Tasks, Employment and Wages: An Analysis of the German Labor Market from 1979 to 2012

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Abstract

Based on long-run data on work activities of German employees, we analyze the associations of tasks, employment and wages in the labor market between 1979 and 2012. We find evidence for employment polarization from 1979 to 1999: routine tasks were substituted by non-routine tasks. The period from 1999 to 2012 is characterized by the reversed pattern; employment in routine tasks expanding at the extent of non-routine tasks. We see the diffusion process of technology and its impact on tasks as the main driver of this pattern. The initial employment polarization is not accompanied by a polarization of the wage structure. A likely explication is the role of labor unions in the German wage setting process. The erosion of the latter also explains why wages are slightly polarized after 1999. Regressing wages on tasks, we do not find strong evidence for polarization, even though non-routine analytic tasks are associated with wage increases and routine manual tasks with wage losses. The main reason against polarization is a robust association of routine cognitive tasks with wage gains. Non-routine manual and (albeit less clearly) non-routine interactive tasks seem to be associated with wage losses.

Keywords: employment, wages, tasks, work activities, polarization, SBTC
JEL Classification: J21, J24, J31

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1 Introduction

The findings of Spitz-Oener (2006) and Dustmann et al. (2009) indicate that in terms of wage inequality and polarization – and contrary to what was previously thought (see e.g. Krugman, 1994) – the German labor market experienced a development similar to the U.S. labor market. In the U.S., wage inequality has risen steadily over the last decades. For Germany, Dustmann et al. (2009), among others, document that wage inequality started to rise in the 1980s and 1990s, too. A possible explanation for this rise is given by the skill-biased technological change (SBTC) hypothesis: it supposes that the introduction of computers to the workplace has affected the workforce differently, and that computer technology can substitute or complement certain jobs. For a long time, the relationship was assumed to be monotonous in skills, i.e. jobs demanding low skills were substituted by technology, whereas jobs demanding high-skilled labor expanded.

This monotonous relationship was challenged when a polarized pattern was observed for the U.S. labor market in the 1990s: employment and wages of low-skilled jobs were not decreasing anymore but had started to increase at the expense of middle-skilled jobs. Autor et al. (2003) therefore argued that not overall skills but specific work activities were at the core of the substitution process. By aggregation of work activities to broader task categories, they showed that computer technology substituted routine work and complemented non-routine work. More importantly, routine work dominated in the middle of the skill distribution, whereas non-routine work has been present both at the very bottom and the top. This nuanced version of SBTC soon became quite popular due to its plausible intuition, and similar patterns of labor development were obtained for other countries, e.g. Spitz-Oener (2006) showed that employment polarization occurred in Germany from 1979 to 1999 and Goos and Manning (2007) analyzed the same phenomenon in the UK.

More recent works have questioned the general validity (or the persistence) of the polarization hypothesis. According to Beaudry et al. (2013), the demand for cognitive tasks reversed after the year 2000 and Green and Sand (2014) showed that even in the US, wage polarization occurred only in one or at best two decades. For Canada, the non-monotonic relationship was not affirmed, and the polarization that was found in one particular region of the country is more likely to originate in a resource boom rather than in technological change.

Regarding the developments in Germany, the labor market underwent significant changes since 2000. A number of fundamental reforms designed to cut the high and persistent unemployment that characterized the German labor market during the 1990s and early 2000s were introduced.[1] In addition, Germany's industry structure experienced substantial changes moving more towards services. This process was aligned with wage moderation that kept labor costs down, and therefore contributed to a steady rise of productivity of the economy. As a result of these reforms and changes, Germany moved from being "the sick man of Europe" to becoming

[1]These reforms contained, among others, a substantial reduction of the duration of unemployment benefit entitlement, an augmentation of the probation period for newly hired employees to reduce hiring (and firing) costs, and stronger incentives (including a stricter provision of benefit sanctions) for job search of the unemployed and welfare recipients.

an "economic superstar" (Dustmann et al., 2014).

Given these significant changes during the last decade, this paper analyzes whether the trends in the employment and wage structure observed until the beginning of the century have continued – or stopped. We study empirically, first, whether job polarization continued after 2000 and, second, whether wages displayed a polarized pattern. To allow for a sufficiently long perspective of the trends, we consider the time from 1979 to 2012. Regarding the employment structure, we extend and update the analysis provided by Spitz-Oener (2006) that ends in 1999, taking account of the findings of Beaudry et al. (2013). Our consideration of the development of wages should contribute to the discussion of whether wage polarization as observed in the U.S. is (or was) an exception instead of a general pattern of developed countries. For these questions, Germany is a particularly interesting object of study since it is more regulated by institutions than the liberal U.S. or Canadian labor market (see chapter 6 of German Council of Economic Experts (2013) for a related discussion).

For the empirical analysis, we use an occupation panel data set that we derived from six large-scale surveys carried out between 1979 and 2012. Each of the surveys provides detailed information on activities performed during work. In addition, they cover a wide range of sociodemographic, personal, job-related and company-related topics. Based on these rich data, we find evidence for employment polarization from 1979 to 1999, where non-routine tasks substituted routine tasks. For the period 1999 to 2012, the pattern reversed: there was employment growth for routine tasks but there were employment losses for non-routine tasks. This is in line with the demand reversal reported by Beaudry et al. (2013) for the U.S. Despite the fact that non-routine tasks are much more important today than in 1979, routine tasks continued to be performed by still a large and significant share of people. In addition, our analysis clearly indicates that work complexity has risen: whereas it was very common to perform only tasks of a single category in 1979 (more than 60% of the sample) and only a minority carried out activities of three or more different task categories (around 10%), this picture is reversed in 2012. This implies that differences across task categories decreased substantially and thus, single task categories are not characteristic anymore for occupations – at least in Germany. Our evidence suggests that this rising complexity may be associated with higher wages.

Regarding the wage structure, we do not find strong indications for polarization in Germany. Wages for all tasks have grown since 1979, while the main increases occurred until 1999. Afterwards, hourly wages stayed virtually constant which is in line with the wage moderation observed in Germany. A small polarization in the wage structure can be found for the period 1999 to 2012. Routine manual tasks faced slight wage decreases, while non-routine tasks faced small increases (both at maximum of 4%). Wages for routine cognitive tasks rose but to a smaller extent than for non-routine cognitive tasks.

The remainder of this paper is structured as follows: In the next section, we review the nuanced version of skill-biased technological change to emphasize the relevant findings for our analysis. Section 3 describes the data sources and the construction of the sample. The first set of empirical results referring to tasks and employment is provided in section 4. Section 5 presents the analysis and corresponding results on tasks and and wages. We replicate the results using other task measures from the literature in section 6. A discussion of the presented findings is given in section 7. The final section concludes.

2 Related Literature

The timely correlation between the adoption of computer-based technologies and the rise in college-educated labor led to the formulation of the skill-biased technological change (SBTC) hypothesis (Katz and Autor, 1999). It supposed that the technological change brought by computer technology has had different implications for the labor force. Particularly, it increased the demand for high-skilled labor at the extent of low-skilled labor. Empirical evidence, though, indicated that the relationship might not be monotonous in skills. Employment and wages of not only high-skilled occupations but also of low-skilled occupations rose. The middle-skilled, on the contrary, experienced a decrease in both terms.

In order to accommodate this hollowing out, Autor et al. (2003) developed a nuanced version of SBTC. They operationalized the way technology affects the labor market through the tasks workers perform: activities limited in scope and well-defined activities ("*routine tasks*") can be expressed easily in a computer code, while the rules of performing problem-solving and more comprehensive communication activities ("*non-routine tasks*") are not sufficiently well understood to develop a computer program. Both types of tasks are imperfect substitutes. Most occupations include routine and non-routine tasks, so rather than substituting whole occupations, SBTC affected the task composition of jobs.

For testing this hypothesis, Autor et al. (2003) defined five task categories: 1) *non-routine manual* (repair, renovate, restore, nurse), 2) *routine manual* (operate, control machines), 3) *routine cognitive* (calculating, measuring, book-keeping), 4) *non-routine interactive* (negotiate, teach, entertain, manage personnel) and 5) *non-routine analytic* (research, evaluation, planning, interpret rules). In their empirical analysis for the U.S. using data from 1960 to 1998, they found the expected task input changes favoring non-routine labor at the cost of routine labor, and concluded that educational upgrading follows task change and not vice versa. By regressing task input differences on computer investment, they found that it predicted declines in routine cognitive and manual task inputs as well as increases in non-routine interactive and analytic task inputs. More evidence in favor of the nuanced version of SBTC has been presented by Autor et al. (2008), where three broader task categories are distinguished: abstract, routine and manual tasks. Their results pointed out that in 1980, there was a higher intensity for abstract tasks for the higher skill percentiles, whereas manual tasks declined with rising skills. Routine task intensity displayed a non-monotonic behavior and was highest between the 20th and 60th percentile. Relying on Census data from 1980 to 2000, the authors showed that employment changes have been linearly rising for higher percentiles in the 1980s, but have been u-shaped in the 1990s with a clear employment decline in the middle percentiles. Due to this u-shaped pattern, the phenomenon is called "polarization" or "hollowing out" of the labor market.

Spitz-Oener (2006) showed an analogous picture of the labor market development for Germany. Using the four Qualification and Career Surveys from 1979 to 1999, her results indicated that non-routine skill inputs rose, while routine inputs declined independently of the level of education. Regressing changes in task inputs on changes in computer use yielded evidence for a complementary relationship of computerization and non-routine analytic and interactive tasks. Routine manual and cognitive tasks were substituted by computer technology. She also found a hollowing out of employment: The first (characterized by non-routine manual tasks), ninth and tenth (non-routine analytic and interactive) skill deciles experienced growth, while especially the second and third deciles (routine manual and cognitive tasks) declined.

Nevertheless, polarization has been more noticeable in Anglo-American countries than in Germany due to different institutional settings. Dustmann et al. (2009), for example, took a closer look at the German wage structure. They argued that the rising inequality at the bottom of the wage structure is better explained by episodic events such as de-unionization and supply shocks (e.g. due to re-unification, inflow of Eastern Europeans) that took place later in Germany than in the U.S. This view was reinforced by the work of Antonczyk et al. (2009) who used the Qualification and Career Surveys from 1999 and 2006. They concluded that a task-based approach cannot explain the increase in wage inequality among male employees from 1999 to 2006. Differences between European countries were highlighted by Oesch and Rodríguez Menés (2011) who analyzed Britain, Germany, Spain and Switzerland. According to their findings, in Germany, routinization explained the hollowing out in the middle of the employment structure, and the essential difference across countries lied in wage-setting institutions which filter the pattern of occupational change. In this line, Dustmann et al. (2014) stressed the important role played by the characteristic institutions of the decentralized wage setting process in Germany's economic performance during the Great Recession since 2008.

Recently, Acemoglu and Autor (2011) highlighted the shortcomings of the canonical model and developed what they called a Ricardian model for the U.S. that explicitly distinguishes between skills and tasks. The authors classified skill groups by their task input in the year 1959 to having comparative advantages in abstract, manual or routine tasks. They found that the two groups specialized in abstract and manual tasks experienced relative wage increases in the 1980s. Skill groups that specialized in routine tasks faced relative wage decreases. This polarization started already in the 1970s for women.

Beaudry et al. (2013) add to the discussion observing that cognitive tasks associated with high-skilled labor underwent a demand reversal after 2000 in the U.S. They viewed cognitive tasks as a stock rather than a flow and included a dynamic adjustment process in the SBTC model to create a boom-bust cycle in the demand for cognitive tasks. During the boom phase, technology diffused and skill upgrading took place because the demand for cognitive tasks increased. During the bust, the supply of high-skilled workers continued to grow but the demand reversed. Hence, skill downgrading occurred: high-skilled workers moved down the occupational ladder to replace workers on lower skill levels. These workers in turn moved downward, too, and replaced even lower skilled workers who partly left the labor force altogether ("cascading down"). As an illustrative example, college workers' jobs became more manual tasks' intensive than ever before in the 2000s.

Autor and Dorn (2013) developed a spatial equilibrium model in which routine-task intensive commuting zones experienced a greater adoption of computer technology, wage and employment polarization and larger inflows of both high-skilled and low-skilled labor. Using Census data from 1980 to 2000, they showed that routine task content predicted computer adoption and the rise in non-college employment in service occupations after 1980. They also documented both employment and wage polarization and pointed out that service occupations were responsible for the non-monotonic behavior at the lower tail of the skill distribution.

