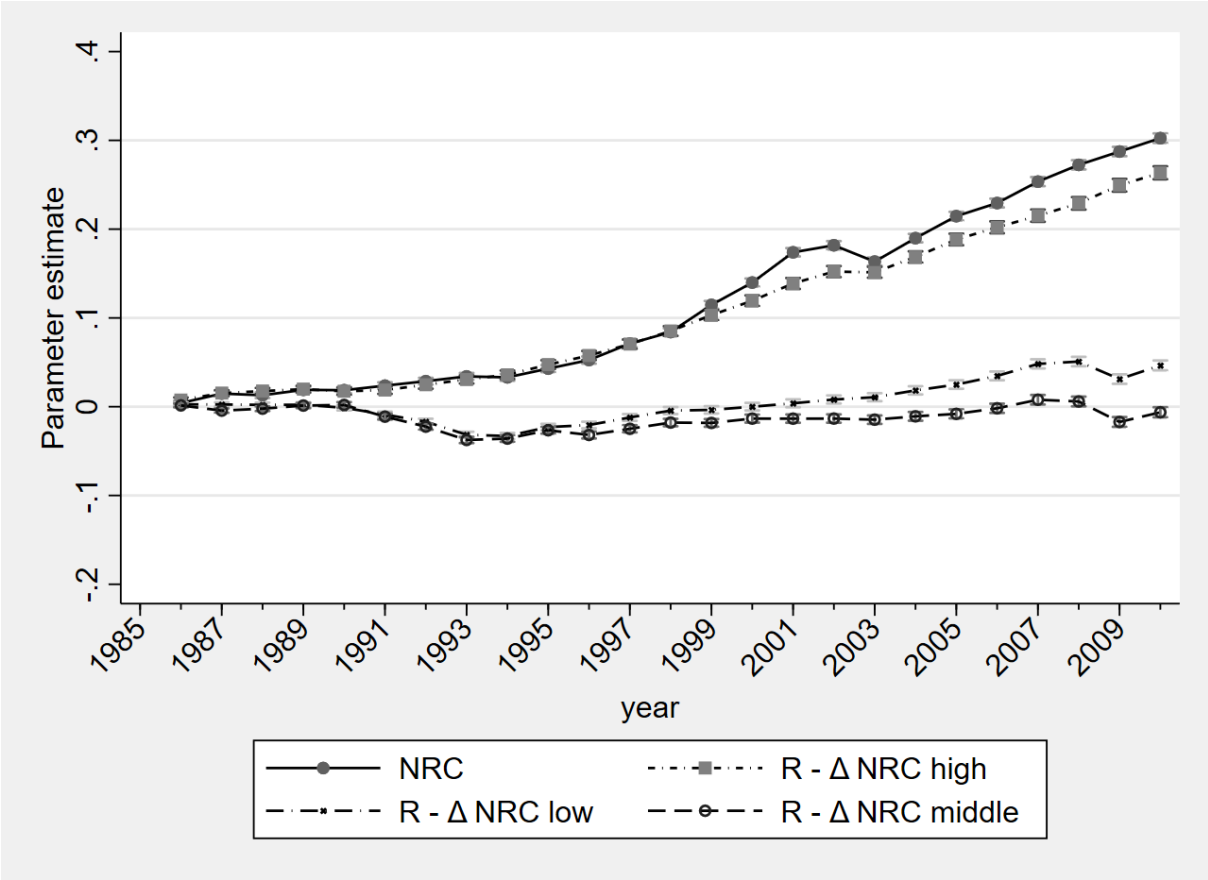
Note: Evolution of occupation wage premia over time. NRC: non-routine cognitive occupations. Reference category: NRM = non-routine manual occupations.

