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Task-Biased Changes of Employment and Remuneration: The Case of Occupations

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Different empirical studies suggest that the structure of employment in the U.S. and Great Britain tends to polarise into “good” and “bad” jobs. We provide updated evidence that polarisation also occurred in Germany since the mid-1980s until 2008. Using representative panel data, we show that this trend corresponds to a task bias in employment changes: routine jobs have lost relative employment, especially in predominantly manual occupations.
We further provide the first direct test for whether task-biased technological change affects employment and remuneration in the same direction and conclude that there is no consistent task bias in the evolution of pay rules. By contrast, compositional changes like the proportion of union members are clearly associated with long-term changes in the remuneration of occupations.

JEL Classification: J21, J24, J31

Keywords: polarisation, technological change, pay rules, occupations, inequality, tasks

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1 Introduction

A consensus reigns among labour economists that recent decades have brought profound changes in the occupational structure of employment. On the supply side, many high-income economies experience the simultaneous effects of an ageing and more feminine labour force, combined with increasing supplies of higher-education credentials and immigrant workers. On the demand side, economists have paid considerable attention to the employment effects of technological change, trade and a growing demand for personal services.

The conventional wisdom as to the effect of technological change has been that better trained workers benefit more from new technologies than those with less training, thereby creating a "skill-bias" in the evolution and remuneration of labour (Katz and Autor, 1999). More recent research suggests that the relationships between education, new technologies and changes in employment or wages are not as straightforward as previously thought (Card and DiNardo, 2002; Lemieux, 2008). While the hypothesis of skill-biased technological change appears to be successful in accounting for the growth of high-skilled employment in the upper tail of the earnings structure, we see mounting evidence that some low-wage occupations are also expanding in the U.S., Britain and a range of European countries (see Goos et al., 2009; CEDEFOP, 2010). In a much-cited article on recent employment changes, Goos and Manning (2007) refer to this phenomenon as job polarisation.

An accurate understanding of changes in occupational employment and earnings is vital for sound economic policy, especially for correctly anticipating future skill needs and job opportunities. In order to refine the analysis of occupational trends, there has been a shift in the literature and among data providers towards a task-based analysis of the evolution of labour demand and supply (witness, for instance, the U.S. Department of Labor's O*NET system for monitoring changing skill needs within occupations). The rationale for looking at task compositions is that this approach allows to better grasp what occupations actually do, i.e. to differentiate jobs according to the specific labour services they perform and the types of technologies they use.

Focusing on the case of Germany, this paper contributes to the existing literature on changes in the employment and remuneration of occupations in three complementary ways. First, after clarifying the main concepts and a review of the literature (Section 2), we document with individual-level panel data the extent to which the German employment structure has been marked by polarisation (Section 3). Existing evidence on polarisation in Germany has concentrated on the 1980s and 1990s (see Spitz-Oener, 2006; Dustmann et al., 2009), and more recent studies cover only short periods (Antonczyk et al. (2009) analyse wage polarisation between 1999 and 2006) or exclude the years after 2004 (Antonczyk et al., 2010). However, as of 2003 the German labour market underwent significant institutional modifications under the banner of the so-called Hartz reforms (see Wunsch, 2005; Jacobi and Kluve, 2006), so that it is worthwhile to verify whether occupational polarisation continues to be observable in more recent data. Our sample suggests that the German occupational employment structure has polarised during the period 1985-2008, but also that changes in occupational remuneration are not in line with observed employment trends. This contrasts with standard labour market models predicting that a positive demand shock increases both employment and earnings.

Second, we use the framework of task-biased technological change developed by Autor et al. (2003) to account for the evolution of occupational employment and remuneration (Section 4). In particular, we show that a significant proportion of long-term employment changes in Germany can be accounted for by distinguishing occupations according to a typology of tasks: occupations that carried out routine tasks in 1985 have lost relative employment shares until 2008, especially in predominantly manual occupations. By contrast, the relative increase in lower-tail employment cannot be accounted for by the dichotomies of manual/non-manual and routine/non routine tasks and appears to be more specific to a group of low-paid service occupations.

Third, our study also contributes to the wider literature on occupational changes since we provide the first direct test for whether task-biased technological change affects employment and pay rules in the same direction. In contrast to the evolution of employment, estimates of a model that controls for intra-occupational changes in the labour composition suggest that the initial task content of an occupation does not have a consistent long-term effect on wages. However, compositional changes like the proportion of union members are clearly associated with changes in occupational remuneration.

2. Polarisation and task-biased technological change

The phenomenon of job polarisation appears under different names in the literature. In the widest sense, it refers to relative employment increases in "good" and "bad" jobs relative to "middling" jobs. However, there is no consensus on how to define "good" and "bad" jobs and alternative criteria are used by different authors. For instance, Doeringer and Piore (1985) predict a polarisation of the labour force into well-paid and stable jobs on internal labour markets and low-paid unstable jobs on the external labour market. Other polarisation studies retain current (Acemoglu, 2001) or initial earnings (Levy and Murnane, 1992; Goos and Manning, 2007) as the criteria for job quality. Other authors define wage polarisation in terms of changes in the wage distribution, for instance as a rise in the ratio between the 80th percentile and the median, combined with a decrease in the ratio of the median and the 20th percentile (Antonczyk et al., 2010). Yet others analyse polarisation in terms of initial skill levels and operationalize skills through average years of schooling (Autor et al., 2006) or by proxying skills through wage premia (Spitz-Oener, 2006). In general, the issue of what constitutes "job quality" appears to be particularly thorny for the case of service jobs (Meisenheimer, 1998; OECD, 2001). In this paper we define polarisation as follows. If we rank all occupations according to their median wage at date *t-1*, then employment (wage) polarisation between *t-1* and *t* means that the employment share (median wage) of occupations situated in the middle of the ranking has decreased relative to occupations at the top and bottom of the wage ranking in *t-1*.

