Long-run Patterns of Labour Market Polarisation: Evidence from German Micro Data

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We thank Peggy Bechara, Britta Matthes and seminar participants at the IAB, the RWI, the University of Dusseldorf, the 2016 IWAEE conference, and the 2016 Scottish Economic Society meetings for helpful comments and suggestions, and Anja Rösner and Jan Wergula for excellent research assistance. We also gratefully acknowledge financial support from the Bertelsmann Foundation

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Abstract

The past four decades have witnessed dramatic changes in the structure of employment. In particular, the rapid increase in computational power has led to large-scale reductions in employment in jobs that can be described as intensive in routine tasks. These jobs have been shown to be concentrated in middle skill occupations. A large literature on labour market polarisation characterises and measures these processes at an aggregate level. However to date there is little information regarding the individual worker adjustment processes related to routine-biased technological change. Using an administrative panel data set for Germany, we follow workers over an extended period of time and provide evidence of both the short-term adjustment process and medium-run effects of routine task intensive job loss at an individual level. We initially demonstrate a marked, and steady, shift in employment away from routine, middle-skill, occupations. In subsequent analysis, we demonstrate how exposure to jobs with higher routine task content is associated with a reduced likelihood of being in employment in both the short term (after 1 year) and medium term (5 years). This employment penalty to routineness of work has increased over the past four decades. More generally, we demonstrate that routine task work is associated with reduced job stability and more likelihood of experiencing periods of unemployment. However, these negative effects of routine work appear to be concentrated in increased employment to employment, and employment to unemployment transitions rather than longer periods of unemployment.

JEL codes: J23, J24, J62, E24

Keywords: polarization, occupational mobility, worker flows, wages, tasks.

1 Introduction

The past four decades have seen dramatic changes in the structure of employment. As documented by Autor et al. (1998), the US witnessed a large reduction in the employment of middle skill workers. At the same time, there have been increases in the employment of high skill, and to some extent, low skill workers. This pattern of employment polarisation has also been demonstrated for the UK by Goos & Manning (2007) and across Europe by Goos et al. (2009), and is likely to continue in the future (Autor 2015).

These changes have been ascribed to the fact that these middle skill jobs involved tasks that were intensively routine in nature. As a result, they were most readily substituted with capital as computer technology became cheaper (Autor et al. 2003). This same technology is factor augmenting to high skilled workers which in turn leads to a growth of complementary, high skill, non-routine intensive jobs. Along these lines, Autor et al. (1998) demonstrate that increased employment of high-skill labour largely occurred within computer intensive industries. The growth in low-skill employment that has occurred has also been concentrated in jobs that are not routine intensive (e.g. personal services). One argument is that this reflects a compositional change in consumption due to the increase in high skill workers (Mazzolari & Ragusa 2013).

This literature provides a compelling view of the impact of structural change on the labour market over the past four decades. With this said, the existing empirical evidence largely takes the form of comparisons of decade upon decade employment numbers and shares at aggregated levels of occupational detail. Until relatively recently, the dynamics of employment transitions implicit in the process of polarisation have been inferred from comparisons of these cross-sectional changes. An almost wholly US literature has developed that uses micro data to examine the contribution of different flows to the evolution of employment polarisation. For instance, both Jaimovich & Siu (2012) and Smith (2013) highlight the decline in inflows to routine work particularly from unemployment. The latter paper in addition provides some evidence of increases in inflows into high and low skilled employment, and more generally that overall job finding rates into non-routine jobs have been rising. Along similar lines, Cortes et al. (2014) examine which specific labour market flows can account for rising job market polarization. They find that the disappearance of routine jobs is mainly due to falling worker flows from both unemployment and non-participation to routine employment, and to rising worker flows from routine employment to non-participation. Cortes et al. (2017) find that most of the fall in routine employment in the US during the last 35 years can be accounted for by the sharp drop in the propensity for routine manual employment among young and prime-aged men with low levels of education. A similar pattern is observed for routine cognitive jobs of prime-aged women with medium levels of education. These groups also experience an increase in the propensity for non-employment and for non-routine manual employment. Cortes and Gallipolli (2018) examine between occupational flows for the US and show that task content heterogeneity, between occupational pairs, has a significant impact on transition costs. While they stress that the majority of mobility costs are not related to tasks, costs related to task differences lead to lower level of occupational mobility than would otherwise be observed. For Germany, Bechara (2017) finds that the employment contraction in routine occupations is largely attributable to young workers and women who increasingly leave routine-intensive jobs and subsequently enter other occupations or into non-participation.[1]

In practice, little is known regarding the actual process of job-loss and reemployment at the individual worker level, particularly the nature of individual worker transitions that result from the reduction in demand for routine intensive work. This seems an important gap in our knowledge as any potential losses due to this pattern of structural change is likely to be most concentrated among routine workers. An exception is the recent paper by Cortes (2016) who uses the Panel Studies of Income Dynamics (PSID) to look at long-run effects of labour-market polarization in the US. He finds evidence of selection on ability for workers switching out of routine jobs. In particular, while low-ability routine workers are

[1] In contrast to our paper, Bechara (2017) focuses on occupational inflow and outflow rates at the 2-digit level as well as differences between men and women in this context.

more likely to switch to non-routine manual jobs, high-ability routine workers are more likely to switch to non-routine cognitive jobs. With respect to wages, his results suggest that workers staying in routine jobs experience less wage growth than workers staying in any other type of occupation. This is characterised by a reduction in the wage premium for routine occupations of 17% between 1972 and the mid-2000s. Furthermore, Cortes et al. (2014) use CPS data to analyse what role labour market flows play for the disappearance of routine jobs in the US since the 1980s.

This paper uses administrative data for Germany to characterise the individual level patterns underlying the process of labour market polarization. Our data is particularly well suited to addressing these issues as it allows us to follow individuals across a long span of time. Specifically we can examine individual level transitions but also how these have changed over the past 4 decades. In doing so we provide evidence on the secular pattern of polarisation over a long time period at a high frequency of observation. As a result, we can characterise the evolution of polarisation over time. In addition, we provide evidence on a range of individual level job transitions. Initially, we provide a range of descriptive evidence on the relative job stability, unemployment experiences and job-to-job transitions for routine task intensive workers. We then move to multivariate analysis in an attempt to assess the role of compositional effects. Finally, we provide suggestive evidence on welfare losses, in terms of unemployment duration and job instability related to employment polarisation.

The contribution of our paper to the existing literature on routinisation is therefore twofold. First, we are, to the best of our knowledge, the first to provide encompassing micro evidence on the long-run effects of labour-market polarization for a European country, thus complementing the evidence provided by Cortes (2016), Cortes et al. (2014) and Cortes et al. (2017) for the US. Second, our analysis goes beyond the existing literature by providing detailed evidence on the nature of the labour market experiences of routine workers, also taking into account occupation-specific measures of task intensity that vary over time. This type of analysis is only possible with the type of panel data at our disposal, which we complement with survey information on occupational task content, i.e. routine intensity.

The paper is structured as follows. In the next section, we provide information on the data used including the administrative data set as well as the data on the task intensity of different occupations. The third section presents the empirical methodology, while the fourth section reports and discusses the results, and the final section summarizes and concludes the discussion.

2 Data

2.1 Worker-level data

Our main data source is the Sample of Integrated Labour Market Biographies (SIAB) for 1975-2014, which is provided by the Institute for Employment Research (IAB). The SIAB is a representative 2% random sample of the Integrated Employment Biographies (IEB) which contains the labour market history of all individuals in Germany that are employed subject to social security contributions, those in part-time employment not earning enough to make social security contributions, those receiving unemployment or social benefits, and those officially registered as job-seeking at the German Federal Employment Agency or participating in programs of active labour market policies. Civil servants and self-employed workers are not included in the data.[2] The information on labour market states is exact to the day. A detailed description of the Sample of Integrated Labour Market Biographies is provided in vom Berge et al. (2013).