Figure 2 **Decomposition of RTI change, 1985-2006**



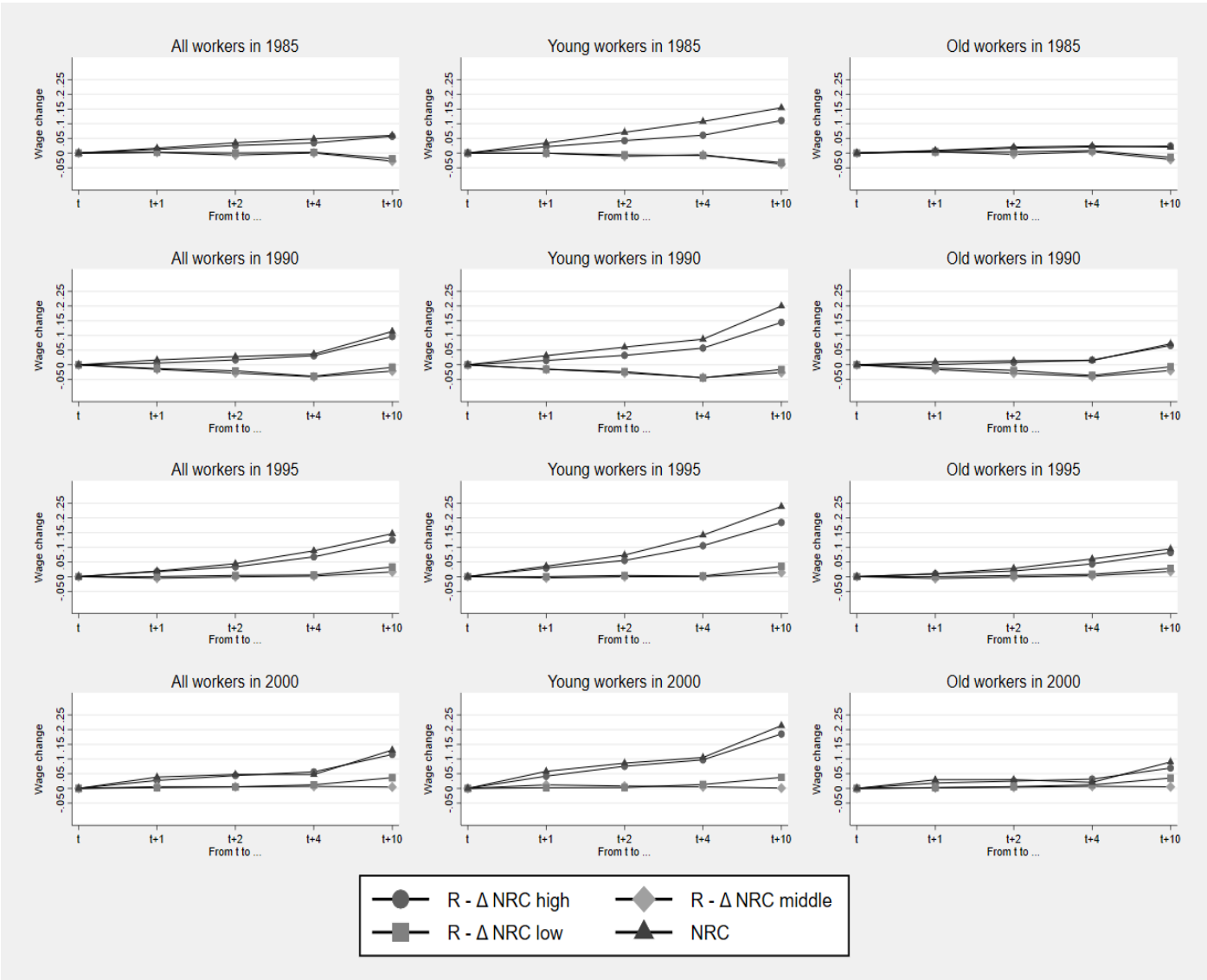
Note: This figure shows the change in overall RTI (Total change) as well as the respective contributions to this total change of the composition of occupations in total employment holding RTI within occupations constant (Between change) and of the RTI change within occupations holding composition constant (Within change).