The theoretical literature on polarisation focuses on three demand mechanisms that could account for such a trend. First, the propensity to offshore labour services is not the same in all occupations, with many production jobs in the middle of the wage distribution being presumably easier to relocate to low- or middle-income countries than service occupations (see Hijzen, 2007; Blinder, 2009). Second, overall income inequality may increase the demand for certain low-paid service jobs: as more income goes to the top earners, the demand (and employment) for low-skill service workers might increase (Gadrey, 1996; Manning, 2004; Autor and Dorn, 2009). Both of these factors undoubtedly affect specific occupations: certain blue-collar manufacturing jobs in the U.S. and Europe have indeed been relocated to emerging economies in Asia or Latin America, and the demand for some service occupations, e.g. in personal care, may be positively linked to wage inequality. However, empirical studies conclude that these factors play a subordinate role for the overall evolution of the occupational employment structure as a whole (see Freeman, 2004; Goos et al., 2009).

By contrast, the hypothesis developed by Autor et al. (2003) (hereafter referred to as ALM) has been more successful in accounting for polarisation: ALM argue that the way that occupations are affected by new technologies depends to a large extent on the tasks that they perform ("task-biased technological change"[1]). The basic idea is that firms substitute routine tasks for technology, a process driven by the well-known fact that the costs for routine operations have decreased dramatically over time (Nordhaus, 2007). Such capital-labour substitutions result in two complementary, but nevertheless distinguishable effects: first, they may lead to job losses (gains) in occupations carrying out routine (non-routine) tasks; and second, they may modify the composition of job tasks within occupations by increasing the incidence of non-routine relative to routine tasks.

[1] Goos and Manning (2007) and Goos et al. (2009) also refer to this process as "routinisation". This term might lend to confusion since it also evokes the phenomenon of standardization or de-complexification of jobs.

In this paper we will focus on the first effect, i.e. on between-occupation differences in rationalisation propensity as a consequence of differences in initial task content. For evidence on the evolution of tasks within occupations over time see, for instance, ALM or Spitz-Oener (2006).

The introduction of new technologies affects occupations differently according to the type of tasks that are predominantly carried out by a given occupation. Historically, manual routine tasks were the first to be substituted for machines: this has been a "thrust of technological change in the Industrial Revolution" (ALM, p. 1284). Despite the prominence of this classic form of capital-labour substitution in Economic History and economic textbooks, the routinisation propensity of manual routine jobs is not clear-cut. Whereas manual routine jobs in industrial production (e.g. assemblers, machine operators) can arguably be relatively easily rationalised through technological innovations, it is more difficult to replace occupations like cleaners or truck drivers with cleaning or driving robots. The impact of technological change on manual routine jobs may therefore depend on the sector of activity (e.g. industrial production versus services).

Next, the massive diffusion of personal computers at the work place has created substitution possibilities for non-manual routine jobs that typically carry out tasks involving repetitive forms of information-processing. As a consequence, occupations hired for predominantly non-manual routine tasks are considered by ALM to be substitutes for computers: clerical occupations such as telephone switchboard operators or typists are hypothesised to see their share in total employment decreasing as a result of technological change.

By contrast, the spread of the same technologies is thought to increase employment shares in high-paid occupations with non-manual non-routine tasks requiring creative problem-solving. Examples of occupations with predominantly non-manual non-routine tasks are judges, psychologists, lawyers or medical doctors. According to the ALM hypothesis, these occupations are not only difficult to replace with machines, but technologies like personal computers are even considered to play a complementary role.

Finally, occupations with predominantly manual non-routine tasks include occupations such as nurses, cabinet makers or plumbers. The ALM framework does not make predictions concerning the impact of technological change for this category. Indeed, at least two factors limit the rationalisation propensity of manual non-routine jobs. First, since these occupations are not associated with cognitive tasks, they are not directly affected by the spread of personal computers (they are neither substitutes nor complements). Second, many manual non-routine occupations in services are resilient to other forms of rationalisation like the replacement by robots or organisational streamlining ("Baumol's Disease"). This has been attributed to the complex eye-hand coordination they require, but also to the idiosyncratic nature of the relationship between producer and client in many service occupations (Gadrey, 2003). In a nutshell, the ALM hypothesis of task-biased technological change predicts increasing employment and earnings for jobs with non-routine non-manual tasks and decreasing employment and earnings for routine jobs. Whether non-routine manual jobs fare better or worse depends on the impact of technological change on the labour supply as displaced labour might shift from routine to non-routine manual jobs.

On the empirical side, ALM present evidence for the occurrence of task-biased technological change in the U.S. They show that even if occupations remain nominally identical, sizeable changes in their task content have been recorded by the Department of Labor Statistics. These within-occupation changes follow a pattern that is in line with the ALM hypothesis: a decline in the usage of routine skills is shown to be correlated with the level of computer adoption at the occupation and industry level.