The SIAB provides information on workers' employment status, age, gender, occupation and education as well as limited information on establishment characteristics (economic sector, establishment size). This data set is representative for all dependent-status workers, and contains information on all

[2] 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, implying that transitions into and out of this state only play a minor role for our analyses.

employment and unemployment spells of the workers covered. From this sample, we further exclude, apprentices, trainees, homeworkers, and individuals older than 65.[3] In line with previous research we focus on male full-time workers aged 18-65. As our period (1975-2014) covers the pre-unification period, we focus on West Germany only.

The data allows us to characterise individuals as being in one of three labour market states at any point in time: employment covered by social security (E), unemployment with benefit receipt (U), and non-participation (N). Non-participants are those individuals not recorded in the data sets. Therefore, this state includes those workers out of the labour market, as well as workers not covered by social security legislation, e.g. civil servants and self-employed workers.

Because of the way the data are collected, both establishments' reports of a new employee and individuals' notifications of moving into or out of unemployment may not be exactly consistent with the actual change of labour market state. For example, workers might report to the unemployment office only a few days after they are laid off. We take this potential measurement error into account in the following way: If the time lag between two employment spells at different establishments does not exceed 30 days, this is defined as a direct transition between the two states recorded. We count it as an intervening spell of non-employment if the time interval between the two records is larger than 30 days.

Since the data set used contains daily information on the employment and unemployment history of every individual in the sample, it is possible to calculate worker flows taking into account every change of labour market state that occurs to an individual within a given time period. We are thus able to compute the flows between employment and non-employment, as well as direct job-to-job transitions (EE flows) using the establishment identification number.

2.2 Measuring routine intensity and related worker flows

The analysis of the employment consequences of routinisation requires the classification of employment into occupations according to task types. As highlighted in Autor (2013) there exist three broad approaches in the literature this.[4] The first is a parsimonious approach as per Goos & Manning (2007), Goos et al. (2009) and Cortes (2016) whereby workers are assigned to routine, non-routine manual and non-routine cognitive categories based on groups of standardised occupational codes. A chief virtue of this approach is that it does not require the measurement of task content at an occupational level, while using relatively aggregated occupational information makes this approach more robust to periodic reclassifications of disaggregated occupational classifications. This comes at the potential cost of the introduction of measurement error due both to within-occupational variation in task intensity, and changes in occupational task intensity over time.

The second approach, as in Autor et al. (2003), relies on occupational task analysis from additional sources to classify jobs in terms of task intensity. In the US context this comes from the Dictionary of Occupation Titles (DOT) (and later O*NET) information on the task composition of occupations. This information is generated from periodic expert evaluations of job task content. This approach more clearly mitigates some of the issues of measurement error inherent in the first approach. However, the relative infrequency of DOT still leads to likely variation between the defined task content of an occupation and what tasks any given worker's job is likely to actually consist of as one moves further away from the DOT date. One of the aims of the O*NET replacement was to limit this information lag by providing more frequent job task information.

The third approach has been used widely in the German Context. Unlike the DOT approach where expert evaluations are used, survey-based information on task content is instead used. This, in part,

[3] Excluding part-time workers from our sample and treating them as non-participants artificially increases our transitions into and out of non-participation. However, as the SIAB data only distinguish between two categories of part-time employment and the number of working hours can be relatively low, we decided to focus on core full-time workers.

[4] For a more detailed discussion of this readers are referred to this article.

reflects the availability of data from BIBB/IAB and BIBB/BAuA Employment Surveys (herein BIBB data) that provide a representative sample of workers and include questions regarding the task content of jobs.[5] In previous work, three different task intensity measures have been generated using this data. Spitz-Oener (2006) and Antonczyk et al (2009) generate different measures of relative task intensity at occupation levels using worker self-reports on the task content of their work. While Baumgarten (2015) computes an alternative measure of routinisation focusing on the use of tools on the job.

We follow the approach of Antonczyk et al (2009) and categorize the activities employees perform at the workplace into routine (R), non-routine cognitive (NRC) and non-routine manual tasks (NRM). This is computed for 54 occupational categories following Tiemann et al. (2008), and for each occupation-time period combination provides a R, NRC and NRM share that sums to 100%. This measure can be expressed as:

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

As an example, for routine tasks, this implies taking the number of routine tasks performed by a person at a specific point in time, and relating this to the total number of activities performed in all task categories (routine, non-routine manual and non-routine cognitive). Taking the averages of individual task intensities provides a continuous measure of Routine Task Intensity (RTI) over time for a given occupational group.[6]

A key advantage of this data is that the survey is conducted at regular six to seven year intervals throughout our period of analysis (1979, 1985/86, 1991/92, 1998/99, 2006 and 2012). This allows us to have time-varying task intensity by occupational groups. As mentioned above, earlier literature has tried to explain the long-term relative decline of different task intensities, while other research has focused on quite short periods. In both cases this leads naturally to an approach where occupation task intensity is fixed at an initial or pre-sample period. A focus of our paper is how worker outcomes at a particular time period are influenced by exposure to different task mixes. Hence, it seems inappropriate to, for instance, examine outcomes of workers in the 1990s based on the task intensity of their occupation fixed at 1979 values. Our main approach is to use the BIBB data to update occupation task intensities over time. This has the advantage that worker outcomes are evaluated more closely to their actual task composition at the time of observation.

A cost of this approach is that, when compared to using initial task values only, there is the potential for marked discontinuities in the task intensity shares at BIBB survey dates. These are not large in practice in terms of continuous measures of task intensity. However, any analysis that, like previous work, is based on categorising workers into different, discrete task intensity groups (e.g. R, NRM and NRC) faces a naturally greater probability of discontinuities at BIBB survey dates in the proportion of occupations (and hence workers) belonging to any given task group. We use a number of approaches to dealing with this issue, but stress that none of these choices 'drive' our results. Initially we provide descriptive evidence that aims at being comparable with longer, but 'snapshot' based, evidence for the US, UK and elsewhere. In doing so, we adopt a similar approach to this particular strand of the literature and fix occupations into three categories at the start of the data. These categories are:

i. Routine (R): Administrative support, operatives, maintenance and repair occupations, production and transportation occupations (among others).
ii. Non-Routine Cognitive (NRC): Professional, technical, management, business and financial occupations.
iii. Non-Routine Manual (NRM): Service workers.

[5] Details about how we deal with the different waves of the task data set are in the appendix.

[6] In unreported estimates we use the alternative approach set out by Spitz-Oener (2006). The nature of our results are largely unaffected by this.

Our next step is to try to examine the evolution of worker outcomes over the period, focusing on two sets of complementary outcomes. First, we seek to provide results on the effect of RTI on the employment probabilities of workers over the short run (1 year) and long run (5 years). Note that this means that our analyses using the RTI measure start in 1979, whereas the analyses using the three task groups starts in 1975; furthermore, the analyses following individual workers for 5 years stop in 2008 in order to avoid the problem of right-censoring. We then subsequently extend this to duration modelling of the effect of RTI on labour market transitions more broadly. In both of these cases, we use RTI as a continuous measure. We deal with the issue of revisions of occupational task shares across BIBB waves by splitting our data into a number of BIBB-Survey data specific periods (e.g. 1979-1984; 1985-1991; 1992-1998; 1999-2005; 2006-2011 and 2012 to present). This allows us to provide evidence on how the effect of task intensity on worker outcomes has changed over the past 3 decades. We again stress, however, that the main thrust of our findings are not materially affected by alternative approaches such as pooling our data across the whole survey period.

3 Methodology

3.1 Descriptive Evidence

We first provide descriptive evidence that aims to paint a picture of the labour market situation of workers according to the task content of their work. Specifically, we provide univariate descriptive statistics on the evolution of task-specific employment shares and unemployment rates, and transition rates between different labour market states and task categories. We exploit a particular strength of our data and examine how these patterns have changed over a long period.