Figure 3 Occupation Wage Premia by task groups (routine subgroups by change in NRCTI between 1985 and 2006)



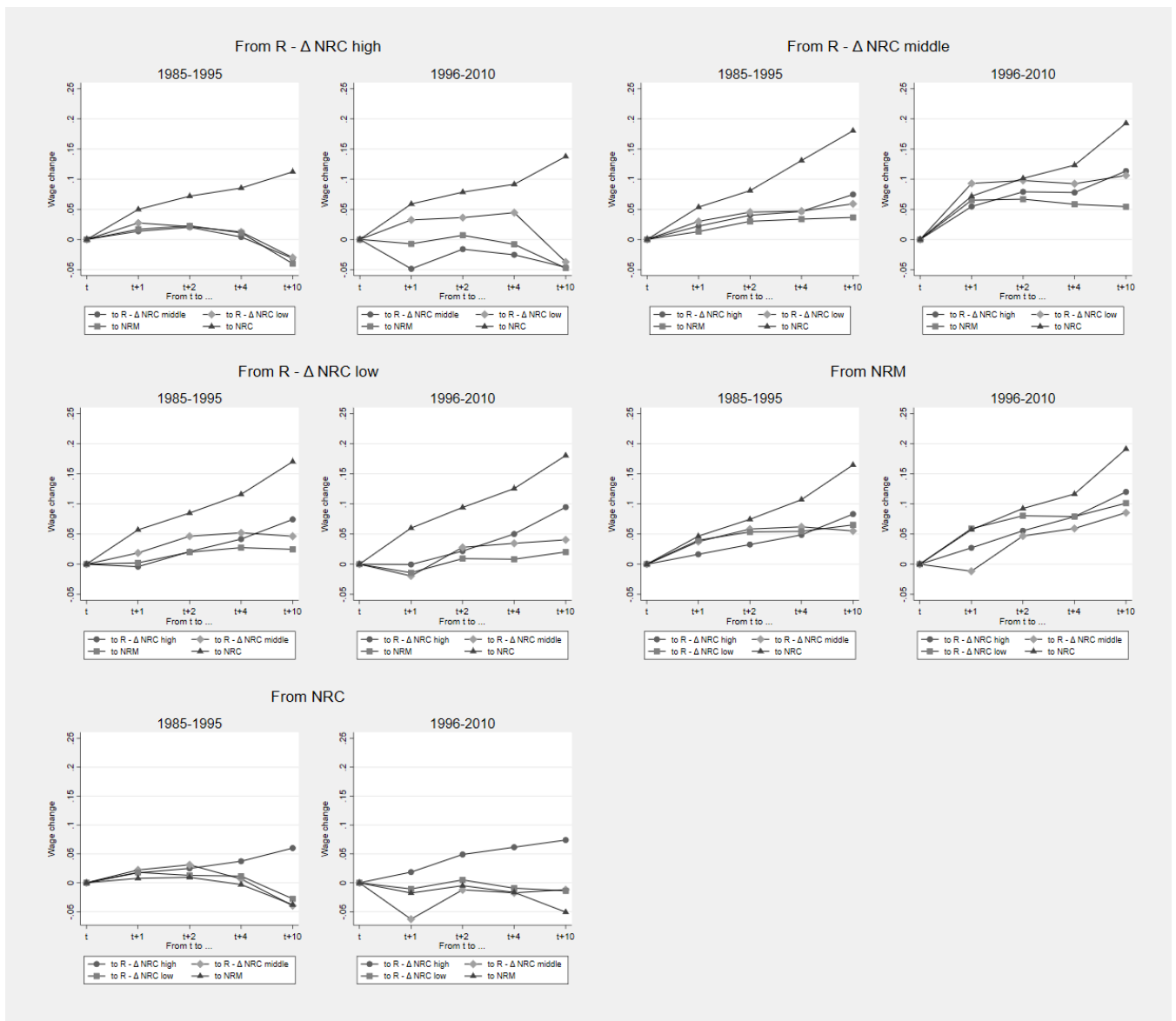
Notes: This figure shows the occupation wage premia over time for occupations which were routine or non-routine cognitive in 1985 (according to the BIBB data). Additionally, the routine task group is divided into three further subgroups by change in NRCTI over time: Routine – NRC increase, Routine –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