Goos and Manning (2007) expand on the ALM model and look at the relation between the median wage of occupations and their task content. They show that in the U.S., routine jobs are predominantly found in the middle, non-routine non-manual jobs in the top, and non-routine manual jobs in the bottom of the earnings distribution. This middling location of routine jobs allows Goos and Manning to establish a link between the substitution of routine tasks and job polarisation. They further find evidence for polarisation of occupational employment in Great Britain for the period 1979-1999. However, the evolution of occupational pay rules and employment does not seem to go hand in hand in their data: lower-tail earnings deteriorate despite the observed growth in employment (Goos and Manning, 2007, p. 131). This may be due to the above-mentioned supply-side effects (displaced routine workers turn to the 'lousy' but growing occupations with manual non-routine tasks), but Goos and Manning also cite institutional factors such a falling unionisation and lower minimum wages to account for this phenomenon.

Next, Autor et al. (2006) find that while labour demand shifts in the U.S. have been monotonic in the 1980s, changes in the 1990s have shown polarisation with routine occupations loosing ground relative to non-routine jobs. Contrary to the British experience, employment and wages appear to co-vary in the U.S. during the 1990s.

Goos et al. (2009) analyse the relationship between initial wages and the evolution of employment shares for a panel of European countries. Looking at ISCO 88 two-digit occupations between 1993 and 2006, they find evidence for job polarisation in Europe as a whole: the four lowest-paying and the eight highest-paying occupations increase their employment share, while the nine middling occupations loose jobs. This is also the case for individual countries like Belgium, Germany, Greece, the Netherlands, Norway, Spain, Sweden and the U.K., but not for Austria, Denmark, Finland, France, Ireland, Italy, Luxembourg, Portugal (see also CEDEFOP (2010) for

European evidence on job polarisation covering the period 2000-2010 and a forecast for 2010-2020). Goos et al.'s model accounts for job polarisation with the task content of occupations and distinguishes between three types of tasks: abstract (intense in non-routine cognitive skills), service (intense in non-routine non-cognitive skills), and routine (intense in both cognitive and non-cognitive routine skills). In a cross-country regression controlling for the off-shoreability and educational composition of occupations, they find that employment between 1993 and 2006 is positively correlated with the importance of abstract and service tasks, but negatively correlated with routine tasks.

As for Germany, Spitz-Oener (2006) presents evidence for job polarisation to have occurred during the period 1979-1998/1999: occupations situated around the third decile of the skill distribution in 1979 lost relative employment, while the lowest decile as well as the upper three deciles have gained employment shares. Dustmann et al. (2009) corroborate this result for the 1980s and 1990s: occupations with high initial levels of formal education have seen their employment share increasing, while occupations with middling education lost relative employment. As for the bottom of the occupational structure, Dustmann et al. find small employment gains for the lowest wage percentiles in the 1980s, and modest employment losses in the 1990s.[2] Antonczyk et al. (2009) exploit updates of the datasets used by Spitz-Oener (2006) to test whether the observed increase in wage inequality between 1999 and 2006 can be attributed to changes in task content. Contrary to the U.S. evidence of Autor et al. (2006), Antonczyk et al. "conclude that the task-based approach can not explain the recent increase in wage inequality among male employees in Germany". Finally, Antonczyk et al. (2010) use the the German IAB employment subsample on which the analysis in Dustmann et al. (2009) is based and compare the German polarisation with data from the U.S. Current Population Survey. Antonczyk et al. (2010), whose analysis is restricted to male full-time workers who are between 25 and 55 years old, find evidence for employment polarisation to have occurred in Germany during the periods 1989-2004 and 1994-2004, while the wage distribution seems not to have polarised.

Hence, previous research on the German evolution of employment found sizeable job gains at the top, losses in the middle, and stagnant employment at the bottom of the occupational structure. However, unlike the U.S. experience during the 1990s, the German employment polarisation seems not to be accompanied by a corresponding evolution of wages. To our knowledge, none of the existing studies on Germany tests directly whether the initial task content of occupations is related to long-term changes in employment and wages.

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[2] See also Burkhauser and Rovba (2006) for evidence that the German income distribution hollowed out during the 1990s.

While extant studies therefore suggest that employment has polarised in different countries (including Germany), at least three points remain unclear. First, empirical evidence on polarisation in Germany is only available until 2004. However, as of 2003 the German labour market underwent significant institutional transformations through the implementation of the Hartz reforms, so that it is interesting to verify whether the polarisation trend observed until 2004 continues in more recent data. Second, we lack a direct test whether the long-term evolution of occupations in Germany is task-biased, i.e. due to their propensity to be rationalised according to the pattern hypothesised by ALM. Third, it is not clear whether task-biased technological change affects employment and wages in the same direction. Existing evidence suggests that in the 1990s U.S. wages and employment covary, while the remuneration of "lousy jobs" in the U.K. and Germany seems to have deteriorated despite positive demand shocks. This raises the question whether the hypothesised demand shifts away from routine (and towards non-routine) occupations have a corresponding downward (upward) effect on pay rules. The remainder of this paper addresses these questions empirically by elucidating the relationships between job types, employment and pay rules for the case of Germany.

3. Changes in employment and remuneration of occupations

3.1. Data source

The data used in this paper stems from the Scientific Use Sample of the German Socio-Economic Panel (SOEP), an extensive and representative household panel provided by the German Institute for Economic Research (DIW). The first wave of the panel was collected in 1984, the latest available in 2008. The length of the observation period is a key advantage of the SOEP over other data sources, given that technological change is arguably a long-term phenomenon that might take several decades to affect earnings and employment. Among other variables, the SOEP contains longitudinal information on household composition, occupational biographies, employment, and earnings. A detailed presentation of the SOEP and its evolution can be found in Wagner et al. (2007). Although the data is compiled annually and available for all years from 1984 until 2008 (except for 1992), information on tasks was only collected in 1985, 1987, 1989, 1995 and 2001: only during these years all surveyed employees have been asked a set of additional questions on the type of work they carry out (see Section 4.2 below).