In the first step of our descriptive analysis, we provide evidence on employment stocks for the three task categories. To aid comparability over time we adopt a variant of the classification approach used by Cortes (2015) and group occupations into task categories that are fixed across time. This has the additional benefit of allowing us to more readily compare changes in occupational / task structure in Germany to existing evidence for the US and elsewhere. We then turn to the BIBB data to provide evidence where, as described above, we allow the task shares of given occupations to vary reflecting underlying changes in job content over time. The distribution of each task type for each wave is provided using the occupation-level employment shares from the BIBB survey data. Finally, we take the occupational level task measures generated from the BIBB data to the SIAB data. This allows the task shares of employment to vary in between BIBB waves according to annual changes in occupational employment. This, in theory, allows for any cyclical variations in task shares to be apparent. In practice, all three approaches provide an estimate of the share of tasks in the labour market at a point in time. As we discuss in the results, these are not always entirely congruent, but provide similar views on the change in task shares over the entire period.

We then proceed from this to examine worker transitions between labour market states, again paying particular attention to the three task groups. In order to do so, we first display a transition matrix between workers employed in the different task groups and unemployed workers who were previously employed in these three task groups. This provides evidence on the probability of a switch between task groups, both directly (job-to-job) and indirectly (through unemployment). Next, we compute the probability of job exit by task group over time. This yields a measure of job stability for routine, non-routine manual and non-routine cognitive workers. We then examine where workers who have separated from their previous job, and who make a direct job-to-job transition, end up in terms of task category. In a similar vein, we provide evidence on unemployed workers according to the task affiliation in their previous job. We thus show the evolution of the unemployment exit rates by task type over time, as well as the destination task groups where workers end up.

3.2 Econometric Analysis

With this as initial information, we then examine how the employment probabilities of workers with a given RTI evolve over the short (1 year) and medium (5 years) term. In order to investigate the determinants of these employment probabilities, we estimate logit models of the form

$$Pr[y_{it} = 1|x_{it}, \beta, \alpha, \gamma] = \Lambda(\alpha_i + RTI_{it}\beta + x_{it}\gamma) \qquad (2)$$

where *Λ(.)* is the logistic cdf with *λ(z) = ez/(1 + ez)*. X_{it} is a vector of individual- and job-specific variables including age, skill level, economic sector, firm size, region (Bundesland) fixed effects, month dummies, as well as the regional unemployment rate. To avoid issues regarding discontinuous changes in RTI due to changes in BIBB based classifications we stack observations from each BIBB year (1979, 1985, 1992, 1999, 2006, 2012). As a result, RTI is the routine task intensity of *ith* individuals job at time *t* described in equation (1) above. β is the coefficient of interest and provides the conditional (average) effect of RTI on an individual's future employment probability. We include BIBB wave dummies in all models. All estimates are robust to alternatively estimating (2) by linear probability model.

In the empirical results we extend (2) in a number of ways. One main extension relates to time variation and non-linearities in task effects. Estimates of β provide the average effect of RTI on employment outcomes of workers across our period of observation. A main interest is in how this has changed over time. To examine this we first interact RTI with a time trend. This provides an estimate of changes in the employment effect of RTI over time. We subsequently include industrial sector – time interactions to isolate this RTI-time effect separately from sector – year specific shocks to employment.

Any differential patterns in employment by task group that are revealed reflect a range of underlying types of labour market transitions, including those related to job loss and re-employment patterns. To examine this we again provide descriptive evidence related to job loss rates and re-employment rates by task group. This is provided overall and by decade, and with a focus on the extent to which re-employment occurs within the same task type or via transitions to alternative types. This is important as it provides evidence of where routine job workers go after job loss. Do they experience lower re-employment probabilities (and hence are more likely to experience longer unemployment durations)?

Examining this again leads directly into multivariate analysis. The most appropriate approach is to estimate models that recognise the underlying duration nature of the data. This leads to the estimation of hazard rate models. As our dataset contains daily information on individual workers' employment histories, we use a semi-parametric specification in continuous time, i.e. a piecewise-constant exponential (PCE) model. As the PCE model is a proportional hazard model, the conditional hazard rate of leaving employment *λ(t|X,RTI)* satisfies the separability condition:

$$\lambda(t|x_{it}, RTI_{it}) = \lambda_0(t)\exp(\gamma x_{it} + \beta RTI_{it}) \qquad (3)$$

where *X* is a vector of individual, potentially time-varying, characteristics, and λ_0 denotes the baseline hazard. Again, RTI measures the task intensity of the *ith* worker's job and β is the parameter of interest. The PCE model assumes that the baseline hazard is constant within a specified time interval, and thus follows a step function with k segments.

$$\lambda_0(t) = \lambda_j,\ a_{j-1} \leq t < a_j,\ j = 1, \ldots, k. \qquad (4)$$

We specify six such segments: 0 to 30 days of employment duration, 31 to 182 days, 183 to 365 days, 366 to 1095 days, 1096 to 2920 days, and more than 2920 days. We estimate (3) separately for job to job, job to unemployment transitions, and unemployment to job transitions. The first set of estimates provides an estimate of the impact of RTI on overall job stability. The second relates to the potentially most negative outcome, job loss coincident with unemployment. While the last provides estimates of the effect of RTI on ongoing difficulties in re-entering employment. An issue with this last set of estimates is how to define an unemployed individual's RTI. Our approach is to use the RTI of their last employment spell. This has the added effect that we can only estimate these models for unemployed individuals who we observe in our data in a job prior to this unemployment spell.

Even though we control for a wide array of observable characteristics, the hazard rates of observationally equivalent individuals may still differ from each other. Ignoring such unobserved heterogeneity in duration models produces incorrect results (cf. Lancaster 1990). To account for unobserved heterogeneity, the proportional hazard model is extended to allow for a multiplicative unobserved heterogeneity term u, which yields a mixed proportional hazard model.[7] The hazard function then becomes:

$$\lambda(t|x_{it}, RTI_{it}, u) = \lambda_0(t)\exp(\gamma \quad x_{it} + \beta RTI_{it}) \qquad (5)$$

where υ follows a Gamma distribution (Abbring and van den Berg, 2007) and is assumed to be independent of regressors and censoring time. The heterogeneity term is shared across different spells of a given individual, causing observations within groups to be correlated.

In all duration models our control vector, X, largely follows that for (2). We include industry, region, year fixed effects and regional unemployment rates to capture differences in economic conditions over time and across regions. Again, we explore time variation and non-linearities in the effect of exposure to different levels of RTI on labour market outcomes.

4 Results

4.1 The Evolution of Task Shares and Intensities 1979 to 2013

Figure 1 displays the annual employment shares by task type for the period 1975 to 2014 based on the initial, Cortes style, classification approach. It is clear that the employment share of routine jobs has strongly declined over the time period under observation, from 69% in 1975 to 48% in 2014 for men (Figure 1). This represents a dramatic reduction in the employment share for these types of jobs. By contrast, the employment shares of non-routine manual have increased from 12% to 20% and from 19% to 32% for non-routine cognitive jobs during the same time period. Again, this fits broadly with the existing evidence for other countries.[8]

INSERT FIGURE 1

The relatively smooth nature of this process over the period is also noticeable. Our data suggest that polarization has been an on-going, gradual, process in Germany, particularly for the increase in NRC and NRM employment. To our knowledge, this is the first time that evidence has been provided allowing for a long-period, and relatively high frequency, view of the polarisation process for a European country. In unreported results, we examined absolute numbers of routine workers over time, rather than employment shares. This revealed evidence of cyclical variations in the decline of routine employment. This is in line with evidence from the US which has suggested that polarisation has been concentrated in recessions (Jaimovic and Siu, 2012).