In contrast to that, Green and Sand (2014) highlighted that wage polarization is more an exception than a rule. Using Canadian Census data, they found employment polarization in the 1980s and 1990s but only some wage polarization in Ontario since 2005. This latter finding was attributed to a resource boom and not to technological change. The authors concluded that the U.S. seem to be the only country with a wage polarization in the 1990s and that demand shifts driven by technology cannot be the primary driver of polarization.

3 Description of the Data

3.1 Data Sources and Construction of Occupation Panel Data Set

Our data stem from scientific use files (SUF) of six surveys on qualification and career that were carried out in 1979, 1985/86, 1991/92, 1998/99, 2006 and 2012.[2] These surveys provide very detailed information on work activities. In addition, the data contain information on sociodemographic background (gender, age, family status, children, wage, education) and company characteristics (industry, sector, size). The Qualification and Career Survey was originally designed to close gaps in official statistics. It was conducted by the Research Data Centre of the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung, BIBB) and the Research Institute of the Federal Employment Agency (Institut für Arbeitsmarkt- und Berufsforschung, IAB) until 1999. The first four waves covered each about 30,000 individuals. Since 2006, the survey is operated by the BIBB and the Federal Institute for Occupational Safety and Health (Bundesanstalt für Arbeitsschutz und Arbeitsmedizin, BAuA), called Working-Population-Survey (Erwerbstätigenbefragung) and includes about 20,000 participants. Data were collected by personal interview in the first three waves, by computer-assisted personal interview (wave four) and computer-assisted telephone interview in waves five and six.

Since the target population differed across waves, we restricted the sample to the smallest common denominator. Exclusion criteria were unemployed, apprentices, foreigners, federal

[2]The SUFs were provided by Leibniz Institute for Social Sciences (GESIS), first four waves, and the Research Data Centre of the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung, BIBB), last two waves.

state of residence and age. The final sample consists of West German residents with German nationality aged between 16 and 65 excluding self-employed, employees in the public sector and private households as well as unemployed persons. After these restrictions, the yearly sample size varies between 8,711 (2012) and 20,436 (1979).

Because different individuals were sampled in each survey, we follow Spitz-Oener (2006) and aggregate the data based on occupation titles to construct an occupation panel data set. Occupation titles are defined according to the German national classification of occupations (Klassifikation der Berufe, KldB). The survey waves until 2006 used the version of 1988 (KldB88), the most recent wave is coded according to the version of 1992 (KldB92). For homogeneity reasons, we converted the entries of the last wave accordingly.[3] The panel data set is not balanced. Reasons for this are changes in the questionnaires over the years providing varying information, particular with respect to some marginal occupations.[4]

3.2 Classification of Work Activities

All surveys assess activities performed during work, although items and degree of detail vary over the years. In 1979 and 1986, participants were first asked to tick off all activities on a list which had occurred at their work lately. Then they had to state which activities were typical (up to three in 1979) or which activities they performed predominantly (1986 and 1992).[5] 1979 was very detailed providing a total of 88 possible activities for each participant. In 1986 and 1992, participants were offered 24 and 25 different activities to choose from. The lowest number of tasks surveyed was 13 in 1999, followed by 15 in 2006 and 16 in 2012. Therefore, there is some heterogeneity over the years. In each survey it is possible (and very likely) that a participant is assigned to a mix of task categories (e.g. a consultant: routine cognitive, non-routine interactive

[3]All SUFs except the one from 2012 included a classification according to KldB 1988. The oldest version in 2012 was KldB 1992 but only on a 2-digit level. The conversion table from KldB 1992 back to KldB 1988 is based on a 4-digit level and thus far more precise. Truncating the 4-digit to 2-digit codes resulted in a number of duplicates, i.e. the code conversion is not unique anymore. It turned out that remaining food occupations (no. 43, KldB 1992) were converted to meat and fish processors (no. 40, KldB 1988). Their number was 109 in 1979, declined to 74 in 1986 and 21 in 2006, but increased due to conversion to 49 in 2012. Since this artificially counteracts the decline and the number for remaining food occupations is implausible as well, we decided to keep no. 43 of KldB92 as no. 43 in KldB 1988, leaving us with 28 participants employed as meat and fish processors and 21 in remaining food occupations.

[4]For example, in 1999 the group of mineral preparers and burners (containing 3 interviewed persons in the other years) was skipped. In 2012 the seven occupational groups of a) animal breeders and fishermen, b) mineral, petroleum and natural gas quarries, c) toolmakers, d) textile producers, e) remaining food occupations, f) carpenters, roofers and scaffolders and g) office specialists and auxiliary workers were not interviewed. The disappearance of these groups should not be a problem either since there were only a maximum of 3 animal breeders or fishermen per year and the numbers of quarries decreased continuously from 11 in 1979 to 1 in 2006. Toolmaker was a declining occupation since 1999 (122) to 2006 (42). Carpenters, roofers, scaffolders already reduced to around a third in 2006 (42) compared to 1999 (114) and textile producers lost importance from 1986 (47) to 1992 (16) and 2006 (3). Thus, these occupations did not suddenly disappear but vanished over time. Although the number of members in the groups of remaining food occupations and office specialists and auxiliary workers did not decline, they represent marginal labor market groups with less than 20 interviewed persons.

[5]The raw data set for 1986 lists three values for each activity (not chosen, belongs to work, predominant). Thus, the selection criteria is "belongs to work" or "predominant" since this is closest to the 1992 data which only provide the information "chosen" or "not chosen". From 1999 onwards, participants were asked to state how often they performed different activities (often, rarely/sometimes, never) and thus "often" is the selection criteria.

and non-routine analytic).

For the empirical analysis, we classify tasks into the following five categories (introduced by Autor et al. 2003):

1) non-routine manual, 2) routine manual, 3) routine cognitive,
4) non-routine interactive and 5) non-routine analytic.

The assignment is based upon the work of Spitz-Oener (2008) and Oesch (2013). Where the assignment of activities following Spitz-Oener leaves some doubt, we used the ISCO 1988 4-digit code descriptions for the task groups of Oesch (2013) as an additional aid. The only divergence in both classifications is the introduction of a sixth group called "non-routine service" occupations. We generate dummy variables for each of the five task categories.

In some cases the assignment of reported work activities to one of the five task categories was ambiguous. "Safe, secure (and regulate traffic)" is related to protective service workers (516 in ISCO 1988), and was thus assigned to non-routine manual occupations. In 1999, however, the activity was denominated "überwachen" in German, i.e. to supervise or monitor something. When it is non-routine, the share of this category for 1999 is too high compared to the other years. 60% perform non-routine manual occupations compared to 30% in 1992 and 43% in 2006. Following the natural association of the German verb "überwachen" and the English translation to supervise or monitor, this activity should be routine manual. The shares change substantially from 49% to 73% – still too high but less than before. The problem occurs because only 13 activities are listed in 1999. Only one of them is clearly routine ("produce"; "herstellen" in German) and two are non-routine activities ("repair","care for somebody"; "reparieren", "versorgen" in German); this is a considerably rougher degree of detail than in the other years. In order to keep this problem as small as possible and to follow the natural association of "überwachen", we defined "safe, secure" as routine manual. In very few cases, assignment was impossible. An obvious example is the activity "analyze, research" surveyed in 1992. "Analyze" is a routine cognitive task, while "research" involves non-routine analytic activities. Since it is of course arguable, where the borders are drawn, we decided to exclude the activity. A similar case occurred for "sort, archive" in the same survey; "sort" is routine cognitive and "archive" non-routine analytic. Activities like working with computers (2006 and 2012) and using the internet or editing e-mails (2012) are too broad to be assigned to a single task category. A detailed overview of task categories' content is provided in Table A.1 in the appendix.

3.3 Descriptives

For the first four waves, monthly gross income is available as a categorical variable only; the more recent waves provide a continuous variable. When reported in categories, we assume a uniform distribution within categories and attribute individuals their category's mean. Since the lowest and highest category are open categories, we take the upper and lower bounds respectively. The earlier waves' values were converted to euros and all values were converted to 2012 prices using consumer price index (CPI) information from the Federal Statistical Office (Destatis). Using the information on hours worked per week, we calculated the hourly wage.

In general, wage has risen since 1979 even though routine manual and non-routine analytic experienced a decrease in 1986. In 1979, performers of non-routine analytic tasks earned on average 2,900€ (expressed in 2012-euros) – nearly 700€ more than other task categories. The difference to the other two cognitive task categories' wages became smaller in 2012 (400€). This can be explained by a larger wage growth for non-routine interactive and routine cognitive tasks (around 1.4 compared to a baseline level of 1 in 1979 and only 1.15 for non-routine analytic, see the first panel in figure 1). Whereas wage differences between non-routine interactive, routine cognitive and routine manual tasks were negligible in 1979, the wage of performers of routine manual tasks was 400€ smaller in 2012. Here, an initial decrease in 1986 and a slower wage growth in 1992 can be seen as the main reasons. Afterwards, there was a steep increase in wages until 2006 for routine manual tasks. All task categories faced wage losses from 2006 to 2012.[6]

On an hourly basis, jobs characterized by routine cognitive and non-routine interactive tasks pay comparable wages, around 13.50€ (expressed in 2012-euros) in 1979 and 19€ in 2012. Routine and non-routine manual tasks yielded about 1€ less in 1979 but the difference had doubled in 2012 (17€). The highest wages are paid for performers of non-routine analytic tasks but wage gains have fallen due to a slower increase over time (1.25 in 2012 with a basis of 1 in 1979, see the second panel in figure 1). Initially, they earned 16.50€ an hour which meant a gap of 3€ compared to the other cognitive task categories. In 2012, non-routine analytic tasks paid 21€ , so the difference amounted to 2€ . Even though monthly gross wage decreased from 2006 to 2012, hourly wages did not fall for cognitive task performers indicating that their working time was reduced accordingly. This was not the case for manual task performers.

Input Figure 1 about here

We consider education in three categories according to the type of school graduation obtained. Low education denotes no school degree or a degree from the lowest track of the German school system (*Hauptschule*). Individuals with a degree from the second highest track (*Realschule*) are classified as having a medium level of education. High education refers to persons having successfully finished the highest school track (*Gymnasium*) and passed the general university entrance exams (*Abitur*). This is required to take up studies at public or private universities. It should be noted that not all students go to university: about 15% to 20% decide to instead participate in the German vocational training system ("apprenticeship system") which combines theoretical elements in occupation-specific schools and practical elements in companies. Vocational training opportunities are also open for students with medium education but may be limited to those with low education.

Overall, educational levels increased steeply over time. In 1979, 90% of routine and non-routine task performers had a low level of education. This share decreased dramatically since

[6] We checked this tendency by comparing the development to that of SOEP data on a similarly defined sample from 1986 to 2012. Applying the same deflators yields a comparable steady increase in wage that is albeit very small from 2006 to 2012.

1992 to around 40% in 2012. Even though cognitive tasks generally demand medium or higher education, 60% had only low education in 1979. In 2012, this share is around 30%. Less than 10% of the manual task performers had a medium education level in 1979. A steep increase by a factor of 4.5 (routine manual) to 5 (non-routine manual) indicates that the typical manual worker obtained a medium school degree in 2012 (see middle panel in figure 2). There have not been great changes for the cognitive task categories with regards to a medium level of education but a steady, albeit slow upward trend is visible (around 30% in 1979 and 40% in 2012). High education has not played a role in manual tasks in 1979. Shares literally exploded especially for non-routine manual tasks (15 times higher in 2006 compared to 1979, see lower panel in figure 2) so that the shares amount to close to 20% in 2012. Most people with high education are found among non-routine analytic task performers. Compared to the other categories, this share did not grow that much (by a factor of 1.4 to 2). This explains why the difference towards non-routine interactive (1.4 to 3) and routine cognitive (2.3 to 4) is lower in 2012 where close to 40% of non-routine analytic task performers have a high level of education.

Input Figure 2 about here

Men dominated the labor force in the earlier years but with the increasing participation of women, this predominance reduced considerably (figure 3). While 85% of both non-routine analytic and routine manual were men in 1979, around 45% are women in 2012. Non-routine interactive tasks are an exception: the majority were and are performed by women in 1979 and 2012, even though the gender distribution is nearly balanced and has favored men from 1986 to 1999. Interestingly, whereas women made up close to 50% of routine cognitive task performers in 1979, their share reduced to 30% in 1999 and has increased again since.