Several filters have been applied to the raw SOEP data. First, since we focus on the evolution of employment and wages, all individuals that are not employed at the time of the interview have been dropped. This step eliminates around 50 percent of all surveyed individuals, mainly children, people in retirement, and working-age individuals that are either unemployed or not active on the labour market. Second, we also dropped all observations for which information on the occupational variable is missing (this concerns around 5 percent of the remaining individuals). Thirdly, given that we want to trace changes in employment and earnings over several decades, we only retain observations in the SOEP for which the region of residence is West Germany and thereby circumvent the problem of the considerable differences in employment structure and remuneration between the old and new *Bundesländer*. In fact, the earnings differential between the two regions continues to be so stark that a regression including the entire SOEP sample would resemble a cross-country estimation juxtaposing two different wage distributions. The sample used in the regression analysis contains 24,416 individual-year observations. Detailed information on specific SOEP variables will be provided below.

3.2. The evolution of employment

We first examine the evidence for polarisation by analysing the evolution of occupational employment. Unless otherwise mentioned, throughout this paper occupations are categorized according to the ISCO-88 three-digit nomenclature (see ILO, 1990). All earnings data used in this paper refer to current gross hourly wages deflated by the 2005 Consumer Price Index. Since the corresponding SOEP variable provides current gross monthly labour income, we computed hourly wages by first converting the monthly into weekly income and then dividing this figure by the actual weekly working hours (including overtime).

[Insert Figure 1]

A graphical method to detect job polarisation is to rank percentage point changes in occupational employment shares between period *t-1* and *t* according to the respective earnings in *t-1*. If the occupational structure has polarised, one should see increasing employment shares at the lower and/or upper tail of the earnings distribution relative to middle-income occupations. Panel (a) in Figure 1 is the corresponding graph for the evolution of German employment between 1985 and 2008. Earnings in Figure 1 are logarithms of hourly median earnings in each occupation in 1985. Employment shares are measured in terms of head counts in each three-digit occupation.[3] The employment changes in Germany clearly reflect a polarisation pattern with considerable increases

[3] The shape of the graphs does not change substantially if actual hours worked are used as employment measure.

for high-wage, similarly large losses in the middle-wage and small or no increases in some low-wage occupations.

Another way of illustrating the evolution of occupational trends is to chart changes in employment shares against the percentiles of the initial earnings distribution as proposed by Dustmann et al. (2009). The resulting graph (panel (b) in Figure 1) reveals a similar pattern of polarisation than the one found by Dustmann et al. for the 1980s and 1990s, with top-income occupations enjoying considerable employment gains and a hollowing out of middling occupations. The biggest losses in employment shares appear to be situated around the 40th percentile of the initial earnings distributions. Overall, the shape of the employment changes in the SOEP data corroborates and updates other studies with German data and suggests that polarisation is a robust and continuing process in Germany.

To test more formally for polarisation, Goos and Manning (2007) proposed a straightforward method based on the following equation:

$$\Delta(EMPLOYMENT\_SHARE)_{i,t} = \lambda_0 + \lambda_1 \log(MEDIAN\_WAGE)_{i,t-1} + \lambda_2 \log(MEDIAN\_WAGE)^2_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

where $\Delta(EMPLOYMENT\_SHARE)_{i,t}$ is the change in the employment share of occupation i between t and t-1, $log(MEDIAN\_WAGE)_{i,t-1}$ is the logarithm of the median wage of occupation i in t-1, and $log(MEDIAN\_WAGE)^2_{i,t-1}$ the square of the initial median wage. Polarisation of the employment structure implies that the linear term is negative and the quadratic term positive, thereby giving rise to a U-shaped curve of employment changes.

[Insert Table 1]

We estimated Equation (1) by weighting each occupation by its initial employment share in 1985 (see Goos and Manning, 2007). Table 1 presents the results with employment measured per capita (panel (a)) and in terms of hours worked (panel (b)) for four time periods: 1985-1989, 1985-1995, 1985-2001 and 1985-2008. All regression coefficients have the expected sign and increase in magnitude the further we move away from the initial date. For the longest period (1985-2008), the U-shape of the relationship between initial earnings and employment changes is strongly significant. This result is robust to whether we measure employment shares in terms of head counts or in terms of hours worked, thereby suggesting that the polarisation trends observed for U.S. and Britain by Goos and Manning (2007) and Autor et al. (2006) occurred also in Germany since the mid-1980s until 2008.

3.3. The evolution of pay rules

We now turn to the evolution of occupational earnings. Standard models of the labour market predict that a given demand shock pulls quantities and prices in the same direction: if the observed trends in occupational employment are caused by shifts in demand – e.g. due to task-biased technological change – then, ceteris paribus, we would expect that changes in quantities and prices are positively correlated.

How did occupational pay rules in Germany develop since the mid-1980s? We estimated the same quadratic model with which we detected a U-shaped evolution of employment shares. If the trends in occupational remuneration match the evolution of employment, we would expect a similar pattern to emerge for the case of occupational pay rules. As can be seen in Table 1 (panel (c)), we do not find strong evidence for this. Most of the coeffients do not have the expected sign and the relationships between initial earnings and changes in earnings is insignificant.