INSERT FIGURE 2

As an alternative view of the same process, Figure 2 provides the average share of workers' job task intensities across the 6 BIBB waves. These numbers result, in effect, from computing the intensities of R, NRC and NRM tasks from the BIBB survey data. This differs from Figure 1 insofar as (a) it provides a measure of overall 'routineness' of work across time (and of the overall intensity in NRC and NRM) and (b) by using the BIBB information we allow the task intensities of any given occupation to change over time. Nonetheless, the general view is the same. There has been a marked reduction in routine task intensity over the past 35 years. The drop is steady from 54% of all tasks in 1979 to about 30% in 2006.

[7] See van den Berg (2001) for a survey of this model class.

[8] For instance, Goos et al. (2014) find for 16 European countries that while the employment shares of the highest-paying occupations (mainly characterized by non-routine cognitive tasks) have increased over the time period 1993-2010, the employment shares of the middle-paying occupations (mainly routine jobs) have declined.

After this point there is essentially no change in the routine task share.[9] Despite the high frequency of the BIBB surveys, the task intensities sometimes change markedly at the beginning of each BIBB period. The reason behind is twofold. First, holding the task intensities constant within the BIBB periods ignores within-occupation changes and causes a dramatic change at the period beginnings. Second, the questions in the BIBB surveys vary to some extent over time. We therefore focus on the survey questions that are repeated across waves, and furthermore merge specific questions with similar content to adjust the number of questions in order to obtain a similar number of questions in each wave and task category.

INSERT FIGURE 3

Finally, Figure 3 reports the routine task share where we weight the BIBB occupation task share by the SIAB employment data. As both represent samples of the same underlying population, the overall patterns of the evolution of task shares are quite similar. However, this approach allows for within BIBB period variation in task shares and hence variation from more short-term employment changes. Taken together this provides a body of evidence that there has been a quite dramatic reduction in routine-intensive tasks in Germany since the 1970s.

INSERT FIGURE 4

Given these reductions in employment, an obvious question to ask is whether this has led to changes in the unemployment levels associated with previously being in a given job-task category. Figure 4 reports task-specific unemployment rates over time. Non-routine cognitive workers and non-routine manual workers feature the lowest and highest unemployment rates, respectively, while the unemployment rate of routine workers is between these two across the period.

4.2 Descriptive Evidence on the Links between Tasks and Employment Transitions.

We next provide descriptive evidence on labour market transitions according to job tasks performed by workers. These are most readily reported using discrete categorisation of workers into Routine, Non-Routine Manual and Non-Routine Cognitive groups. The most straightforward means of doing this is, again, in the spirit of Cortes et al (2014).

Table 1 provides evidence regarding the transition probabilities from one year to the next between employment in different task types, unemployment, and non-participation. Employment probabilities are highest for non-routine cognitive workers, followed by routine workers and non-routine manual workers. The latter workers also fare worst in terms of job-finding probabilities. Somewhat surprisingly, routine workers have the highest job-finding probabilities, which seems to be an indication of a high level of churning for this type of worker.

INSERT TABLE 1

It also becomes apparent that direct changes between different task categories for employed workers are uncommon, the corresponding annual transition rates are generally below 2%. An exception to this are transition rates from non-routine manual to routine employment, which amount to nearly 6%. Switching task categories is more common for unemployed individuals, although still relatively low. For example, the probability that a (previously) routine worker who is unemployed finds a job as a non-routine cognitive worker is 3.38%. Again, the transition rate from (previously) non-routine manual workers to a routine job is the exception. Non-routine manual workers who are unemployed display an equal probability of being in non-routine manual work and of being in routine work one year later.

INSERT FIGURE 5

[9] In addition to our baseline approach, we applied further specifications to estimate the task intensities. The decreasing pattern of routine task intensity is visible in all approaches. See Figure A1 for more detail on the different approaches applied.

Figure 5 provides additional information regarding transitions over time by task type. Specifically, it provides the probability of a job episode ending according to a worker's task type. The main driving force behind these job exit probabilities seem to be cyclical during most of the observation period, e.g. with an increase during the bursting of the dot-com bubble of the early 2000s. In a similar vein to Figure 1, non-routine manual workers have the highest probability of job exit across the period of 1980-2010. Routine workers have lower job exit probabilities than non-routine manual workers, but higher exit rates than non-routine cognitive workers.

INSERT FIGURE 6

Figure 6 provides information on transitions conditional on a worker making a job-to-job transition and according to their initial task type. For each task type there are high levels of state dependence. A worker who makes a transition is substantially more likely to move to another job in the same task category. More importantly, there is evidence that this level of state dependence has increased over time for two task types. Both non-routine cognitive and non-routine manual workers are more likely to transit between jobs in the same task type at the end of our observation period than at the start. This appears to follow a steady path over time, and is most marked for non-routine manual workers. At the same time as this, routine workers witnessed a marked reduction in this state dependence. Moreover, this change appears to have been driven at least in part by what could be considered movements up the occupational ladder into non-routine cognitive work. This provides initial evidence that part of the patterns seen earlier in Figures 1, 2 and 3 reflect differences in transitions across tasks.

Turning to workers who have become unemployed, Figure 7 features the unemployment exit rate of workers in the three task categories. First, it becomes apparent that unemployment exit rates showed a marked decline in the 1980s and early 1990s, reflecting the structural worsening of labour market conditions in Germany. Since the mid-1990s, and particularly since the mid-2000s, this trend has been reversed with unemployment exit rates constantly increasing, which is in line with the strengthening performance of the German labour market highlighted by (Dustmann et al. 2014). Somewhat surprisingly, previously routine workers are the most likely group to exit unemployment over the entire observation period. In unreported estimates, we again explored transitions in the spirit of Figure 6. Doing this reveals that the unemployed, previously routine, workers mainly return to routine jobs. Non-routine manual workers also largely return to the same task category after a spell of unemployment, however with a lower probability. Many of them actually switch to routine jobs. However, this transition from non-routine manual unemployment to routine employment has become less frequent over the observation period. For non-routine cognitive workers, there is also strong state dependence, with no obvious time trends.

4.3 Labour market histories over the short and medium run

We now turn to multivariate estimation of the effect of RTI exposure on employment. Employed workers are stacked in 6-7 year intervals (i.e. according to the BIBB wave years described above: 1979, 1985, 1992 etc.) in order to estimate the probability of remaining in employment after 1 year and 5 years, respectively, using the logit model described in equation (2). We include a range of controls along with our variable of interest, the RTI of the job. The resultant estimates are presented in Table 2.[10] The first column provides the average conditional effect of RTI exposure on employment probability at t+1. This demonstrates that higher RTI is associated with a lower probability of still being in employment one year in the future. The corresponding marginal effect amounts to -0.026. Since RTI is measured on a 0-1 continuum, this marginal effect can be interpreted as a 2.6 percentage point reduction in the likelihood of being employed one year later if a worker moved from a job with zero routine task intensity to a job that is entirely routine. As such a change in RTI is unrealistic, we compute the change in employment probability if the RTI of a job increases by one standard deviation. The standard deviation of RTI across our time period is 0.202, hence a one standard deviation increase in

[10] In unreported estimates we clustered standard errors at the year of observation level, our standard errors were essentially unchanged by this and in case did this change the pattern of statistical significance.

RTI is associated with a decrease in the likelihood of being employed one year later of 0.53 percentage points (2.6 * 0.202). Given that the mean rate of employment loss over one year amounts to 13 percent, this can be viewed as a small, but substantial, reduction in employment probability due to a worker being exposed to RTI tasks.