Input Figure 3 about here

4 Empirical Analysis I: Tasks and Employment

In this section, we analyze whether the German employment structure can be described as polarized from 1979 to 2012. According to Spitz-Oener (2006), this is the case from 1979 to 1999, i.e. for this period employment in non-routine tasks increased while employment in routine tasks decreased or expanded less than employment in non-routine tasks. Taking into account the demand reversal highlighted by Beaudry et al. (2013), the picture looks probably different in the second period from 1999 to 2012.

Even though non-routine tasks have experienced a significant rise since 1979, routine tasks have not simply been replaced by them. This is indicated by the shares of people who perform routine manual or routine cognitive task categories. Shares of both categories have maintained at the same level or have even risen. In 1979, each of the non-routine cognitive tasks was performed by only 20% of the sample (figure 4). Non-routine manual tasks did play a marginal role with about 10%. The most important tasks at that time were routine cognitive (50%) followed by routine manual (40%). It should be noted that since workers usually perform more than one task category, shares do not sum up to 100%. The dominance of routine work content diminished in both 1986 and 1992, even though their shares maintained a high level. The main reason was a rising importance of non-routine tasks. In 1992, the shares of both non-routine analytic and non-routine interactive already passed the 40% threshold. The divergence became more prevalent during the 1990s with a decreasing importance of routine manual tasks (30% in 1999), while non-routine manual climbed up to 55%. Non-routine cognitive tasks, and in particular non-routine interactive that reached the largest share of 70% in 2012, continued to gain importance. Routine cognitive tasks also experienced a rise of importance (60%).

Input Figure 4 about here

Until 1999, our results are comparable to those reported by Spitz-Oener (2006). Incorporating the more recent waves, though, refutes the conclusion that routine manual tasks (and to some extent also routine cognitive tasks) continuously become less important while non-routine activities in general replace them. The drop of routine manual tasks in 1999 was entirely reversed in 2006. In 2012, the 50%-level of 1986 was re-reached. Instead of declining, routine cognitive tasks rose by more than 20 percentage points to constitute the most performed category with a share of about 80%. Contrary to that, non-routine interactive and non-routine analytic tasks maintained the 1999 level of 70% and 50%. The share of non-routine manual tasks declined to slightly above 40% in 2012. Thus, even though non-routine tasks are more important today than in 1979, routine tasks continue to be an essential part of work life.

Another conclusion that can be drawn from figure 4 is that workplace heterogeneity has increased substantially. Since employees can perform more than one task, adding up the shares yields 140% for 1979 but more than 280% for 2012. Put differently,today it is very common to perform more than one or even two different task categories at work. This is also reflected by figure 5. It depicts the share of participants who performed one, two, three, four or all five categories in the six survey years. The formerly predominating homogeneity, i.e. people performing only one category (more than 60% of the employees in 1979), has been replaced by rising heterogeneity. Today, more than 30% of the employees perform tasks from three different categories, and 20% tasks from even four. The shares of employees carrying out tasks of all five categories and of those with tasks from one category only, are equally large today (15%). Complexity is no longer the exception but has become the rule of workplace reality.

Input Figure 5 about here

This finding is supported by analyzing individual task category performance in the corresponding context (results not displayed). The share of mainstream task performers, who primarily carry out the same task category that dominates their company's NACE sector has fallen from 42% in 1979 to 33% in 2012. In other words, even within sectors, task heterogeneity has risen and less people perform the mainstream tasks. A similar observation holds when we consider subsamples with different main sector tasks. The largest of these subsamples is that of NACE sectors with routine cognitive tasks. Whereas routine cognitive tasks account for

38% of the subsample's activities in 1979, the share declines to less than 30% in 2012. In the subsample of non-routine interactive tasks as the mainstream category, the mainstream dominance decreases from 50% to 30%. Similarly, the prevalence is weakened in the routine manual (from 60% to 35%) and non-routine manual subsamples (from 40% to slightly above 20%). The descriptive picture therefore indicates that both workplace heterogeneity and complexity have risen over the last three decades.

As a final aspect of the analysis of tasks and employment, we consider employment growth (table 1). Over the whole period, employment in non-routine tasks has increased by between 16% (analytic) and 69% (manual), whereas employment in routine tasks has decreased by between 16% (cognitive) to 36% (manual). A closer look reveals that this development resulted from even stronger changes in the period from 1979 to 1999. Losses and gains have been larger in both directions during that time. In contrast, the development during the following period until 2012 showed a complete reversal: non-routine tasks decreased by between 12% (interactive, analytic) to 31% (manual), while routine tasks have increased by between 26% (cognitive) to 52% (manual).

Input Table 1 about here

Summarizing the findings on employment, the results indicate there was some employment polarization in Germany in the period between 1979 and 1999, but not since then. Although routine tasks have been substituted by non-routine tasks until the turn of the century, the situation reversed after 1999 which fits to the demand reversal emphasized by Beaudry et al. (2013) for the U.S. Taking into account that complexity in terms of number of tasks performed has risen, too, we suggest that the initial substitution of routine for non-routine tasks was reversed as work content changed. A substantial part of formerly routine tasks may have become non-routine during substitution, but eventually routine again in later years due to technological progress.

5 Empirical Analysis II: Tasks and Wages

5.1 Hourly Wage: Calculation and Description

Similarly to the previous section, we analyze the relationship between wages and tasks. There is empirical evidence that employment polarization is accompanied by wage polarization in the U.S. (Autor et al., 2003 and Autor and Dorn, 2013), i.e. that routine tasks earn less than non-routine tasks. For other countries, this relationship is less clear (e.g. Green and Sand, 2014 for Canada) and regarding Germany, Dustmann et al. (2009, 2014) and Antonczyk et al. (2009) underline the institutional labor market differences to the U.S.

Regarding the average remuneration by task in 2012 (table 2), non-routine interactive tasks pay more than routine cognitive tasks (close to €0.40 per hour). The initial difference of more than €2 (expressed in 2012 euros) towards non-routine analytic tasks reduced to less than €1 (cf. section 3). Since 2006, non-routine manual tasks have paid nearly €0.50 more per hour than routine manual tasks. Cognitive tasks pay about €2.00 to 3.50 more than manual tasks. Dispersion in 2012 is €0.70 lower than in 1979. In 1979, the lowest paying task, non-routine manual, yielded €12.19 an hour compared to €16.49 of non-routine analytic which amounts to an hourly wage difference of €4.31. In 2012, the lowest wage is €16.77 (routine manual) and the highest €20.38 (non-routine analytic), so only €3.61 difference. Considering median instead of mean hourly wages does not change these observations much.

Input Table 2 about here

Turning to the growth of wages by tasks over time (see table 3), it becomes obvious that wages grew substantially between 1979 and 1999. This growth did not affect categories differently along the routine/non-routine line. Manual tasks experienced the largest growth of about 35% (non-routine) and 37% (routine). Among the cognitive tasks, growth was highest in routine (36%). Remuneration of non-routine interactive tasks also grew by about 36%, whereas remuneration of non-routine analytic tasks experienced the smallest growth (22%). After the turn of the century, wage growth slowed down and was much smaller between 1999 and 2012 than in the twenty years of the first period. Nevertheless, the growth patterns from 1999 to 2012 can be interpreted as slightly polarized: Wages for non-routine task categories increased between 3.4% (analytic) and 7.6% (interactive), whereas wages for routine cognitive tasks increased by only 2%; routine manual tasks even decreased by 2.9%. These patterns also hold for mean monthly wages and for hourly and monthly median wages (not displayed).

Input Table 3 about here

5.2 Estimation Strategy

Given the patterns obtained from the descriptive analysis, we estimate the influence of each of the five task categories on wages in the following. To formalize our strategy, we denote the unit of observation by o (occupation) and the time by t. Accordingly, Y_{ot} is then the log average wage of occupation o in t and TI_{ot} is a vector of the five task categories. When we regress wages on current tasks, endogeneity might be an issue (Acemoglu and Autor, 2011) and OLS may provide biased estimates. Breusch-Pagan Lagrange mulitplier tests indicated that the data differs significantly across occupations. Hausman-tests on random or fixed effects advised to use fixed effects. We estimate the following fixed-effects model:

$$Y_{ot} = TI'_{ot}\beta + X'_{ot}\gamma + \alpha_o + u_{ot}. \tag{1}$$

The coefficients of interest are given by vector β denoting the effects of tasks on wages. We consider different ways to measure tasks in this equation. We begin by task dummy variables indicating whether or not activities from a task category were performed (=1) or not (=0). The estimated coefficient in the cross-sectional models is hence the change in log wages if the corresponding task category is performed all other things equal (*ceteris paribus*). In the panel dataset we lose the dummy variables that due to the construction of the dataset (averaging over occupations) can take on values between 0 and 1. We thus interpret the coefficients for an increase of ten percentage points in the corresponding task measure (from 0.25 to 0.35 for example). In addition to task dummies, we consider two alternative measures from the literature, namely the task measures developed by Spitz-Oener (2006) and Antonczyk et al. (2009), which we will explain in section**??**.

Since a number of other influences on Y_{ot} are likely, X_{ot} represents a matrix of control variables. We estimated different model specifications regarding the number and types of covariates considered. As a point of reference, we started with a model containing only the task categories as independent variables (without any additional controls).[7] In a second step, we added sociodemographic variables (gender, age, age squared, cohabitation/marriage, children, level of education) to the model. The final model additionally accounted for job and company controls that have proved relevant in the related literature (tenure, tenure squared, firm size (less than 10, 10 to under 50, 50 to under 100, 100 to under 500, 500 and more employees), NACE sectors (A & B: agriculture and fishery, C & D: mining and manufacturing, E: Energy and water supply, F: construction, G & H: commerce and hotels, J: finance, K: real estate etc., L & Q: public administration, M - P: public and private services). In addition to consideration of the whole time period, we also estimated the model for the period 1979 to 1999 (first period) and 1999 to 2012 (second period) separately.

5.3 Effects of Tasks on Wages: Results of Panel Models

Table 4 displays the estimated coefficients for each task category with occupation fixed effects for the full and subperiods. Model 1 does not include any additional control variables, model 2 introduces sociodemographic covariates and model 3 adds job and company controls. Without any covariates, performing cognitive tasks raises log hourly wages. The highest increase comes through non-routine interactive tasks (2.22% if this variable was to increase by 0.1, i.e. 10 percentage points). A 10 percentage points shift of routine cognitive tasks increases log hourly wages by about 1.56% and non-routine analytic tasks are associated with wage increases of 1.47%. These influences are albeit not robust to the inclusion of sociodemographic and company covariates. The five task categories are not even jointly significant in more complex models (p-values of 0.188 and 0.446). This could be a hint that tasks are endogenous in our estimation of current wages Acemoglu and Autor (2011).

Taking a closer look on the subperiods reveals that tasks do not play an important role in the second period from 1999 to 2012: only the coefficient for non-routine analytic tasks is significant in the base model (a 10 percentage points shift increases log hourly wages by 2.36%) and the task categories are not even jointly significant for log hourly wages in the base model. Contrary to that, tasks do matter in the first period (1979-1999): throughout all specifications, the task categories are jointly (highly) significant. Interestingly, non-routine analytic tasks do not have a statistically significant impact on wages. A 10 percentage points increase of routine cognitive

[7] Since we use occupations as the unit of observation and individual data has been collapsed to occupation means wave by wave, we can consider (the occupation average of) all five task categories in our models.

tasks increases log hourly wages by 1.2% (0.93% with all controls) and a 10 percentage points shift of non-routine interactive raises wages by 3.65% (2.13% with sociodemographic controls). The most significant impact comes from a 10 percentage points shift of routine manual wages which are associated with wage decreases of up to 1.36% (significantly negative coefficient for all specifications).

The signs of the coefficients for routine manual and non-routine analytic are the ones we would expect in a polarized wage structure but the sign for routine cognitive tasks is the exact opposite. Hence, we cannot conclude that the German wage structure is polarized – not even from 1979 to 1999 due to positive coefficients for routine cognitive tasks. What becomes clear is that tasks played a more important role in this first period than from 1999 to 2012.