To test directly for whether changes in occupational employment match changes in pay rules, we have computed the corresponding correlation coeffients (panel (d) in Table 1). In contrast to the existing evidence for the U.S., our results suggest that the link between changes in employment shares and changes in (log) median earnings is extremely weak in Germany.[4] This is far from the predictions of standard labour market theory in which demand shifts affect quantities and prices symmetrically. The next section provides further evidence that if occupational trends are caused by demand shifts, the impact of these shifts is much more visible on the quantity side than in observed changes of occupational pay rules.

4. Task-based analysis of occupational changes

4.1. Model

In order to test formally whether observed changes in occupational employment and remuneration can be accounted for by task-biased technological change, we formulate the following model:

[4] This contrasts somewhat with Dustmann et al. (2009), who find a weakly positive relation between changes in employment and changes in wages for Germany for the 1980s and 1990s in the upper part of the wage distribution.

$$\Delta(EMPLOYMENT)_{i,t} = \alpha + \sum_{k=1}^{3} \beta_k (TASKS)_{k,i,t-1} + \sum_{l=1}^{7} \delta_l \Delta X_{l,i,t} + \varepsilon_{i,t} \quad (2)$$

$$\Delta \log(MEDIAN\_WAGE)_{i,t} = \alpha^* + \sum_{k=1}^{3} \beta_k^* (TASKS)_{k,i,t-1} + \sum_{l=1}^{7} \delta_l^* \Delta X_{l,i,t} + \varepsilon_{i,t}^* \quad (3)$$

The dependent variable in Equation (2) is the change in the share of occupation *i* in total employment between *t-1* and *t*. Equation (3) explains the change in the logarithm of the median hourly wage of occupation *i* for the same period. The main explanatory variables in both equations is the proportion of task type *k* in occupation *i* at *t-1*. The variable $TASKS_k$ are therefore the proportions of non-manual non-routine, non-manual routine, manual non-routine and manual routine jobs in each occupation. If technological change affects the evolution of employment and remuneration of occupations differently according to their respective task content, we would expect that the initial share of manual and non-manual routine tasks at *t-1* has a negative, and the share of non-manual non-routine tasks a positive impact on relative employment and wage changes.

It should be noted that a change in occupational employment can either be the result of demand shifts (e.g. technological change, trade) or supply shifts (e.g. expansion of formal education, female labour force participation, increasing average seniority). To identify the impact of initial task content, it is therefore crucial to control for changes in the composition of occupations. This is the rationale for including the change in a vector of control variables, ΔX, in the model. The change in *X* captures an array of compositional changes that occurred in occupation *i* between *t* and *t-1* (see below).

4.2. Operationalisation of task categories

The evidence on tasks in both ALM and Goos and Manning (2007) is based on the same source, namely the task definitions in the U.S. Dictionary of Occupational Titles (DOT). This dataset is compiled by examiners of the Department of Labor who evaluate more than 12,000 different occupations and their characteristics according to standardized evaluation guidelines, namely the Handbook for Analyzing Jobs.

In this paper, we use an alternative method to measure the task content of occupations, namely subjective evaluations of jobs by incumbent employees. In particular, the Scientific Use Sample of the SOEP in 1985, 1987, 1989, 1995 and 2001 contains 14 questions collecting information on job characteristics and working conditions such as tasks, supervision, and health hazard of the job. Out of the 14 questions, three can be linked directly to task types.

ALM define routine tasks as those that follow clear rules and procedures that can be "specified in computer code and executed by machines" (p.1283). Our operationalisation of routine tasks is based on whether a work post is characterised by diversity and monotony of procedures, arguing that the less diversified and the more monotone a job is, the more it is possible to identify the underlying rules and procedures and, in fine, replace them with technology. In particular, individuals in the SOEP were asked whether they (a) fully, (b) partially, or (c) not at all agree with the questions "Do you carry out diverse tasks?" and "Does your work allow you to constantly learn new things that are useful for your professional development?". We defined routine jobs as those whose incumbents answered (b) or (c) to both questions, i.e. they did not fully agree that their tasks were diversified and that work experience was useful in their current job.

To distinguish between manual and non-manual jobs, we used the question "Do you have to perform physically demanding work in your job?". While this operationalisation deviates from the exact semantic content of the notion "manual" – a watchmaker might very well work mainly with her hands but not find her job physically demanding –, the distinction between physical and non-physical work appears to be most pertinent for our question. A difference in the rationalisation propensity between jobs is likely to be linked to their respective degree of physical effort: the more physical a job is, the more it is likely to involve complex eye-hand coordination absent in non-physical jobs whose tasks mainly consist of symbolic rather than physical transformations.

Both strategies to measure the task content of occupations have advantages and disadvantages. The administrative evaluation of jobs in the U.S. DOT has the advantage of being based on objective criteria spelt out in the Handbook for Analyzing Jobs. All examiners are supposed to apply identical criteria to all occupations, whereas individual survey data such as the one we use in this paper arguably contains more variation in the interpretation of the different aspects of routine or non-routine work. For instance, whether an individual finds her professional activity diversifed may depend on her personal experience in other jobs, something that is by definition unequally distributed among respondents.[5] However, the higher subjectivity of the SOEP measures is also an advantage since the information on task content is collected from people who know very well the jobs under evaluation, namely the people working in them on a day-to-day basis. The survey data allows therefore to tap into in-depth knowledge on task content and is likely to reflect more accurately the diversity of tasks within a given occupation. Finally, a clear disadvantage of the DOT for econometric work is the lower frequency in which the former has been updated: the Fourth Edition of the DOT was published in 1977 and the Revised Fourth Edition in

[5] This problem would be less salient for the longitudinal variation of tasks within occupations given that the same individuals are interrogated in subsequent years.