INSERT TABLE 2

Column 2 displays results that extend this to ask whether this RTI penalty has changed over the sample period. It reports coefficients on RTI and RTI interacted with a time trend. Whilst caution must be taken with adding interaction and main effects in a non-linear model, the signs and relative magnitude of these terms are informative. The initial RTI effect, which can be interpreted as the effect of RTI on employment stability at the start of our period, is essentially zero. RTI exposure was unrelated to employment stability in the late 1970s. The interaction term suggests that this changed over the past decades. Interpreting interaction terms in non-linear models is difficult. To provide a rough guide, we re-estimated this model using a linear probability model. The estimates suggest that a worker who was in an entirely routine job (i.e. RTI intensity = 100 per cent) would face an annual decrease in 1 year employment stability of 1.5 percentage points when compared to a worker who performed no routine tasks. Again, recognizing that this is an unrealistic comparison we rescale this effect by the standard deviation of RTI across our period of analysis. Doing so suggests that a one standard deviation increase in RTI was associated with a reduction in one-year employment stability of just over 10 percentage points over the past 35 years. This, we believe, is a quite dramatic reduction in employment stability. Column 3 includes industrial sector and year interaction terms. This is motivated by a concern that occupations are not distributed evenly across industrial sectors. Hence, conditional associations between RTI and employment could, at least in part, reflect sector-specific temporal shocks. In practice, this introduction does not markedly affect our estimates. The initial RTI effect moves closer to zero, but the rate of change over the period is essentially unaltered.

Columns 4 to 6 report analogous estimates for employment probability after five years, where again we include sector and year interaction terms. As column 4 shows, the probability of employment probability after 5 years is negatively affected by exposure to RTI. This average effect across the period is of a similar magnitude to that reported for employment after 1 year. Computing the marginal effect shows that workers in completely routine jobs (i.e. RTI=1) have a 6 percentage points lower likelihood of being in employment after 5 years than workers with completely non-routine jobs. Again we standardize the size of this effect. A one standard deviation increase in the RTI of a job is associated with a 1.2 percentage point reduction in being in employment after five years.

Column 5 and 6 report estimates where again we include an interaction between RTI and time. In the case of employment probability after five years, the introduction of industrial sector and time interactions is more consequential than for the employment probability in t+1, i.e. the coefficients of interest change more when comparing specification 5 and 6 than when comparing specification 2 and 3. This is an indication that controlling for sectoral shocks matters more in the longer run (t+5) than in the short run (t+1). The estimates reported in column 6 suggest that exposure to RTI was, in the late 1970s, associated with greater employment stability over a 5 year period. However, this changed dramatically over the following 35 years, as evidenced by the interaction term between RTI and time. It is furthermore noticeable that the employment penalties associated with RTI exposure are larger for employment probability in t+5 (compare columns 3 and 6).

Again, to aid interpretation, we re-estimated the model from column 6 as a linear probability model. These results suggest that RTI exposure was associated with a reduction of 5-year employment stability of 1.3 percentage points every year across the period. This, when again scaled by a one standard deviation increase in RTI, means that five year employment stability falls by approximately 9 percenage points across the 35 year period. Taken together, this suggests short term negative effects of RTI exposure on individual's employment stability that are exacerbated over the longer-term.

The estimates reported in Table 2 reflect conditional effects averaged across all workers. One question that naturally arises is the extent to which these effects are likely to be heterogeneous over different worker types. Two main dimensions likely to be particularly important are the age and skill levels of workers. Table 3 reports estimates that correspond to the specifications in columns (1) and (2) from Table 2. Hence the first column reports the average effect (across the period) of RTI exposure on employment stability, while the 2nd and 3rd column provide the starting (1979) effect on employment stability such that they provide the effect of RTI at the start of the period and trend effect of RTI on employment stability across the whole period. In terms of average effects, the negative effects on employment stability are concentrated among prime-age workers (26-35), with some indication that the negative effects are greater for medium skill workers. For all age groups RTI exposure decreases employment stability over our period of observation. There is variation in the initial effect of RTI on employment stability by skill levels. Low skill workers, even in 1979, faced lower employment stability if in jobs with high RTI. This RTI effect remains constant for these workers, while for both medium and high skill workers RTI is increasingly associated with employment instability over time.

INSERT TABLE 3

4.4 Task-specific job stability and unemployment exit rates

These differences in employment probabilities by task intensity could reflect a mixture of two different factors. Specifically, task intensity could influence job stability, and/or exit rates out of unemployment. We try to disentangle these channels.

Table 4 provides estimates of the probability of exiting from employment to any other employment state (employed or unemployed). In this way, it provides estimates of the effect of RTI exposure on job stability. All estimates are reported as hazard ratios. We follow a similar strategy to the earlier models of employment stability by reporting models with increasingly complex specifications. The first column reports the average effect of RTI on the probability of making an employment transition. This effect is sizeable, again scaling this effect shows that a one percentage point increase in RTI leads to an approximate 0.4% increase (exp(0.34)-1) in the likelihood of exiting your current job. Recalling that the standard deviation of RTI is 0.202, this again is a large effect. Interacting this effect with time (column 2 and 3) reveals that this risk of exit is increasing at approximately 0.04 percentage points every year, this represents a non-negligible increase in job instability over our period of analysis.

INSERT TABLE 4

These overall exit rates may hide a mixture of job-to-job transitions and job-to-unemployment transitions. Welfare losses attached to technological change are most likely to be concentrated in the latter transitions. This leads us to re-estimate our duration models where instead the hazard state is exit from employment to unemployment. These results are reported in Table 5 and reveal more dramatic patterns of the effect of RTI exposure on job stability. RTI exposure is associated with markedly higher risk of subsequent exit to unemployment. A one percentage point higher RTI leads to an increase in the likelihood of entering unemployment of approximately 0.65%. This risk has trended up rapidly across the last 4 decades. This provides evidence that a feature of job polarization has been an increasing risk of experiencing a period of unemployment for workers performing routine tasks.

INSERT TABLE 5

This leads to an obvious question regarding the ability of these workers to subsequently exit unemployment and how this has changed over time. We estimate hazard models of the likelihood of exiting unemployment to employment where we use the RTI of the last employment spell as the main variable of interest. Insofar as this has any effect on re-employment probabilities this is informative of potential labour market scarring effects of RTI exposure. In practice, we find no evidence of this (Table 6). Previously holding an RTI-intensive job is associated, if anything, with a *higher* likelihood of re-entering employment, and this is trending upwards over time. This suggests that the increasing job instability of RTI-intensive work over the period has been coincident with countervailing effects on re-employment probabilities. This has the potential to have mitigated some of the welfare losses associated with this job instability and the changes in occupational structure, more generally.

INSERT TABLE 6

The effects reported in Tables 4 to 6 are averaged across all workers. Again we seek to explore heterogeneity of effect across age groups and skill level. These results are reported in Table 7 grouped by the effect on risk of job exit, risk of job exit to unemployment, and subsequent likelihood (risk) of finding a job for the unemployed. For risk of job exit, and job exit to unemployment there is little evidence of variation by age, although workers in jobs with high RTI aged 26 to 35 appear to face a higher likelihood of job exit to unemployment. The effects on subsequent job finding are more pronounced, RTI exposure for workers aged 36 and above is associated with an increased subsequent job finding rate. There is no effect for younger workers. Furthermore, we find evidence for strong heterogeneous effects with respect to skills, i.e. routine intensity strongly increases the unemployment exit probability of high-skilled workers. This is not apparent for low-skilled workers.

INSERT TABLE 7

5 Conclusion

The past 4 decades have seen dramatic changes in the structure of the labour market. Rapid decreases in computing costs have led to a sharp reduction in the demand for jobs that are intensive in routine tasks. The existing literature highlights the aggregate patterns of labour market polarisation associated with this. We revisit this issue using German administrative data that allows us to address a range of questions currently unanswered in the literature. We present, to our knowledge, the first evidence on changes in task intensity of jobs over a long period and at an annual level. This allows us to examine the trend in polarisation over time which is important as the previous literature has suggested both periods of heightened polarisation and/or accentuated cyclical patterns. Our first main finding is to show that neither are the case in Germany. In this context, polarisation represents a steady secular change over the period of 1975 to 2014. Any cyclical patterns are dominated by this process. This is important as it suggests ongoing structural change without episodes of heightened changes in employment task shares.