Input Table 4 about here

5.4 Effects of Tasks on Wages: Results of Cross-Section Models

In addition to the panel models, we estimated models using the raw individual data of the cross sections (OLS regressions, see table 5). Coefficients of these models can now be estimated more efficiently, since we have more data and more variation. Nevertheless, the endogeneity aspects mentioned above may play a role and the obtained results have to be interpreted with caution. In 1979, both non-routine and routine manual tasks decreased log hourly wages by 4.8% to 9.3% (with all covariates). Routine cognitive had a positive impact (5.1%), whereas non-routine interactive was insignificant with the full set of control variables (-4.1% in the base model). The largest influence on wages is found for non-routine analytic tasks: performing them increased log hourly wages by 13.9% (30.5% in the base model). The picture is similar for 1986 except for non-routine manual tasks which led to small (2.4%) wage increases. In contrast, the impact of non-routine interactive tasks is not clear since the coefficient changes sign (-2.5% in the base specification, 4.2% with all controls). The magnitudes of the other tasks are comparable to those for the year 1979. The estimations based on data for 1992 yield very similar results. In 1999, non-routine manual tasks decreased log hourly wages (4.8% with all controls) and the impact of routine manual tasks was not robust (changing sign).

Both 2006 and 2012 mark a change: independently of their routine/non-routine nature, manual tasks were associated with wage decreases (about 4% for non-routine and 8 to 10% for routine), whereas performing cognitive tasks yielded wage increases of 4 to 5% for routine cognitive tasks, about 7% for non-routine interactive, and 9 to 11% for non-routine analytic. Hence, our earlier impression that tasks played a less important role in determining wages in the second period becomes somewhat attenuated: it seems that their importance in terms of explaining the data's variation rose up to 1992 (13.1%), then decreased to 6.2% in 1999 and finally increased again to 11.5% in 2012.

Input Table 5 about here

All in all, the fact that non-routine manual tasks mostly led to wage decreases and that routine cognitive tasks always increased wages contradict the polarization hypothesis. On the other hand, there were clear wage penalties for routine manual task performances and large wage increases for non-routine analytic tasks.

As a final aspect, we consider changes in task-wage associations over time. To analyze this aspect, figure 7 provides the wave-by-wave varying task-wage effects calculated from year-effects, task-category-effects, interaction effects and a constant. The corresponding coefficient estimates were obtained by fixed effects estimation. The largest wage increases in all years except 1979 are associated with routine cognitve tasks and the second (or third) largest increases with non-routine analytic. Routine and non-routine manual tasks yield smaller increases in log hourly wages. Non-routine interactive tasks bring larger gains in some years (1979, 1999, 2006) and smaller gains in others years (1986, 1992). In 2012, the effects are all of very similar magnitudes around 0.7. The impact of routine cognitive tasks is not only persistently positive but also important in magnitude.

Input Figure 7 about here

5.5 Complexity

As illustrated in section 4, workplace heterogeneity has increased substantially since 1979 when most people performed only a single task category in their job. Today, it is quite common to perform tasks of three or more different categories. This subsection aims at analyzing whether this rising complexity is compensated for by wages. Complexity is measured by a variable taking on values between 1 and 5 depending on how many tasks an individual performs. We then calculated the standardized complexity measure and used it as the main explanatory variable instead of the five task categories. We began by estimating the simple base model with standardized complexity as the only explanatory variable and successively augmented the model with the same covariates as in the previous subsections. The estimated coefficients for the standardized complexity measure are displayed in table 6.

Input Table 6 about here

Without any other covariates, an increase in complexity by one standard deviation is associated with a wage increase of 16.6%. Complexity explains 78% of the variation in log hourly wages. The coefficient drops to 4.4% with sociodemographic controls and becomes insignificant when company controls are added.[8] For the second period (1999-2012, see the last panel in table 6), the complexity effect is much lower (7.1% compared to 16.3%). Its explanatory power is lower, too (77.2%). The changes in complexity from 1979 to 1999 were considerably larger than from 1999 to 2012. This could indicate that initially, there may have been a larger compensation for rising complexity that became smaller when it was common to perform more task categories.

[8]Regressing complexity on sociodemographic and company controls yields several highly significant coefficients – age, children, having a partner, middle and high education and some industry controls – and an adjusted R^2 of 0.689. So when adding covariates, that explain complexity itself, are added to the equation, these covariates capture most of the effect that was attributed to complexity in the base model.

6 Alternative Task Measures

The analysis of section 5 considered task categories by dummy variables. This approach is limited with respect to task intensities. For a dummy variable there is no difference between a person who performs one out of five routine cognitive activities and another one who performs all five of them – both persons have the value 1 for their routine cognitive variable. Similarly, the use of dummy variables does not allow to differentiate between a person who performs only routine cognitive tasks and another one who performs non-routine interactive and non-routine analytic tasks, too. In order to take this valuable information into account, we consider two different task measures in this section.

The first alternative is a task index suggested by Spitz-Oener (2006) and the second one a task measure proposed by Antonczyk et al. (2009). Both measures yield information about how intensively an individual performs activities of a task category. The measures are calculated by dividing the individual number of activities performed in a category by (a) the total number of activities performed in that category (Spitz-Oener) or (b) the total number of activities performed by the individual (Antonczyk et al.). This increase in information comes at the cost that the interpretation of the estimated coefficients becomes less simple compared to the dummy variables. The coefficients for the task dummies indicated by how many percent log hourly wages change due to performing a category (compared to not performing it). The alternative task measures can increase by different amounts making a clear interpretation as in the previous section impossible. In fact the changes differ (a) for each task and year for the Spitz-Oener index or (b) for each individual and year for the Antonczyk et al. measure. Therefore, we simply report the coefficients' sign, size and significance in the following.

Within category task measure (Spitz-Oener, 2006)

The task index suggested by Spitz-Oener (2006) informs about the intensity with which an individual performs a task category:

$$TI_{ijt}^{SO} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in } t}{\text{total number of activities in category } j \text{ at time } t}, \tag{2}$$

and is calculated for each individual i in wave t and task category j.

Accounting for task intensities, i.e. how many activities of a task category a person performs, all routine tasks have lost in terms of employment compared to the non-routine tasks (see figure 6). Routine cognitive tasks accounted for 33% in 1979 but dropped to 22% six years later. Even if routine manual tasks have already begun to lose importance in the mid 1980s, the sharpest drop of 11 percentage points occurred between 1992 and 1999. On the other hand, we find that non-routine manual tasks nearly doubled from 1979 to 1986 to 16%. Non-routine interactive tasks account for another 6 percentage points. In 1992, the biggest change was a four percentage point increase in the share of non-routine abstract tasks, whereas the share of non-routine manual tasks decreased by two percentage points. While routine manual tasks halved from 1992 to 1999, non-routine manual and non-routine interactive benefited by seven percentage points each. By and large, if substitution led to employment losses, this happened in the 1980s for routine cognitive. Routine manual tasks, on the other hand, experienced a slower substitution up to 1992 and then a fall. Nevertheless, both routine task categories expanded since 1999, indicating some renaissance in demand.

Input Figure 6 about here

The results of the panel models are reported in table 7. Turning first to the results for the full period, it becomes obvious that non-routine analytic tasks significantly increase hourly wages. Put differently, if the occupation requires more work activities of this task category this will raise the employee's wage. Moreover, routine manual and routine cognitive tasks are also associated with wage gains. The effects are statistically significant only in the basic specification (model 1) and the coefficient for routine cognitive is not robust in its sign with the addition of further controls. Non-routine interactive tasks appear to reduce wages but the effect is only significant in the model with all controls. Non-routine manual tasks could have brought slight (insignificant) gains.

Input Table 7 about here

The results for the two subperiods differ somewhat. From 1979 to 1999, non-routine analytic tasks decreased wages (table 7, first period). Routine cognitive tasks, on the other hand, increased wages. Also non-routine manual tasks were associated with wage increases but effects are not significant in all model specifications tested. In contrast to that, routine manual tasks did not contribute to wage increases in that period, as indicated by the very small and not significant coefficients. For non-routine interactive tasks, we find neither significant nor robust estimates.

In the second period (1999-2012), the only significant estimate we get is in the base model without covariates (table 7, second period). Performing non-routine analytic tasks increased wages. All other coefficients are statistically insignificant and mostly also small in size. As for the sign, manual tasks and non-routine interactive experienced wage declines whereas both routine cognitive and non-routine analytic change to a negative effect in the full specification. Polarization would imply that either routine tasks experienced wage declines or increases that are smaller than the ones for their non-routine counterparts. Neither the signs nor the compared magnitudes support a polarized wage structure.

In the cross-section models (table 8), we find that, in general, cognitive tasks have always been associated with wage increases (except for non-routine interactive in the base specifications in 1979, 1992 and 1999). The tasks' joint explanatory power follows the same pattern as described above in subsection 5.4. The largest effects come through non-routine analytic tasks but their impact becomes smaller with every year (in the full specification from 2.102 to 0.176). Routine manual tasks have been consistently associated with wage decreases. This holds on a weaker level for non-routine manual tasks as well. Both categories' losses have been highly significant through all specifications after 1999. One possible explanation for this picture is that formerly strong wage protections diminished in the 1990s, when an era of wage moderation and an erosion of the generally-agreed bargained wage settings began (see section 7). The role of non-routine interactive tasks appears to be unclear and changing over time. Routine cognitive and non-routine analytic tasks experienced wage increases but these diminished over time. This fits to other studies' findings that the relative returns to college (and in particular the gap between academic and non-academic skills) decreased substantially in Germany since 1979.

Input Table 8 about here

When allowing for changes in task-wage associations over time, we find that non-routine manual tasks correlate with lower wages except in 2012 (figure 8). All other tasks experience wage increases (exception: routine cognitive tasks in 1992 and 2006). The largest increases (except for 2006) are found for non-routine analytic tasks.

Input Figure 8 about here

Between categories task measure (Antonczyk et al., 2009)

The task measure suggested by Spitz-Oener (2006) relates the number of task activities performed by an individual at a certain point in time to the total number of activities in that same task category. Therefore, it yields information about the intensity of the individual performance of a certain task category. This measures' major advantage is to grasp the relative importance of tasks for occupations. However, from an individual perspective, it lacks some important information. If a person dedicates all her time to one particular task only, the intensity could not exceed $1/n$ if there were n different activities in the task measure by construction. Moreover, if a person also dedicates time to other activities of another task category (e.g. two thirds of the available time) and the rest to the one activity considered in our example (i.e. one third), the task measure indicates the same intensity $1/n$ as before. Obviously, in this case the work activity is less important for the individual than before.

This person-centered approach is also intuitive, and we repeat our analyses using a task measure that relates the number of activities performed in a task category by an individual to the sum of all activities the individual performs. This alternative measure was proposed by Antonczyk et al. (2009) and is calculated as follows:

$$TI_{ijt}^{AFL} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in } t}{\text{total number of activities performed by } i \text{ at time } t} \tag{3}$$

This task measure, hence, informs about what role a task category plays for the individual. All five task categories considered now add up to one for each person. Table 9 presents the corresponding results obtained for changes of employment and changes of wages. Over the full time period, routine tasks decreased, whereas non-routine tasks increased in employment. These movements were particularly pronounced in the first period (1979-1999). In the second period (1999-2012), we see a reversal of the observed pattern. More importantly, the magnitudes of the employment effects are comparable to those obtained by the task measures used throughout the empirical analysis above.

Input Table 9 about here

In contrast, with respect to the changes of wages over time within task categories, it turns out that effects are now much smaller and even negative for routine manual tasks and non-routine analytic tasks overall. The latter finding is again driven by the development during the first period, where non-routine analytic wages decreased by nearly 8%. In the second period, the pattern also suggests a slight polarization of wages: Both routine task categories face wage losses, albeit those for routine manual tasks are much larger (5.5%). Non-routine task categories, on the other hand, see wage increases even though these are quite small for non-routine analytic tasks. By and large, these results confirm the observed patterns of employment polarization from 1979 to 1999 and its reversal thereafter. In addition, they indicate a slight wage polarization from 1999 onwards.

In the regression analysis, we left out non-routine manual tasks due to multicollinearity. The other task categories' coefficients are displayed in table 10 and to be interpreted with non-routine manual as the reference category. Thus, compared to non-routine manual tasks, routine manual tasks decrease log hourly wages, whereas routine cognitive and non-routine interactive tasks increase wages (model 1). In specifications with covariates, no task categories are significant individually nor jointly. The first subperiod gives a similar indication for individual coefficients but task categories are jointly significant even in models with covariates. In the second period, no task category is significant (except for joint significance in the full specification).