Figure 4 Wage Growth by Age and Cohort



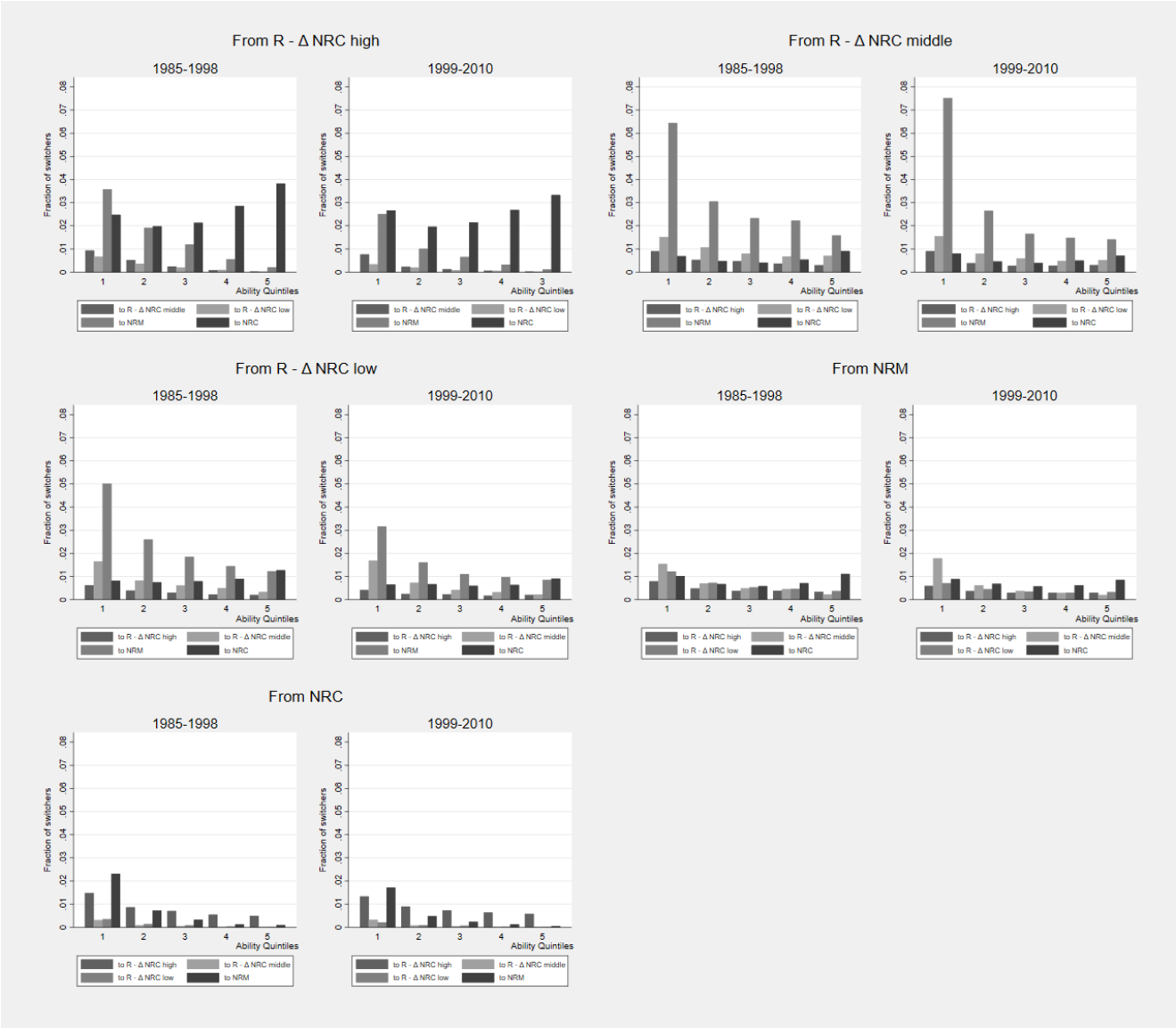
Notes: This figure shows the wage growth for different task groups over time and for young workers (25-34 years old) vs. old workers (35-50 years old). We subsample different years and regress wage growth on workers who in starting year t were in one of the task groups. Reference category: NRM.