With this as a starting point we seek to understand the worker transitions contributing to these patterns. Again, this is an analysis for which our data is particular well suited and where there is little existing evidence. Our results suggest that exposure to jobs with higher routine-task content is associated with higher risk of being out of employment in both the short term (after 1 year) and medium term (5 years). Subsequent results show that this employment penalty to routineness of work has increased over the past four decades.

The reasons for the employment penalty to routineness of work were then traced back to routine task work being associated with reduced job stability and an associated higher likelihood of making a transition to unemployment and thus experiencing periods of unemployment. By contrast, we find that previous work with high RTI for unemployed persons is associated with higher job-finding rates out of unemployment which thus at least partly compensates for the negative effects of RTI on employment stability. Further research is required to understand the extent to which these patterns of labour market transitions for routine workers are associated with individual welfare losses.

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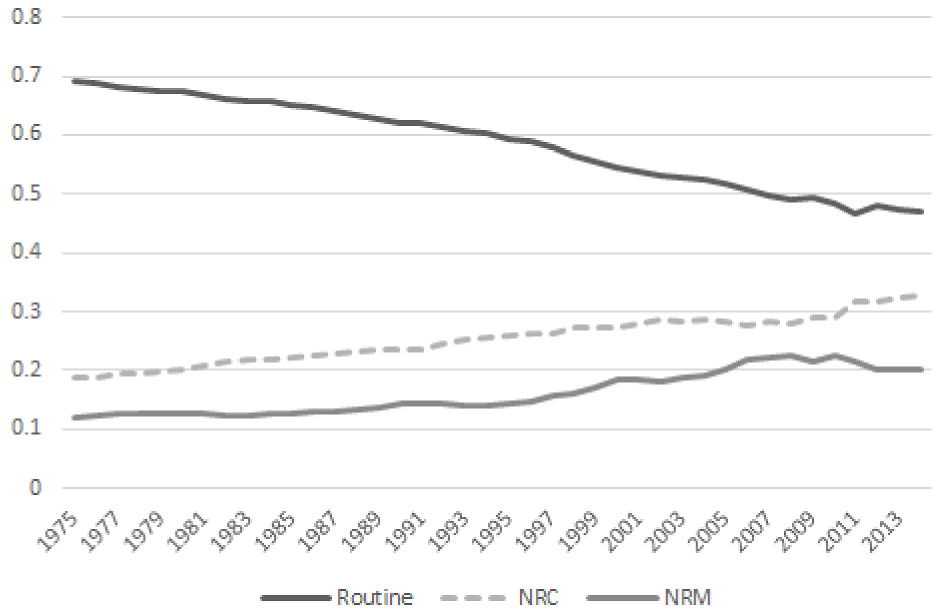
Figure 1a: Employment shares of task categories, 1975-2014, men



Source: SIAB 1975-2014, own calculation.

Figure 2: Average Task Intensities of Employment from the BIBB data

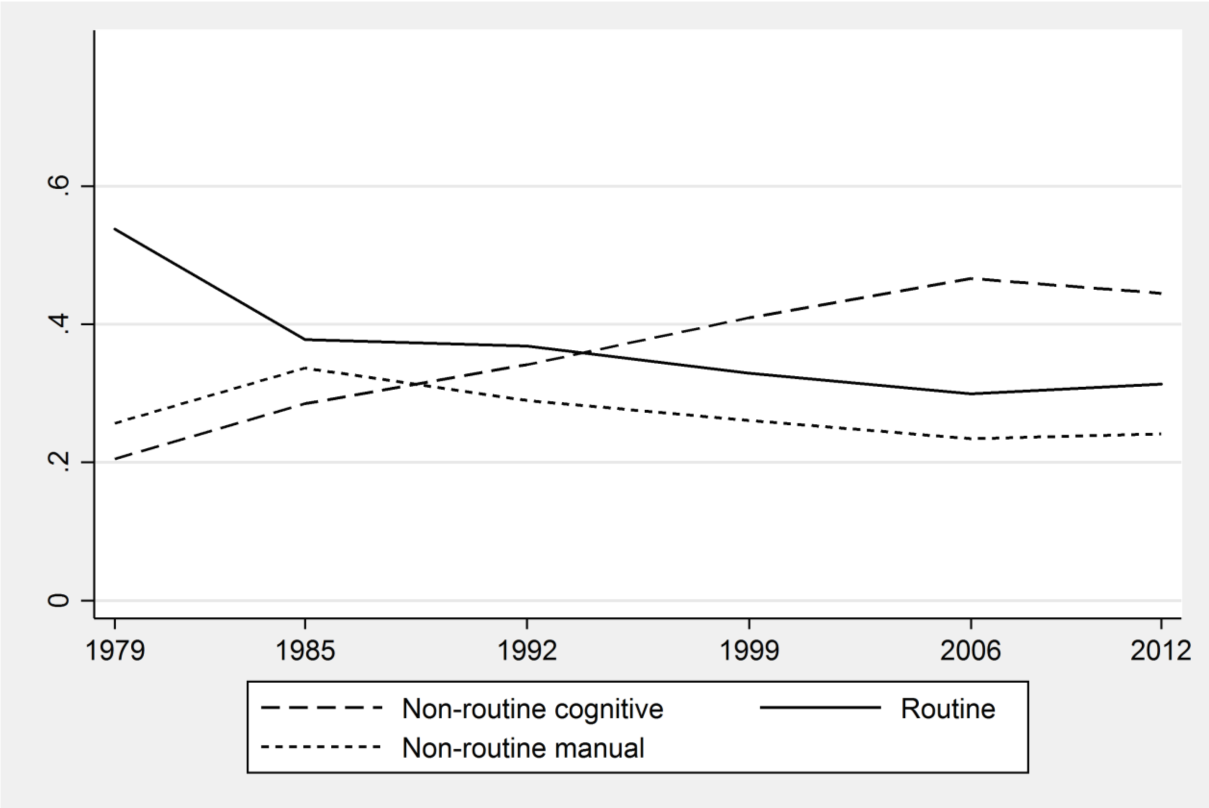
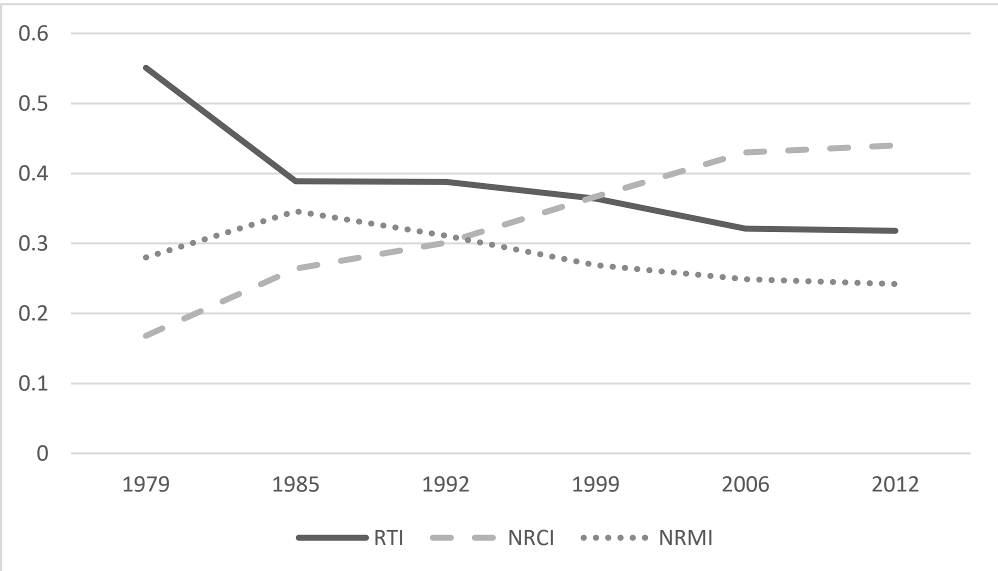
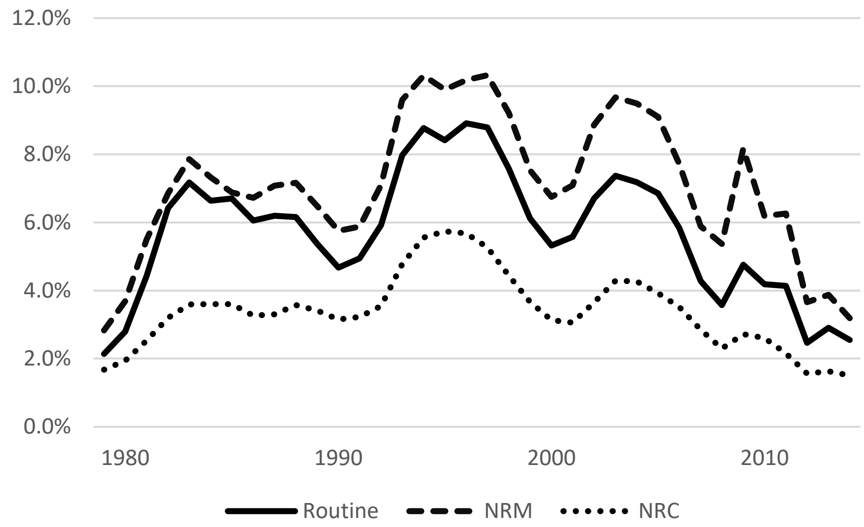