1991, whereas the SOEP updates information on job characteristics roughly every five years for the period under study. Given these differences between the two sources, it appears to be worthwhile to investigate whether survey-based task content is significantly correlated with the evolution of occupations as has been found in the DOT data. Table 2 presents the evolution of employment shares for the different task categories in our final sample of individuals. All observed trends are in line with the ALM hypothesis: non-manual non-routine jobs display constantly increasing employment shares between 1985 and 2001. By contrast, the category of non-manual routine jobs has lost employment shares while the proportion of manual routine jobs has remained roughly constant (increased by less than 1 percentage point).

[Insert Table 2]

To illustrate the richness of the data, Figure 2 shows the initial task composition of the ten occupations with the highest increase (panel (a)) and highest decrease (panel b)) in employment shares between 1985 and 2008. The figure clearly shows that the occupations that gained employment carry out predominantly non-manual tasks, and most of them have more than 20 percent of non-manual non-routine tasks. By contrast, the occupations that lost employment over the same period had high initial levels of manual routine tasks. Although manual non-routine tasks are predominantly found in the occupations with decreasing employment, some of the occupations in panel (a) also carry out such tasks (e.g. nursing and midwifery associate professionals, social worker associate professionals). Figure 2 also shows that there is considerable diversity within identical occupational categories, even if measured at the detailed ISCO-88 three-digit level. None of the occupations can be associated with a single type of task, which is why it would be misleading, for instance, to refer to an occupation as being exclusively non-manual non-routine or exclusively manual routine: in practice, all task types can be found in each occupation.

[Insert Figure 2]

The link between job polarisation, on the one hand, and task-biased technological change, on the other hand, hinges on the fact that the different task categories are unevenly distributed across the initial wage structure. To verify that this is the case in our data, we have calculated the task composition of occupations at different wage levels in 1985 and 2001, respectively. Figure 3 shows the respective task composition of wage deciles according to the median wage of three-digit occupations. As can be seen, most of the task types are indeed distributed unevenly across the wage distributions. Occupations in the upper deciles are predominantly non-manual. In particular, the share of non-manual non-routine tasks in occupations belonging to the highest two deciles in 1985 was higher than 40 percent. By contrast, the proportion of manual routine tasks is higher in occupations whose median wage is situated in the lower deciles. Interestingly, the proportion of manual non-routine tasks appears to be more broadly distributed, with a proportion of around 10 percent in most deciles. This peculiar distribution of manual non-routine tasks is similar to the findings by Goos and Manning (2007) for the US, where as much as 33 percent of occupations in the upper tercile require manual non-routine skills.

[Insert Figure 3]

4.3. Model specification and descriptive statistics

Besides an occupation's task content, employment shares and hourly wages, the estimation of Equations (2) and (3) requires the measurement of a range of additional variables that control for changes in the occupation's labour composition. In our specification, the vector of control variables X contains the following information: the proportion of temporary employment contracts ($TEMPORARY\_CONTRACTS_{i,t}$); the proportion of trade union members[6] ($UNION\_MEMBERS_{i,t}$); the proportion of women ($GENDER\_RATIO_{i,t}$); the proportion of foreigners, where foreigners are defined as workers with a non-German nationality ($FOREIGNERS_{i,t}$); the average job tenure in the occupation ($TENURE_{i,t}$); and the educational composition of the occupation, measured in three levels using the ISCED classification of educational attainment ($EDUCATION_{r,i,t}$): low = ISCED level 0, 1 and 2; medium = ISCED level 3 and 4; high = ISCED level 5 and 6 (see CEDEFOP, 2010).

[Insert Table 3]

Descriptive statistics for all variables are presented in Table 3. The levels in the table correspond to the 107 occupations observed in 1985, changes refer to the 106 occupations that remained in the sample in 2008. The average number of individual observations in each occupation was around 39 in both years.

The secular trends evidenced in the literature appear also in our data: on average, union

[6] There is no information on union membership in the SOEP for the year 1995. The figures have been proxied with union membership in 1993.

membership is declining at the occupational level by 7 percentage points; the proportion of women and foreigners within occupations have increased by 7 and 3 percentage points, respectively; the ageing of the work force led to an increase in average job tenure of 0.88 years; and, finally, medium and high levels of education increased to the expense of low-level education. The share of temporary contracts within occupations increased slightly from 10 to 11 percent.[7] All descriptive statistics suggest that our sample is representative for the German labour market, and in particular for the compositional changes that occurred during recent decades.

4.4. Estimation results

Our baseline model includes the initial level of task shares in 1985 and the changes that occurred in the dependent and control variables during the periods 1985-1995, 1985-2001, and 1985-2008 (see Table 4). Employment shares are measured in terms of actual working hours (an alternative per capita measure is included among the robustness tests in Section 4.5). All standard errors are robust to autocorrelation and heteroskedasticity. Like in Goos and Manning (2007), all observations are weighted by initial employment shares. This procedure ensures that the regression results are not biased by compositional changes in small occupations. Given that the variables used in our model are computed from a sample of employee-level observations, the weighting of occupations by employment shares also takes into account that average values are measured more precisely in occupations with many observations.