Figure 5 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 6 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.

Appendix

TABLES

Table A1 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) |
| Number of full-time workers in establishment | 1788.18 | (5913.86) | 1245.35 | (5106.95) | 1697.27 | (5755.74) |
| Mean imputed wage of full-time workers in establishment | 115.46 | (35.55) | 105.61 | (29.11) | 138.97 | (52.73) |
| 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 | |

Table A2 **Sample descriptives, task classification following Cortes (2016)**

| | Routine | | Nonroutine Manual | | Nonroutine Cognitive | |
|---|----------------|-----------|--------------------------|-----------|-----------------------------|-----------|
| No. of observations | 3,008,751 | | 706,438 | | 1,487,308 | |
| Share | 57.83 | | 13.58 | | 28.59 | |
| No. of individuals | 297,979 | | 115,856 | | 156,855 | |
| Averages | | | | | | |
| Log (daily) wage | 4.64 | (0.28) | 4.52 | (0.33) | 4.91 | (0.31) |
| Log (daily) imputed wage | 4.66 | (0.33) | 4.52 | (0.35) | 5.07 | (0.51) |
| Age | 40.08 | (11.10) | 39.44 | (11.16) | 41.16 | (10.14) |
| Number of full-time workers in establishment | 1370.73 | (5244.36) | 1863.90 | (6440.07) | 1744.11 | (5720.76) |
| Mean imputed wage of full-time workers in establishment | 111.68 | (32.43) | 103.72 | (31.72) | 139.17 | (53.36) |
| Job tenure (in years) | 7.97 | (7.02) | 6.73 | (6.62) | 7.48 | (6.90) |
| Labour market experience (in years) | 13.39 | (7.84) | 12.42 | (8.04) | 13.31 | (7.84) |
| Task measures | | | | | | |
| RTI | 0.43 | (0.16) | 0.37 | (0.16) | 0.25 | (0.10) |
| NRM | 0.35 | (0.17) | 0.38 | (0.16) | 0.15 | (0.12) |
| NRC | 0.22 | (0.19) | 0.25 | (0.20) | 0.60 | (0.17) |
| Fractions within the task group | | | | | | |
| No vocational training | 11.91 | | 21.31 | | 2.70 | |
| Vocational training | 84.30 | | 75.55 | | 60.56 | |
| University or university of applied science | 2.94 | | 1.76 | | 36.08 | |
| Missing | 0.85 | | 1.38 | | 0.66 | |
| Mining industry | 1.78 | | 0.42 | | 0.64 | |
| Manufacturing industry | 46.88 | | 37.70 | | 34.94 | |
| Energy and water supply industry | 1.84 | | 0.45 | | 1.48 | |
| Construction industry | 16.33 | | 2.33 | | 2.74 | |
| Trade and repair industry | 13.12 | | 17.83 | | 11.78 | |
| Catering industry | 0.34 | | 3.40 | | 2.72 | |
| Transport and news industry | 7.00 | | 10.76 | | 2.44 | |
| Finance and insurance industry | 0.78 | | 0.56 | | 10.57 | |
| Real estate and housing, renting of movable property, business service industry | 4.49 | | 10.78 | | 15.00 | |
| Public services industry | 4.65 | | 5.57 | | 4.00 | |
| Education industry | 0.36 | | 1.23 | | 2.75 | |
| Health industry | 0.86 | | 4.86 | | 7.09 | |
| Other services industry | 1.56 | | 4.11 | | 3.83 | |
| Missing | 0.01 | | 0.00 | | 0.01 | |
| Foreign workers | 9.93 | | 16.23 | | 4.77 | |
| Censored wages | 6.08 | | 2.63 | | 36.96 | |

Table A3 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) |
| Number of full-time workers in establishment | 1385.57 | (5131.35) | 1826.59 | (6035.97) | 2165.62 | (6493.73) | 1245.35 | (5106.95) | 1697.27 | (5755.74) |
| Mean imputed wage of full-time workers in establishment | 121.71 | (42.10) | 107.11 | (31.36) | 116.88 | (29.95) | 105.61 | (29.11) | 138.97 | (52.73) |
| 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 | |

Table A4 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 |

Note: 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.