Figure 3: Average Task Intensities of Employment from the IAB data, 1979 to 2012



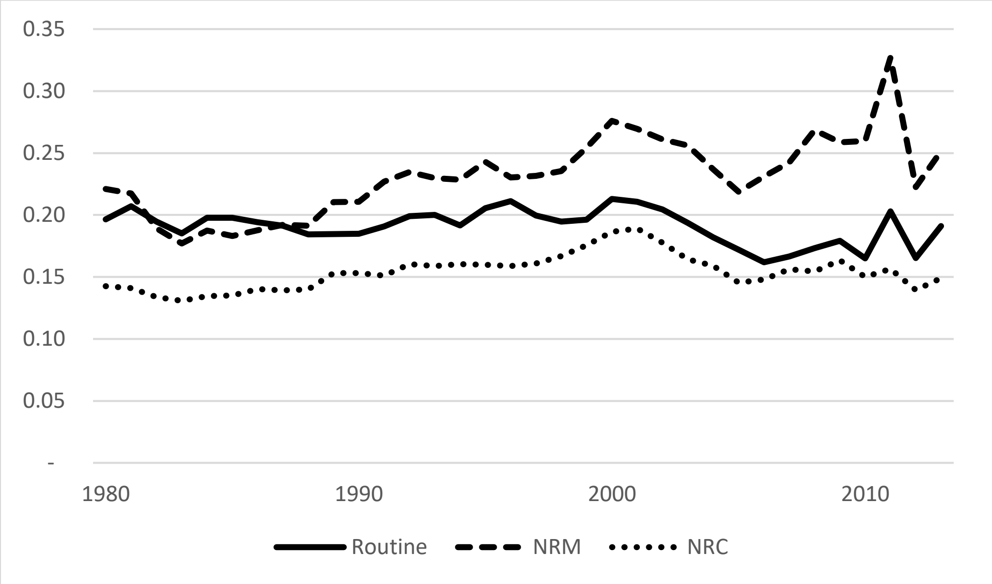
Source: SIAB 1975-2014, own calculation. – RTI: Routine task intensity; NRCI: Non-routine cognitive task intensity; NRMI: non-routine manual task intensity.

Figure 4: Task-specific unemployment rates, 1979-2014.



Source: SIAB 1975-2014, own calculation.

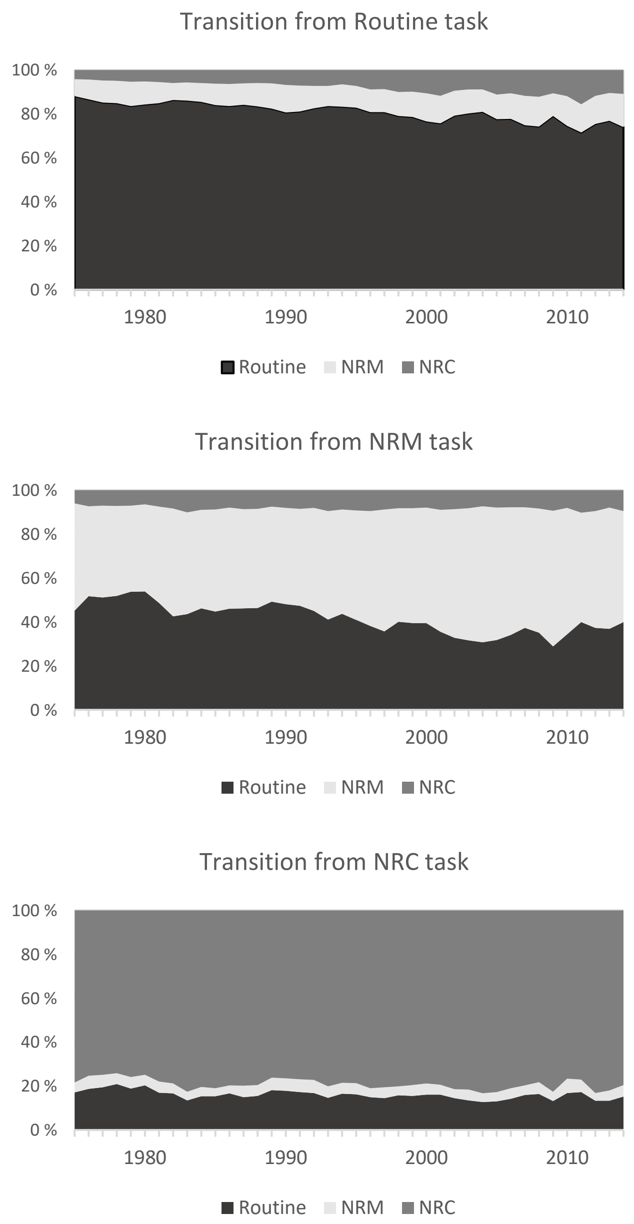
Figure 5: Probability of job exit, by task categories, 1980-2014



Source: SIAB 1975-2014, own calculation.

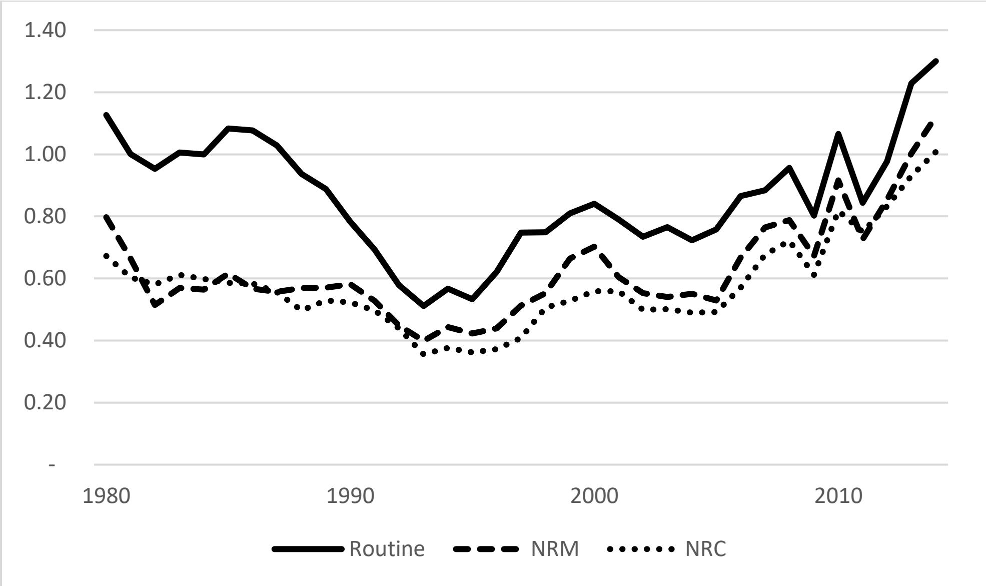
Note: *Job exit defined as making a transition to a different establishment, a different task category, or to unemployment.*

Figure 6: Transition shares from employment, conditional on making a transition, by task categories, 1975-2014



Source: SIAB 1975-2014, own calculation.