[Insert Table 4]

Columns 2 through 4 in Table 4 show the regression results for the change in occupational employment shares (Equation (2)), columns 5 through 7 present the corresponding results for changes in (log) median hourly earnings as dependent variable (Equation (3)). All estimated models have a reasonably good fit and the adjusted coefficients of determination increase with the length of the observation period (for 1985-2008, the R-squared of Equations (2) and (3) are 0.53 and 0.21, respectively).

In all regressions, the reference category are the manual routine tasks that ALM hypothesise

[7] As for the composition of the workforce in terms of industries, during the period at hand the German economy has been marked by a shift from manufacturing- to service-sector employment. The share of the former in total employment has decreased from 36.14 % in 1989 to 26.39 % in 2001, while wholesale and retail trade (NACE code G) has increased by 3.12; real estate, renting and business activities (NACE code K) by 4.01; and health and social work (NACE code N) by 2.64 percentage points between 1985 and 2001.

to be negatively affected by technology-related demand shifts. The ALM framework makes the following predictions for our estimation parameters: relative to the reference category, we expect the initial level of both non-manual and manual non-routine tasks to affect employment and remuneration positively. Sign and significance of non-manual routine tasks depend on whether the substitution potential of routine tasks was greater for manual or non-manual activities.

4.4.1. Tasks and employment: strong evidence for task-biased technological change

Our results suggest that an occupation's initial task composition helps explaining the evolution of employment in the predicted way. An occupation's 1985 share of non-manual non-routine tasks is strongly positively related to relative changes in employment during all periods (see Table 4). The corresponding coefficient increases in magnitude the further we move away from the starting year, a sign that the task bias is a secular and continuing trend. This confirms our observation in Figure 2 that many occupations with sizeable increases in employment carried out non-manual non-routine tasks, like business professionals, computing professionals, or legal professionals.

In addition, the difference between the coefficients of routine and non-routine non-manual tasks is statistically significant (the corresponding p-value for 1985-2008 is 1.6 percent), again indicating that routine tasks are detrimental for employment. This is in line with the prediction of the ALM framework that non-manual jobs with more clerical and repetitive tasks should have been affected negatively by technological change.

This being said, the negative employment effect has been much stronger for manual than for non-manual routine jobs. This suggests that routine tasks had a negative impact on employment, but the size of technology-related substitutions was far greater in manual than in non-manual occupations. In other words, it appears that it was easier for firms to substitute routine tasks in manual jobs such as manufacturing labourers or blue-collar machine operators than in white-collar routine jobs. This in line with the fact that all ten observations with high employment losses in Figure 2 are blue-collar occupations.

Next, the coefficient of manual non-routine tasks is not always positive. Only for the period 1985-1995 we observe a significant positive impact of non-routine task content in manual jobs. After 1995, there is no significant difference between routine and non-routine manual jobs.

Some of the control variables are significant in the baseline model. Changes in union membership are positively correlated to the evolution of employment shares between 1985 and 2008. The same holds for the proportion of foreigners in an occupation. By contrast, an increase in the gender ratio was negatively associated with employment changes for 1985-2001, but the coefficient becomes insignificant afterwards. Increases in mean job tenure are negatively related to employment changes during the entire observation period.

Our results are therefore broadly in line with the hypothesis of task-biased technological change and the pattern of employment changes in Germany (see Figure 1). First, the relative increase of high-paid occupations matches the positive impact of non-manual non-routine tasks in the upper part of the wage distribution. Second, as we move from the top towards the middle-income occupations, employment increases become smaller. This corresponds to the significantly lower (but still positive) employment effect of non-manual routine tasks that are relatively concentrated in the third quartile of the 1985 earnings distribution (see Figure 3). Third, the hollowing out in the second quartile observed in Figure 1 corresponds to the negative employment effect of manual routine tasks. The institutional reforms that were implemented on the German labour market since 2003, notably a range of active labour market policies targeting increases in low-wage employment (Wunsch, 2005; Jacobi and Kluve, 2006), do not appear to have affected these trends in any substantial way: results for 1985-2001 are relatively similar to the more recent period 1985-2008.

[Insert Figure 4]

However, the regression results are not able to explain the upward bend in the lowest deciles observed in Figure 1 and we do not see a significantly positive employment impact of manual non-routine jobs. An explanation for this could be the fact that manual non-routine tasks are less concentrated in the lowest deciles than in the U.S. or Britain (see Goos and Manning, 2007). In Germany, the access to many occupations that carry out such tasks is regulated through the system of apprenticeships and manual non-routine tasks can be found at various strata of the wage distribution (see Figure 3). A closer look at the low-wage occupations in the left tail of the U-shaped curve in Figures 1 suggests that gains in employment shares are linked to low-skill services rather than non-routine tasks: indeed, the lower tail consists of occupations such as "other personnel service workers", "domestic and related helpers, cleaners and launders", "housekeeping and restaurant service workers" and "personal care and related service workers". As shown in Figure 4, these are predominantly manual occupations that carry out both routine and non-routine tasks – but many low-wage service occupations also perform non-manual tasks. This lends support to approaches that explain employment polarisation at the *lower* tail with the increase in low-wage service occupations with diverse task content (e.g. Gadrey, 2003; Goos et al., 2009; Autor and Dorn, 2009), whereas the decrease in the *middle* and the increase at the *top* of the distribution can be associated with the task dichotomies manual/non-manual and routine/non-routine.