Input Table 10 about here

For yearly cross sections, we find that in general, cognitive tasks bring wage increases compared to non-routine manual tasks (table 11). The exception are the impacts of routine cognitive and non-routine interactive in 1986 and 1992, which depend heavily on covariates (positive signs with and negative signs without additional control variables). Routine manual tasks are associated with wage losses except for 1979 and 1999. Comparing these results to the cross section analyses with task dummies and the within task measures, these results make sense: cognitive tasks nearly always had positive impacts on wages and routine manual tasks had smaller wage increases or larger wage losses than non-routine manual which is the base category for table 11. The previous findings for the yearly cross section results hold in general with the between categories task measure, too:

Input Table 11 about here

All in all, the use of alternative task measures does not alter our impression from section 5: non-routine analytic and routine cognitive tasks are mostly associated with wage increases and routine manual task with wage losses. The impact of on-routine interactive tasks is less clear but especially the cross section results point to positive effects. Non-routine manual tasks seem to be somewhat sensitive to the measure chosen and the time period. In the cross sections, non-routine manual tasks are associated with wage decreases except for the dummy variables and within task measure framework in the years 1986 and 1992 (positive coefficients).

7 Discussion

The empirical results indicate that there was some employment polarization in Germany during 1979 and 1999. The question is why this was not accompanied by a similar polarization of wages. At the same time, while we find a reversal of employment polarization from 1999 onwards, there are indications of a small wage polarization in that same period.

Firstly, and in line with Beaudry et al. (2013), a likely reason for the stop of employment polarization after 1999 may be that the demand for (non-routine) cognitive tasks reversed. From 1979 to 1999, during a phase where computer technology diffused throughout the economy, the demand for non-routine cognitive tasks rose. Non-routine analytic tasks were needed to make full use of the immense analysis opportunities computer programs provided, non-routine interactive tasks were demanded to intensify communication between all economic actors. At the same time, computers could replace many routine cognitive tasks and their demand decreased. The process for manual tasks would look similar: routine manual tasks could be replaced by technology that had to be maintained and repaired (non-routine manual tasks). When the economy's process of adaptation to the new technology was completed, demand for non-routine tasks stopped to rise, while supply still continued to rise. At the same time, work content may have changed again so that a substantial part of the non-routine tasks during the adaptation process became routine. Once technology had diffused and the economy had adapted, new working processes and patterns were well-established. Analysts and repairers for example knew their methods and had gained experience in dealing with problems which became less and less as initial bugs were discovered and fixed.

Secondly, whereas employment basically obeys the rules of demand and supply, wage setting processes are far more complex (and rigid) when institutions enter. Even though no explicit minimum wage existed in Germany during the whole period considered, unions have played a major role in the wage setting process indicating implicit minimum wage barriers for the majority of the workforce. A process of decentralization in wage setting began in the 1990s. Since then, a variety of different types of wage-contracts appeared. Firms can participate in individual-level collective bargaining or firm-level collective bargaining, or they can "orient" their wages according to similar agreements. Individual-level collective bargaining further allows for opening clauses that concern hours worked or wages paid. All in all, Germany has faced a sharp deunionization and an erosion of collectively bargained wages. In this context, these developments could be an explanation for why wage polarization did not take place before 1999, and why we see a weak polarization pattern after that time: if routine task performers were more likely to be member of a union (or to work in a unionized sector), their wage would have been prevented from falling or increasing only by a small amount.

There is an extensive body of literature on German labor unions and wage inequality. According to Dustmann et al. (2009), the reduction in union coverage is responsible for 28% of the wage inequality at the lower end of the wage distribution and for 11% of the wage inequality at the upper end of the wage distribution. A problem, however, lies in the potential endogeneity of union coverage, i.e. both workers and companies may select themselves into coverage. Taking this into account, Antonczyk (2011) shows that the causal effect of union coverage on wage itself is close to zero. On wage disparity, in contrast, there is a negative effect: the residual standard deviation is 20 to 26% smaller. This gives a hint that unions do not focus on increasing the wage level but on reducing wage inequality which would in turn explain why polarization did not develop while unions were an important player in the wage setting process.

Related to that, Antonczyk et al. (2011) provide a review of the literature on wage inequality and the role labor unions play in Germany. They highlight three empirical findings. Firstly, wage inequality has risen sharply over the last 25 years. Even though only the upper end of the wage distribution was concerned by this development in the 1980s, the 1990s began to see increasing inequality at the lower end, too. Secondly, union membership rates have fallen steadily since 1980. Only 20% of the employees were union members in 2000. In terms of coverage, 60% of West German full time employees in the private sector were covered by an industry-wide bargaining contract in 2001. In 2006, this number has fallen to 47% for men and 41% for women. At the same time, coverage by company level agreements decreased slightly (nearly 1%). This latter evidence clearly refutes any substitution process between the different types of collective bargaining agreements. The most important factors determining union coverage are industry, tenure and company size. In industries like data processing, research and other services coverage is low, whereas the banking and insurance and the postal services and telecommunication sectors display high albeit declining coverage. The decomposition analysis provided by Antonczyk et al. (2011) shows that only 2% of the reduction can be explained by changing characteristics (e.g. industry structure), whereas the rest is accounted for by changing coefficients. The authors thus conclude that union coverage reduction is a general trend that primarily occurs within industries. Finally, the share of low qualified people stopped to decline since the mid-1990s, so that there was employment polarization in Germany. The wage structure displays no polarization with regards to the wages at the lower end of the distribution where inequality has been increasing. Additionally, the low-pay sector has been expanding.

The literature seems thus to provide a plausible explanation for our finding of a slight wage polarization after 1999 but not before, and thus exactly opposite to the observed employment polarization. Unions' coverage and influence was high in the first period and due to the inherent preferences of unions, stark wage inequalities were prevented. When union coverage declined, so did unions' power and influence over the wage setting in the German labor market. Even though this process began in the first period, the effects took some years to appear until previous collective bargaining agreements ended. The erosion of union power was then reflected in the new agreements which were less protective against wage inequalities than before. Coverage decline accelerated with the Fall of the Iron Wall and the emergence of new markets but also production opportunities for companies. It makes sense that there is considerably reduced union influence in the second period which begins some years later. The reduced power in turn allowed the development of a slight wage polarization from 1999 to 2012.

8 Conclusion

The results of Spitz-Oener (2006) provided strong indications that the German labor market was marked by an employment polarization due to technological change. Employment shifted from jobs demanding routine activities towards those characterized by non-routine activities that were not substituted but complemented by computerization. Similar patterns of polarization in employment and wages were formerly observed for the U.S. labor market, implying possible similarities of the German labor market despite some substantial institutional differences. Several developments in the recent past – among them the discussion of Germany's conversion from the "Sick Man of Europe" to the continent's superstar, labor market reforms addressing the high unemployment rates from the 1990s and early 2000s, a changing industry structure and wage moderation – led us reconsider the polarization hypothesis for Germany. The work of Spitz-Oener (2006) built on data until 1999 before the demand reversal for cognitive tasks started in the U.S. (Beaudry et al., 2013). Additionally, there is not much evidence for polarization outside the U.S. (Green and Sand, 2014). We thus asked whether the German employment polarization continued after 2000, and whether wages also displayed a polarized pattern. Our data consist of six surveys on qualification and careers which include detailed information on activities performed during work. We constructed measures for non-routine manual, routine manual, routine cognitive, non-routine interactive and non-routine analytic tasks.

On a descriptive level, our results showed that employment has underwent polarization from 1979 to 2012: routine tasks were substituted for non-routine tasks. However, this overall result was clearly driven by an employment polarization from 1979 to 1999. Since then the pattern is reversed. We observed employment growth for routine tasks and employment losses for non-routine tasks. In general, manual tasks are more volatile than cognitive tasks. Non-routine manual tasks appear to be most volatile, i.e. they benefited most from the growth in the first period but were hit harder since 1999. The reverse in employment polarization raises the question whether the labor market follows a certain repetitive pattern in the long-run that is characterized by cyclical changes in demand for certain groups of tasks. Taking into account that complexity in terms of number of task categories performed has risen, too, we suggest that the initial substitution of routine for non-routine tasks was reversed as work content changed. A substantial part of formerly routine tasks may have become non-routine during substitution, but eventually routine again in later years due to technological progress. In 2012, complexity is no longer the exception but has become the rule of workplace reality. This implies that differences across task categories decreased substantially and that single task categories are not characteristic anymore for occupations in Germany.

Regarding the wage structure, we do not find strong evidence for polarization. Wages for all tasks have grown since 1979. Again, the main increases occurred up to 1999. Afterwards, hourly wages stayed virtually constant which is in line with the wage moderation in collective bargaining observed in Germany. The only indications of polarization of the wage structure occurred precisely in this period. Routine tasks faced slight wage decreases, while non-routine tasks experienced small increases (both at maximum of 4%). We confirm the robustness of these results with an alternative task measures. Using different econometric models, we do find relatively robust evidence that non-routine analytic tasks are associated with higher wages and routine manual tasks with lower wages. At the same time, routine cognitive tasks are often associated with wage gains. The evidence is less robust for non-routine manual tasks which are mostly associated with wage losses and for non-routine interactive tasks which sometimes appear to decrease wages and increase them in other specifications. Even though the results for non-routine analytic and routine manual are in line with polarization, the other tasks' influence on wages seems to go the opposite direction as predicted by the theory. We find some evidence that the rising complexity may be associated with higher wages (or at least was until 1999) but sociodemographic and company control variables seem to account for this effect.

Our findings left us with the two main questions, the first one asking why the initial employment polarization reversed after 1999. We put forward the demand reversal for cognitive tasks by Beaudry et al. (2013) as a likely explanation. The introduction of computer technology substituted many administrative (routine cognitive) and simple manufacturing tasks (routine manual) and created new jobs in analyzing data (non-routine analytic), diffusing information (non-routine interactive) and maintaining and repairing the new technology (non-routine manual). When technology was well-established throughout the economy and people had acquired experience in dealing with problems, many of the non-routine activities became routine work again, thereby reversing the earlier substitution process partly. In trying to answer the second question – why the initial employment polarization was not accompanied by a similar polarization of the wage structure – we regard labor unions' influence in the German wage setting process as crucial. Antonczyck (2011) provides evidence that labor unions put emphasis on reducing wage inequality which explains why no wage polarization developed when unions were still strong economic players. Having faced sharp deunionization over years, unions' power was reduced considerably after the turn of the century. Hence, a smaller part of the workforce was covered by union wages and the the loss in bargaining power resulted in less protection against wage inequality.