Figure 7: Unemployment exit rate, by task category, 1979-2014



Source: SIAB 1975-2014, own calculation.

Table 1: Transition matrix between different labour market states and task categories

			Year t+1				
			Employment			Unempl.	Non-Part.
			Routine	NRC	NRM		
Year t	Employ-ment	**Routine**	90.08	1.28	1.33	2.95	4.37
		NRC	2.02	92.23	0.57	1.91	3.27
		NRM	5.69	1.39	83.04	4.06	5.82
	Unemploy-ment	**Routine**	21.64	3.38	5.48	56.91	12.59
		NRC	8.07	17.83	3.13	60.01	10.97
		NRM	12.53	2.9	12.56	56.53	15.48

Source: SIAB 1975-2014, own computation.

Table 2: Routine Task Intensity of Current Job and Probability of Employment after 1 year and 5 years, 1979-2013, Logit Odds ratios

	After 1 year			After 5 years		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RTI	0.732***	1.055	0.993	0.706***	0.800***	1.326***
Time	0.990***	1.055***	0.940***	0.384***	0.716***	0.720***
RTI x Time		0.852***	0.845***		0.939***	0.731***
Year Dummies	X	X	X	X	X	X
Sector x Year Dummies			X			X
Observations	1258912	1258912	1052440	1052441	1052441	1052440

Control variables included in all regressions, age groups, skill groups, economic sectors, establishment size, region (Bundesland), year, regional unemployment rate, constant. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

Table 3: Routine Task Intensity of Current Job and Probability of Employment after 1 year, 1979-2013, Logit Odds Ratios

	SPECIFICATION 1	SPECIFICATION 2	
	RTI	**RTI**	**RTI x Time**
AGE			
18-25	0.91**	1.10	0.90***
26-35	0.65***	1.04	0.82***
36-45	0.62***	0.90	0.85***
46-55	0.54***	0.72***	0.89***
56-65	0.90**	1.34***	0.85***
SKILL			
LOW	0.78***	0.78***	0.99
MEDIUM	0.73***	1.00	0.87***
HIGH	0.82*	1.60***	0.76***

Models correspond to columns 1 and 3 in Table 3. Control variables included in all regressions, age groups, skill groups, economic sectors, establishment size, region (Bundesland), year fixed effects and regional unemployment rate, constant. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

Table 4: Routine Task Intensity and the Risk of Job Exit (to employment/unemployment), hazard ratios

	(1)	(2)	(3)
RTI	0.340***	0.340***	-0.190***
time		0.002***	-0.012***
RTI x time			0.035***
	5812823	5812823	5812823

Control variables included in all regressions: Duration dummies: 0 "0 - 3 months", 1 "4 - 12 months", 2 "1 - 2 years", 3 "2 - 5 years", 4 "5 - 10 years", 5 "> 10 years"; Age groups, skill groups, economic sectors, establishment size, region (Bundesland), regional unemployment rate, year dummies. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

Table 5: Routine Task Intensity and the Risk of Exit to Unemployment, hazard rates

	(1)	(2)	(3)
RTI	0.498***	0.498***	-0.244***
time		0.005***	-0.017***
RTI x time			0.050***
	5433626	5433626	5433626

Control variables included in all regressions: Duration dummies: 0 "0 - 3 months", 1 "4 - 12 months", 2 "1 - 2 years", 3 "2 - 5 years", 4 "5 - 10 years", 5 "> 10 years"; Age groups, skill groups, economic sectors, establishment size, region (Bundesland), regional unemployment rate, year dummies. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

Table 6: Routine Task Intensity and the Risk of Exiting Unemployment to Employment, hazard rates

	(1)	(2)	(3)
RTI	0.124***	0.124***	-0.443***
time		0.452***	0.438***
RTI x time			0.032***
	2195087	2195087	2195087

Control variables included in all regressions: Duration dummies: 0 "0 - 3 months", 1 "4 - 12 months", 2 "1 - 2 years", 3 "2 - 5 years", 4 "5 - 10 years", 5 "> 10 years"; Age groups, skill groups, economic sectors, establishment size, region (Bundesland), regional unemployment rate, year dummies. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

Table 7: Routine Task Intensity and the Risk of Job Exit (to employment/unemployment) by age and skill group, hazard ratios

	(1) RTI: Risk of job exit	(2) RTI: Risk of job exit to unemployment	(3) RTI: Job-finding rate of unemployed
Age			
18-25	0.272***	0.327***	0.001
26-35	0.454***	0.791***	0.042
36-45	0.267***	0.383***	0.143***
46-55	0.371***	0.419***	0.216***
56-65	0.336***	0.375***	0.320***
Skill			
Low	0.336***	0.314***	-0.145***
Medium	0.298***	0.433***	0.166***
High	0.694***	1.474***	0.537***

Models correspond to column 2 in Tables 5, 6 and 7. Control variables included in all regressions, age groups, skill groups, economic sectors (not for column 3), establishment size, region (Bundesland), year fixed effects and regional unemployment rate, constant. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

APPENDIX

The BIBB data and Computation of Task Intensity Measures

The first four waves of the task data were conducted under the name "Qualification and Career Survey" in a collaboration of German Federal Institute for Vocational Education and Training (Bundesinstitut für Berufsbildung: BIBB) and the Institute for Employment Research (Institut für Arbeitsmarkt- und Berufsforschung: IAB). The 2006 and 2012 waves were conducted as "BIBB/BAuA Labour Force Survey", which were jointly carried out by BIBB and the Federal Institute for Occupational Safety and Health (Bundesanstalt für Arbeitsschutz und Arbeitsmedizin: BAuA).

In the cross-section BIBB surveys, workers state which activities they perform at their workplace from a given list. Although the surveys include a rich set of workplace activities, the number and the definition of the surveyed activities differ across waves. While the 1979 wave covers approximately 90 activities, the number of activities decreased to 19 in the 2012 wave. In order to create a task intensity measure that is consistent over time, we excluded the activities that appeared only in one wave. We merged some of the activities into one variable in order to deal with the changing definitions of the variables and to maintain a total number of activities which is similar in each survey. For example, the activity "buying, selling, advertising" in the 1985 wave was split into two separate variables as "buying and selling" and "advertising" in 1999; we thus merged these two variables to make the comparison to the previous wave easier.

The answer categories in the surveys were also different across waves. While in some waves the answer category was binary, in other waves workers were asked whether they performed an activity "often", "sometimes", or "never". In case of three-category answers, we classified the answer categories "sometimes" and "never" together to have a consistent binary variable.

We tested the robustness of our results by applying four alternative definitions of task intensity measures to deal with the inconsistencies across waves mentioned above. In the "restricted" approach, we merge even more survey questions compared to the baseline approach in order to keep the number of questions in all three task categories as close to each other as possible. The "lenient" definition assumes that an activity is applied when the answer to survey questions is "always" or "sometimes" whereas the baseline category uses only the answer category "always". "Lenient-Restricted" approach applies the lenient definition to the restricted set of merged variables. Finally the "excluded variables" definition ignores the survey questions which were not repeated in all the waves. The results of these robustness analyses are available from the authors upon request.

Figure A1: Average Task Intensities of Employment from the BIBB data, different measures