Table A5 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 |

Note: 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. old (age 35-50 years) workers.

Figure A1 Occupation Wage Premia by Task Groups (Cortes approach)

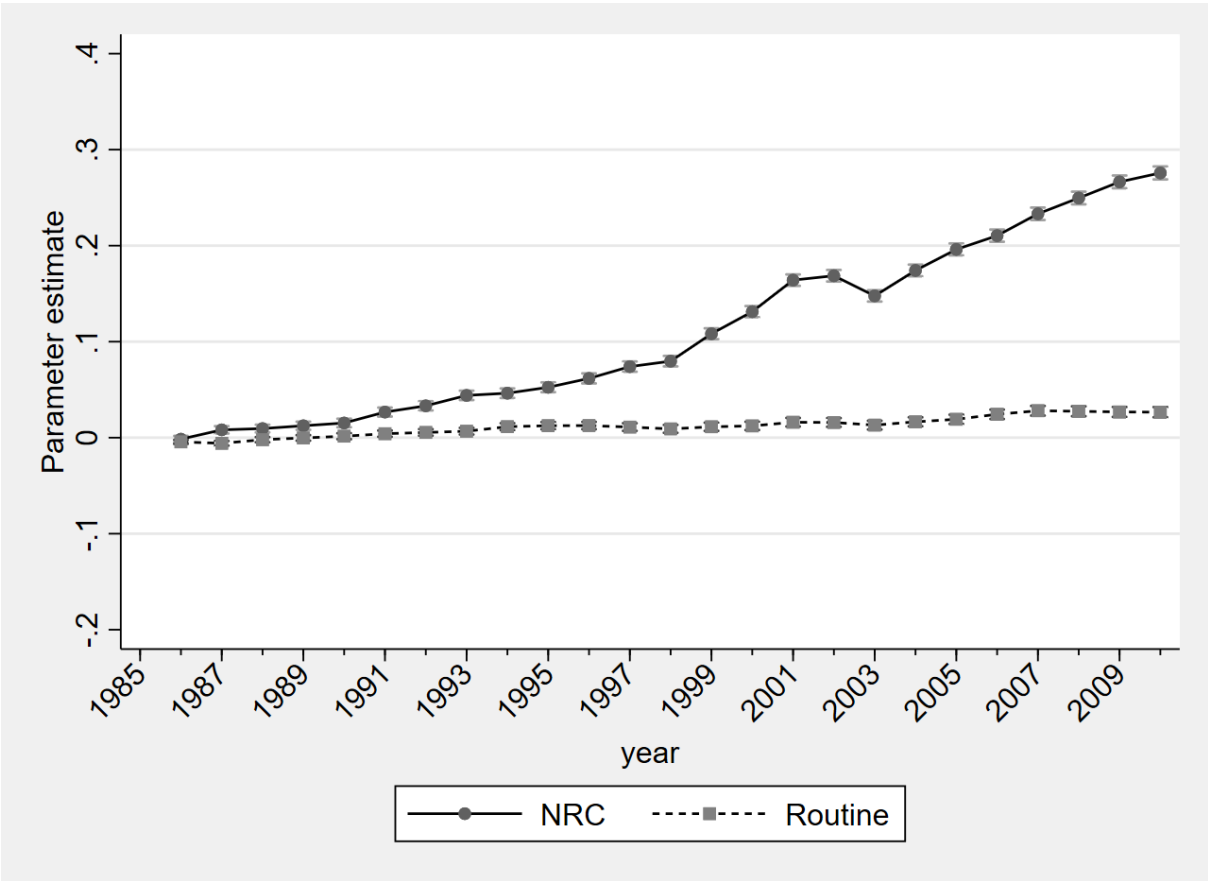


Figure A2 Robustness Checks: Occupation Wage Premia by Task Groups