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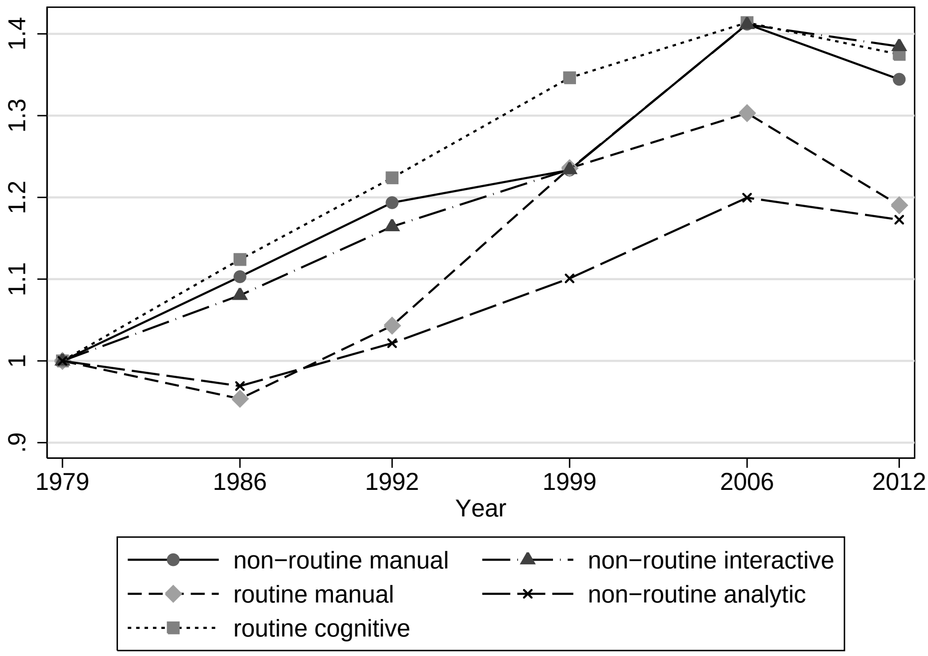
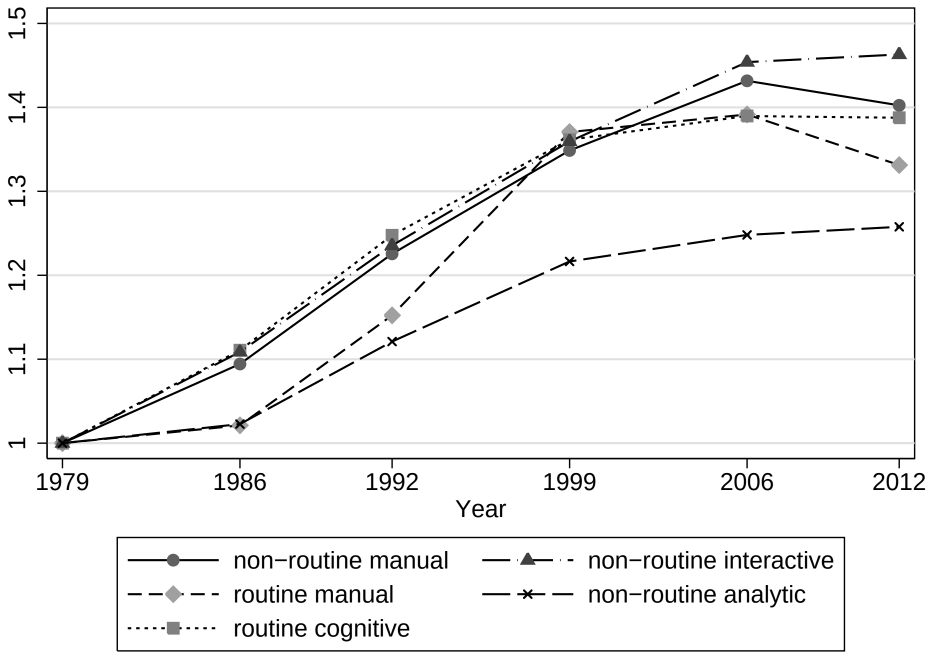
Figures

Figure 1: Development of Wages (1979 to 2012)[a]

monthly gross wages

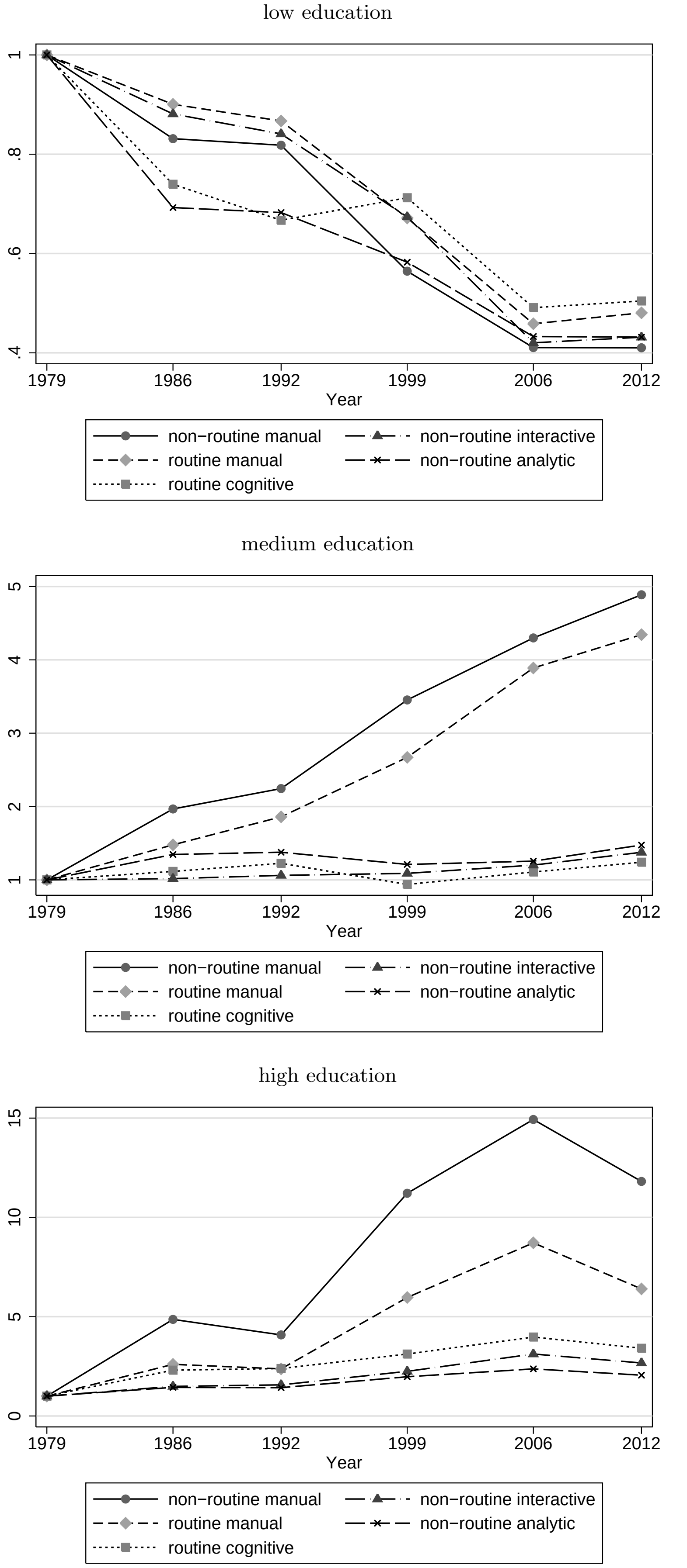


hourly wages



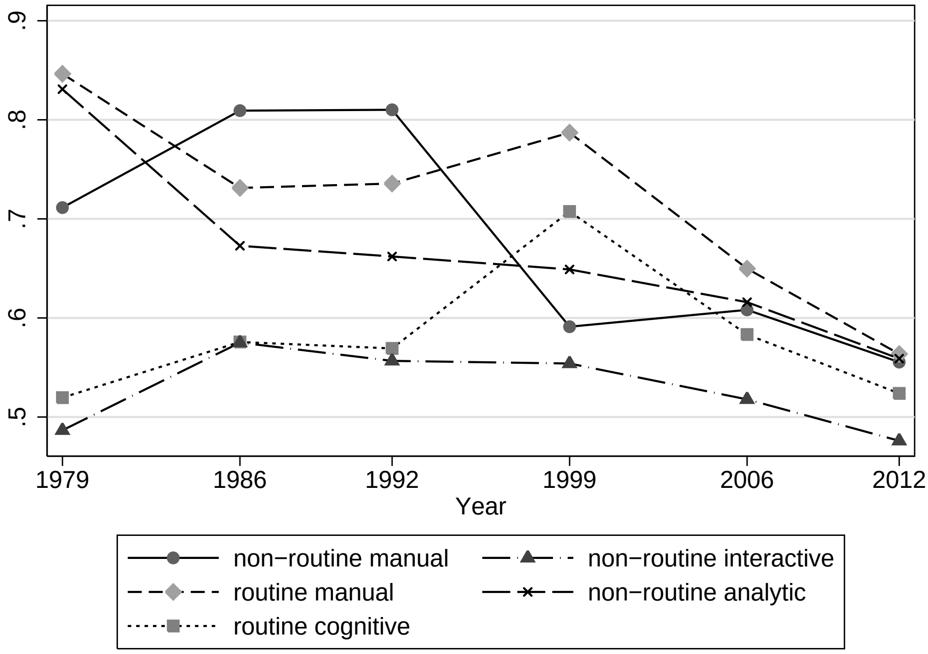
[a] Indicators with base year 1979=1. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Figure 2: Development of School Graduation Levels (1979 to 2012)[a]



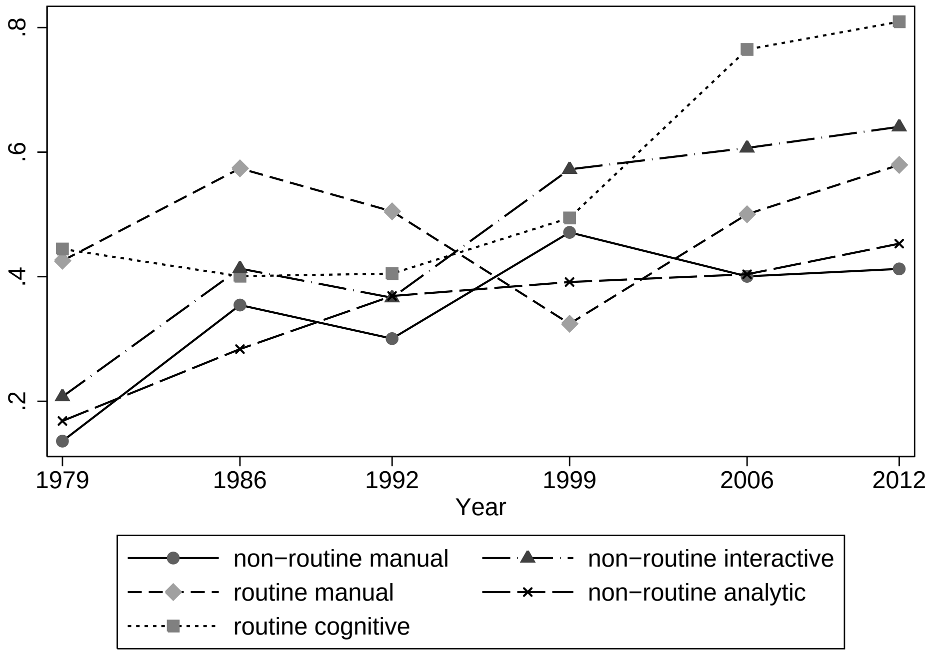
[a] Indicators with base year 1979=1. Low school graduation: none or Hauptschule; middle school graduation: Realschule; high school graduation: Abitur. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Figure 3: Development of Male Shares (1979 to 2012)[a]



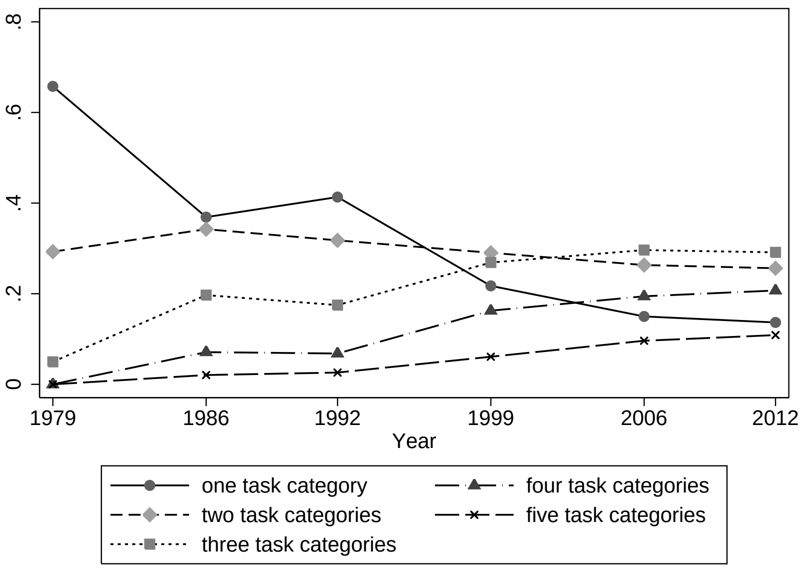
[a] 0.7 means 70% are men. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Figure 4: Share of Participants Performing the Tasks (1979 to 2012)[a]



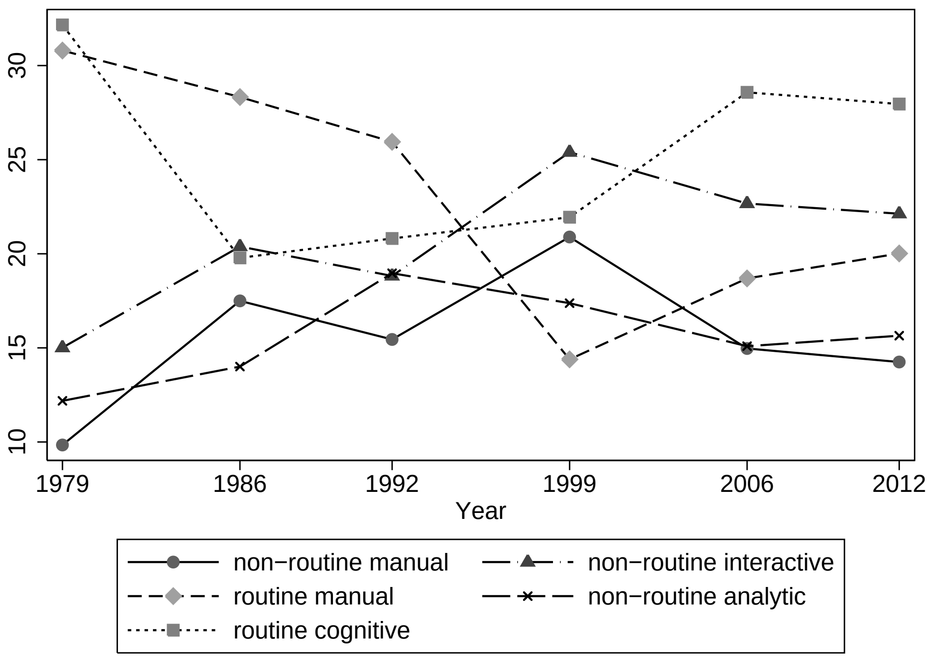
[a] Since participants can perform tasks of different categories, shares do not sum up to 1. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Figure 5: Share of Participants Performing a Certain Number of Tasks (1979 to 2012)[a]



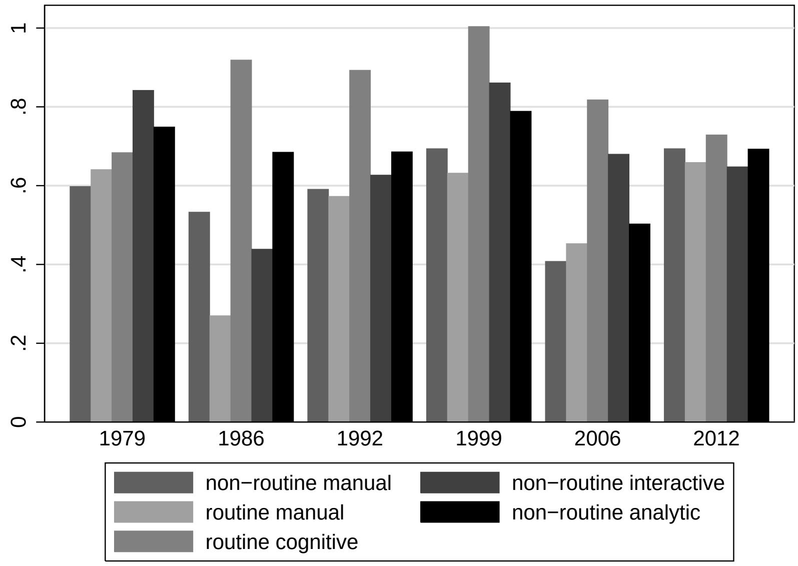
[a] Shares of participants performing a certain number of tasks. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Figure 6: Employment Shares by Task Categories (1979 to 2012)[a]



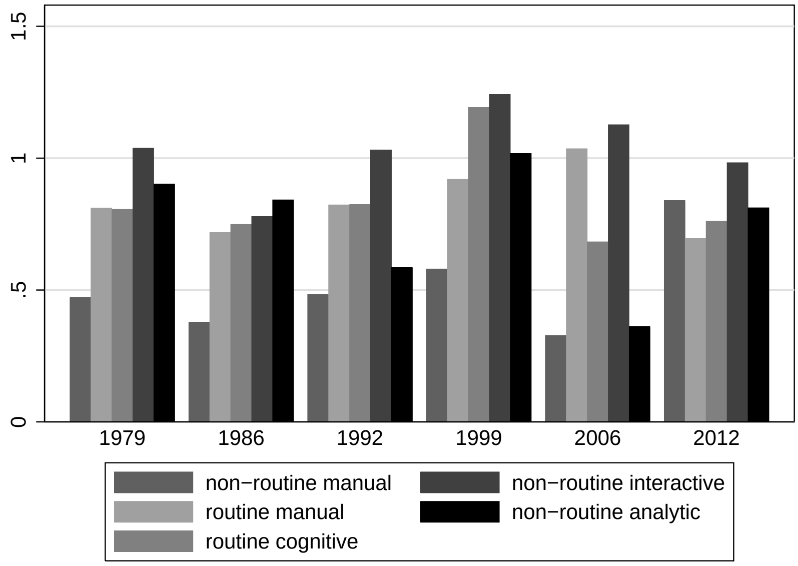
[a] Employment shares by task categories. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Figure 7: Variation of Task-Coefficients by Waves (1979 to 2012, with task dummies)



Coefficients are calculated by coefficients of year, of task category and the interaction effects. Data sources: IAB, BIBB, BAuA. Own calculations. See text for further details.

Figure 8: Variation of Task-Coefficients by Waves (1979 to 2012, within category task measure)



Coefficients are calculated by coefficients of year, of task category and the interaction effects. Data sources: IAB, BIBB, BAuA. Own calculations. See text for further details.

Tables

Table 1: Changes in Employment by Tasks (in percent)[a]

	employment		
	1979-1999	1999-2012	1979-2012
non-routine manual	112.31	-31.80	44.81
routine manual	-53.28	39.10	-35.01
routine cognitive	-31.77	27.40	-13.07
non-routine interactive	69.17	-12.87	47.39
non-routine analytic	42.58	-9.95	28.40

[a] Task measure calculated according to equation 2. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Table 2: Annual Remuneration by Tasks (in €)[a]

	1979	1986	1992	1999	2006	2012
non-routine manual	12.16	13.30	14.90	16.39	17.40	17.05
routine manual	12.45	12.72	14.35	17.07	17.33	16.58
routine cognitive	13.74	15.27	17.15	18.71	19.10	19.07
non-routine interactive	13.35	14.80	16.50	18.16	19.42	19.54
non-routine analytic	16.40	16.77	18.38	19.95	20.46	20.62

[a] Hourly wages. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Table 3: Changes in Wages by Tasks (in percent)[a]

	log hourly wages		
	1979-1999	1999-2012	1979-2012
non-routine manual	34.86	3.99	40.24
routine manual	37.06	-2.87	33.13
routine cognitive	36.15	1.92	38.77
non-routine interactive	35.95	7.61	46.30
non-routine analytic	21.64	3.39	25.77

[a] Task measure calculated according to equation 2. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Table 4: Regression Estimates on Log Hourly Wages (Fixed Effects Models) with task dummies

model	non-routine manual	routine manual	routine cognitive	non-routine interactive	non-routine analytic	N	p-value model	p-value tasks	adj. R^2
				full period					
1	0.054	0.057	0.156***	0.222***	0.147**	484	0.000***	0.000***	0.790
	(0.041)	(0.061)	(0.036)	(0.068)	(0.065)				
2	0.053	−0.008	0.054	0.046	0.023	484	0.000***	0.188	0.839
	(0.036)	(0.045)	(0.041)	(0.065)	(0.059)				
3	0.023	−0.063	0.055	−0.074	0.037	402	0.000***	0.446	0.848
	(0.045)	(0.047)	(0.047)	(0.075)	(0.073)				
				first period, 1979-1999					
1	0.016	−0.104**	0.120***	0.365***	0.084	325	0.000***	0.000***	0.833
	(0.035)	(0.041)	(0.038)	(0.062)	(0.070)				
2	−0.038	−0.122***	0.050	0.213***	−0.075	325	0.000***	0.000***	0.895
	(0.027)	(0.038)	(0.037)	(0.057)	(0.062)				
3	−0.055	−0.136***	0.093*	0.138	−0.018	243	0.000***	0.001**	0.900
	(0.055)	(0.049)	(0.049)	(0.106)	(0.105)				
				second period, 1999-2012					
1	−0.060	0.090	−0.003	0.062	0.236*	240	0.362	0.362	0.775
	(0.107)	(0.085)	(0.106)	(0.166)	(0.129)				
2	0.001	0.018	−0.058	0.040	0.069	240	0.084	0.967	0.811
	(0.094)	(0.077)	(0.101)	(0.128)	(0.101)				
3	−0.003	0.126	−0.103	−0.032	−0.042	240	0.000***	0.467	0.858
	(0.081)	(0.077)	(0.093)	(0.108)	(0.101)				

Model 1: base model with five task categories; model 2: with additional sociodemographic controls (gender, age, age squared, children, partner, education), model 3: with additional job and company controls (tenure, tenure squared, company size, NACE sectors). P-value "tasks" denotes the test for joint significance of the task categories. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Data sources: IAB, BIBB, BAuA. See text for further details.

Table 5: Regression Estimates on Log Hourly Wages (by Years, OLS estimation, task dummies)

year	model	non-routine manual	routine manual	routine cognitive	non-routine interactive	non-routine analytic	N	p-value model	p-value tasks	adj. R^2
1979	1	−0.038***	−0.004	0.062***	−0.041***	0.305***	20436	0.000***	0.000***	0.075
		(0.011)	(0.010)	(0.010)	(0.011)	(0.011)				
	2	−0.048***	−0.093***	0.051***	0.000	0.139***	18358	0.000***	0.000***	0.301
		(0.010)	(0.010)	(0.009)	(0.010)	(0.010)				
1986	1	0.104***	−0.072***	0.067***	−0.025**	0.247***	14058	0.000***	0.000***	0.105
		(0.010)	(0.011)	(0.012)	(0.010)	(0.012)				
	2	0.024**	−0.077***	0.071***	0.042***	0.114***	10710	0.000***	0.000***	0.361
		(0.011)	(0.012)	(0.013)	(0.011)	(0.013)				
1992		0.101***	−0.043***	0.063***	−0.038***	0.266***	13243	0.000***	0.000***	0.131
		(0.011)	(0.011)	(0.012)	(0.010)	(0.011)				
	2	0.004	−0.064***	0.042***	0.035***	0.137***	10265	0.000***	0.000***	0.428
		(0.012)	(0.011)	(0.011)	(0.010)	(0.011)				
1999	1	−0.110***	0.037***	0.133***	−0.008	0.208***	12779	0.000***	0.000***	0.068
		(0.010)	(0.012)	(0.011)	(0.011)	(0.012)				
	2	−0.048***	−0.019*	0.051***	0.030***	0.116***	12127	0.000***	0.000***	0.284
		(0.010)	(0.011)	(0.010)	(0.011)	(0.011)				
2006	1	−0.085***	−0.113***	0.110***	0.042***	0.194***	9322	0.000***	0.000***	0.072
		(0.014)	(0.014)	(0.017)	(0.014)	(0.013)				
	2	−0.038***	−0.083***	0.047***	0.079***	0.090***	9012	0.000***	0.000***	0.460
		(0.011)	(0.011)	(0.014)	(0.011)	(0.011)				
2012	1	−0.080***	−0.206***	0.076***	0.031**	0.200***	8711	0.000***	0.000***	0.115
		(0.013)	(0.013)	(0.016)	(0.014)	(0.012)				
	2	−0.039***	−0.097***	0.038***	0.071***	0.106***	8112	0.000***	0.000***	0.479
		(0.011)	(0.010)	(0.013)	(0.011)	(0.010)				

Model 1: base model with five task categories; model 2: with additional sociodemographic and company controls. *P*-value "tasks" displays the test of joint significance of the task categories. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Data sources: IAB, BIBB, BAuA. Own calculations. See text for further details.

Table 6: Regression Estimates on Log Hourly Wages (Fixed Effects Models) with Complexity

model	complexity	N	p-value model	adj. R^2
		full period		
1	0.166***	484	0.000***	0.780
	(0.011)			
2	0.044**	484	0.000***	0.839
	(0.018)			
3	0.007	402	0.000***	0.847
	(0.024)			
		first period, 1979-1999		
1	0.163***	325	0.000***	0.783
	(0.018)			
2	0.019	325	0.000***	0.881
	(0.021)			
3	−0.009	243	0.000***	0.890
	(0.029)			
		second period, 1999-2012		
1	0.071**	240	0.041**	0.772
	(0.035)			
2	0.007	240	0.016**	0.814
	(0.035)			
3	−0.024	240	0.000***	0.856
	(0.033)			

Model 1: base model with complexity (standardized); model 2: with additional sociodemographic controls (gender, age, age squared, children, partner, education), model 3: with additional job and company controls (tenure, tenure squared, company size, NACE sectors). *P*-value "tasks" denotes the test for joint significance of the task categories. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Data sources: IAB, BIBB, BAuA. See text for further details.

Table 7: Regression Estimates on Log Hourly Wages (Fixed Effects Models) with Spitz-Oener task measures

model	non-routine manual	routine manual	routine cognitive	non-routine interactive	non-routine analytic	N	p-value model	p-value tasks	adj. R^2
					full period				
1	0.025	0.138**	0.215*	−0.042	0.506***	484	0.000***	0.000***	0.790
	(0.119)	(0.067)	(0.116)	(0.171)	(0.147)				
2	0.109	0.101	0.032	−0.210	0.316**	484	0.000***	0.001***	0.839
	(0.094)	(0.063)	(0.096)	(0.147)	(0.129)				
3	0.144	0.114	−0.028	−0.306*	0.242*	402	0.000***	0.047**	0.848
	(0.103)	(0.077)	(0.099)	(0.161)	(0.141)				
					first period, 1979-1999				
1	0.218**	0.001	0.352**	0.277	−0.071	325	0.000***	0.000***	0.833
	(0.094)	(0.078)	(0.143)	(0.204)	(0.239)				
2	0.103	0.036	0.128	−0.047	−0.084	325	0.000***	0.000***	0.895
	(0.085)	(0.063)	(0.110)	(0.168)	(0.196)				
3	0.218	0.087	0.105	−0.033	−0.435*	243	0.000***	0.001**	0.900
	(0.134)	(0.073)	(0.108)	(0.246)	(0.262)				
					second period, 1999-2012				
1	−0.168	−0.077	0.193	−0.325	0.369**	240	0.209	0.209	0.779
	(0.154)	(0.190)	(0.179)	(0.303)	(0.158)				
2	−0.093	−0.092	0.003	−0.200	0.200	240	0.046**	0.662	0.815
	(0.156)	(0.145)	(0.161)	(0.210)	(0.156)				
3	−0.090	−0.070	−0.041	−0.184	−0.006	240	0.000***	0.693	0.856
	(0.162)	(0.121)	(0.156)	(0.198)	(0.154)				

Model 1: base model with five task categories; model 2: with additional sociodemographic controls (gender, age, age squared, children, partner, education), model 3: with additional job and company controls (tenure, tenure squared, company size, NACE sectors). P-value "tasks" denotes the test for joint significance of the task categories. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Data sources: IAB, BIBB, BAuA. See text for further details.

Table 8: Regression Estimates on Log Hourly Wages (by Years, OLS estimation, SO task measure)

year	model	non-routine manual	routine manual	routine cognitive	non-routine interactive	non-routine analytic	N	p-value model	p-value tasks	adj. R^2
1979	1	−0.246***	−0.016	0.449***	−0.417***	3.713***	20436	0.000***	0.000***	0.068
		(0.049)	(0.182)	(0.098)	(0.102)	(0.149)				
	2	−0.165***	−0.854***	0.835***	0.296***	2.102***	18358	0.000***	0.000***	0.299
		(0.048)	(0.188)	(0.095)	(0.100)	(0.138)				
1986	1	0.384***	−0.225***	0.115***	0.018	0.677***	14058	0.000***	0.000***	0.117
		(0.030)	(0.039)	(0.021)	(0.037)	(0.031)				
	2	0.077**	−0.256***	0.102***	0.140***	0.337***	10710	0.000***	0.000***	0.365
		(0.031)	(0.037)	(0.021)	(0.037)	(0.031)				
1992	1	0.315***	−0.453***	0.097***	−0.021	0.652***	13243	0.000***	0.000***	0.139
		(0.030)	(0.063)	(0.020)	(0.028)	(0.027)				
	2	0.003	−0.468***	0.043**	0.113***	0.336***	10265	0.000***	0.000***	0.431
		(0.034)	(0.066)	(0.019)	(0.027)	(0.026)				
1999	1	−0.184***	0.054***	0.177***	−0.084***	0.473***	12779	0.000***	0.000***	0.129
		(0.019)	(0.018)	(0.018)	(0.024)	(0.024)				
	2	−0.085***	−0.030*	0.061***	0.016	0.259***	12127	0.000***	0.000***	0.313
		(0.017)	(0.018)	(0.016)	(0.022)	(0.023)				
2006	1	−0.265***	−0.213***	0.158***	0.088***	0.344***	9322	0.000***	0.000***	0.083
		(0.035)	(0.026)	(0.024)	(0.026)	(0.020)				
	2	−0.116***	−0.175***	0.101***	0.137***	0.138***	9041	0.000***	0.000***	0.458
		(0.030)	(0.021)	(0.019)	(0.021)	(0.017)				
2012	1	−0.202***	−0.473***	0.098***	0.044*	0.367***	8711	0.000***	0.000***	0.134
		(0.032)	(0.026)	(0.023)	(0.024)	(0.019)				
	2	−0.105***	−0.252***	0.071***	0.098***	0.176***	8112	0.000***	0.000***	0.483
		(0.031)	(0.023)	(0.020)	(0.019)	(0.016)				

Model 1: base model with five task categories; model 2: with additional sociodemographic and company controls. *P*-value "tasks" displays the test of joint significance of the task categories. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Data sources: IAB, BIBB, BAuA. Own calculations. See text for further details.

Table 9: Changes in Employment and Wages by Tasks (in percent)[a]

	employment			log hourly wage		
	1979-1999	1999-2012	1979-2012	1979-1999	1999-2012	1979-2012
non-routine manual	112.36	-31.81	44.81	1.8	1.03	2.86
routine manual	-53.21	38.90	-35.01	3.37	-5.54	-2.36
routine cognitive	-31.82	27.51	-13.07	2.74	-0.94	1.77
non-routine interactive	69.16	-12.87	47.39	2.54	4.64	7.30
non-routine analytic	42.52	-9.91	28.40	-8.26	0.55	-7.76

[a] Task measure calculated according to equation 3. Data sources: IAB, BIBB, BAuA. Own calculations. See text for details.

Table 10: Regression Estimates on Log Hourly Wages (Fixed Effects Models) with AFL task measure

model	routine manual	routine cognitive	non-routine interactive	non-routine analytic	N	p-value model	p-value tasks	adj. R^2
				full period				
1	−0.200*	0.227*	0.419***	0.020	484	0.000***	0.000***	0.710
	(0.110)	(0.127)	(0.152)	(0.174)				
2	−0.106	−0.057	0.079	−0.161	484	0.000***	0.307	0.838
	(0.074)	(0.085)	(0.092)	(0.111)				
3	−0.099	0.024	0.001	−0.131	402	0.000***	0.571	0.848
	(0.080)	(0.100)	(0.139)	(0.166)				
				first period, 1979-1999				
1	−0.242***	−0.050	0.541***	0.035	325	0.000***	0.000***	0.783
	(0.072)	(0.091)	(0.168)	(0.158)				
2	−0.069*	0.097	0.295***	−0.045	325	0.000***	0.000***	0.892
	(0.041)	(0.060)	(0.094)	(0.109)				
3	−0.108	0.240***	0.248	0.099	243	0.000***	0.000***	0.901
	(0.070)	(0.089)	(0.177)	(0.209)				
				second period, 1999-2012				
1	0.165	0.391	0.237	0.582	240	0.784	0.784	0.761
	(0.290)	(0.363)	(0.329)	(0.501)				
2	−0.085	−0.125	−0.055	−0.114	240	0.087*	0.991	0.811
	(0.188)	(0.269)	(0.265)	(0.324)				
3	0.007	−0.263	−0.211	−0.464	240	0.000***	0.395	0.859
	(0.150)	(0.248)	(0.267)	(0.292)				

Note: Due to mulitcollinearity, non-routine manual is omitted from the estimation. All other task coefficients are to be interpreted to the base category non-routine manual. Model 1: base model with five task categories; model 2: with additional sociodemographic controls (gender, age, age squared, children, partner, education), model 3: with additional job and company controls (tenure, tenure squared, company size, NACE sectors). P-value "tasks" denotes the test for joint significance of the task categories. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Data sources: IAB, BIBB, BAuA. See text for further details.

Table 11: Regression Estimates on Log Hourly Wages (by Years, OLS estimation, AFL task measures)

year	model	routine manual	routine cognitive	non-routine interactive	non-routine analytic	N	p-value model	p-value tasks	adj. R^2
1979	1	0.061***	0.134***	0.021	0.534***	20289	0.000***	0.000***	0.067
		(0.016)	(0.015)	(0.018)	(0.020)				
	2	−0.012	0.165***	0.112***	0.317***	18234	0.000***	0.000***	0.299
		(0.015)	(0.015)	(0.018)	(0.019)				
1986	1	−0.183***	−0.035*	−0.183***	0.478***	14022	0.000***	0.000***	0.090
		(0.017)	(0.019)	(0.020)	(0.028)				
	2	−0.080***	0.130***	0.067***	0.328***	10814	0.000***	0.000***	0.357
		(0.018)	(0.023)	(0.024)	(0.029)				
1992	1	−0.157***	−0.018	−0.210***	0.417***	13052	0.000***	0.000***	0.120
		(0.016)	(0.018)	(0.017)	(0.022)				
	2	−0.064***	0.116***	0.071***	0.309***	10110	0.000***	0.000***	0.424
		(0.017)	(0.020)	(0.020)	(0.023)				
1999	1	0.218***	0.442***	0.148***	0.654***	11243	0.000***	0.000***	0.100
		(0.028)	(0.030)	(0.024)	(0.031)				
	2	−0.007	0.180***	0.114***	0.360***	10753	0.000***	0.000***	0.322
		(0.025)	(0.026)	(0.022)	(0.030)				
2006	1	−0.033	0.295***	0.272***	0.704***	8835	0.000***	0.000***	0.063
		(0.047)	(0.041)	(0.043)	(0.052)				
	2	−0.114***	0.148***	0.201***	0.325***	8587	0.000***	0.000***	0.459
		(0.040)	(0.034)	(0.035)	(0.042)				
2012	1	−0.162***	0.310***	0.309***	0.744***	8711	0.000***	0.000***	0.113
		(0.043)	(0.039)	(0.038)	(0.046)				
	2	−0.110***	0.172***	0.217***	0.374***	8112	0.000***	0.000***	0.480
		(0.040)	(0.035)	(0.034)	(0.039)				

Note: Due to mulitcollinearity, non-routine manual is omitted from the estimation. All other task coefficients are to be interpreted to the base category non-routine manual. Model 1: base model with five task categories; model 2: with additional sociodemographic and company controls. P-value "tasks" displays the test of joint significance of the task categories. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Data sources: IAB, BIBB, BAuA. Own calculations. See text for further details.

Table A.1: Activities Recorded in Surveys and Assignment to Task Categories

	non-routine manual	routine manual	routine cognitive	non-routine interactive	non-routine analytic
1979	repair, maintain; serve/nurse, cleaning	operate, regulate, maintain machines; cultivate, breed, extract raw materials; cook, produce, process; manufacture, assemble, build; load, send goods, advance mail	pack, sort, store; control, measure, analyze material, products, texts, data; correspondence, administration	educate, care, treat; publish, entertain; advertise, negotiate; represent; buy/sell; rent, lease, broking	plan, construct, draw; coordinate, instruct colleagues, management; safety, accident prevention, ecology; law application
1986	repair, maintain; serve, accommodate; nurse, treat	construct, install; operate and regulate machines; cultivate, breed;extract raw materials; produce, process; pack, load, drive; clean; secure	writing, calculations, book-keeping	publish, entertain; buy, sell, advertise; instruct colleagues educate, teach	plan, construct; dispose, direct; interpret rules; EDP, program
1992	serve; nurse, hairdressing	building,construction, equipment; operate machines; waste disposal; pack, post; clean	buy/sell, purchase	buy/sell, advertise; hire staff	construct, design; coordinate, dispose
1999	repair; serve	produce; monitor	measure, control; buy, purchase; analyze information	consult; marketing; train, teach; negotiate	develop; organize
2006	repair, maintain; serve, accommodate, cook; care, nurse, treat	operate machines, monitor; produce	measure, control, quality control; purchase	consult, inform; advertise, marketing, PR; train, teach, educate	research, construct; organize, plan working processes
2012	repair, maintain; serve, accommodate, cook; care, nurse, treat	operate machines, monitor; produce; clean, recycle	measure, control, quality control	consult, inform; advertise, marketing, PR; train, teach, educate	research, construct; organize, plan working processes