4.4.2. Evolution of pay rules: compositional changes matter, but no consistent task bias

The model of changes in median hourly earnings unveils a different set of factors (see columns 5-7 of Table 4). Most importantly, the initial task composition is not consistently associated with the evolution of occupational pay rules. The only significant task coeffients correspond to non-manual routine and manual non-routine tasks in the regressions covering the period 1985-2008. Note that the positive wage effect of manual non-routine occupations is not matched by simultaneous employment gains for this category. This suggests that any positive demand effect for this task category would have translated into higher wages rather than a rise in employment. The biggest problem for an explanation of occupational pay rules with a technology-related demand effect is the consistently insignicant coefficient for non-manual non-routine tasks, a category that experienced strong employment increases over the period at hand.

However, Table 4 also shows that the compositional changes that occurred in an occupation are often significantly related with the evolution of pay. First, we observe negative coeffients for the share of temporary contracts and union membership. An increasing share of temporary contracts depressed median earnings significantly over the period 1985-2001. The corresponding coefficients are also negative for the other periods, although statistically insignificantly different from zero. By contrast, changes in union membership are significantly and positively correlated with variations in wages. This suggests that institutional factors continue to play an important role for the evolution of occupational pay rules.

Gender and nationality appear to be only weakly related to changes in occupational remuneration. An increase in the share of women in an occupation depresses hourly earnings for all periods, but is only significant for 1985-1995. This could be interpreted as evidence for gender-based pay discrimination, although the negative regression coefficient could also be driven by self-selection or asymmetric sorting of women into low-pay occupations. There appears to be no pay penalty associated with an increase in the share of workers with a foreign nationality.

Finally, the coefficient for the proportion of highly educated workers in an occupation has the sign one would expect from human capital theory: an increase in high educational credentials increases occupational pay relative to low levels of education. The size of this effect increases through time and becomes significant for the period 1985-2008.

4.6. Robustness tests

We implement three robustness tests for the results presented above. First, we test whether results are sensitive to the choice of the reference year; second, we evaluate the impact of an alternative employment measure; and third, whether the estimates are modified by the inclusion of an occupation's initial educational composition in addition to the initial task composition.

4.6.1. Model 1: Sensitivity to reference year

[Insert Table 5]

All regressions in Table 4 are based on the same reference year, namely 1985. One might be worried whether the results are sensitive to the choice of the starting year. In particular, the estimated coefficients might not reflect broader trends if the task composition of occupations or the set of control variables measured in 1985 are driven by year-specific circumstances. To test whether this is the case in our sample, we have estimated the baseline regressions with 1989 as reference year. Model 1 in Table 5 presents the coefficient estimates for the evolution of employment shares and median wages for the period 1989-2008. As can be seen, the results for Model 1 resemble closely the baseline regression for 1985-2008 in size and significance of all variables. In addition, the coefficients for most significant variables are slightly smaller in the regressions for 1989-2008 than for 1985-2008, further suggesting that the observed phenomena is a long-term trend and not linked to any particular year. We therefore conclude that the results presented in the previous section are robust to the choice of the reference year.

4.6.2. Model 2: Working hours versus number of jobs

While hours worked is arguably the best indicator for effective employment, one may be concerned whether results change if employment is proxied with the total number of jobs in an occupation. Model 2 in Table 5 shows the estimated parameters of the employment and wage equations based on changes in head counts per occupation between 1985 and 2008. The impact of non-manual non-routine tasks is again positive and statistically significant. The significant difference between routine and non-routine non-manual occupations is also confirmed with a p-value of 0.03. As in the baseline model, the difference between non-manual and manual non-routine occupations is sizeable and strongly significant (p-value = 0.00). Again, the same control variable are significant as in the baseline model.

The only notable difference between the two alternative employment measures is that we do not find a significant difference between non-manual and manual routine tasks when shares are based on head counts instead of hours worked. This indicates that during our observation period, rationalisations affected the working hours of routine occupations stronger than the number of jobs. An explanation for this could be that working hours are easier to adjust in response to technological changes than the number of employees. We conclude that our results are fairly insensitive to the choice of the employment measure.

4.6.3. Model 3: Task bias versus education bias

Finally, we test the sensitivity of our results to the inclusion of additional human capital variables. This test is motivated by three factors. First, tasks and levels of formal education are correlated so that it is relevant to investigate whether the observed task-bias is genuine or simply reflecting a spurious correlation with education. Second, changes in the educational composition within an occupation might be related to initial levels, so that the exclusion of the latter could lead to an omitted variable bias. Third, including both the initial level of tasks and education allows to measure directly whether employment and wage changes are task-biased and/or education-biased.

Model 3 in Table 5 shows the regression output with the initial composition of educational attainment in the regression. Only the initial level of medium education is found to be significantly related to changes in employment, albeit with a negative coefficient. Moreover, in the augmented wage equation, neither initial levels nor changes in educational composition are significant. These results are not in line with the skill-biased technological change hypothesis. Indeed, the latter suggests that employment and wages should rise (decline) in occupations where the initial level of education is high (low) and/or increasing (decreasing).

By contrast, the inclusion of initial levels of education hardly affects the coefficients of the task variables. In addition, the adjusted determination coefficients do not increase much (e.g. 54 % compared to 53 %, without the initial educational composition, in the employment regression). In other words, our robustness test suggests that the evolution of employment is the result of a task bias rather than an education bias. The impact of education is, therefore, far from being as determinant as one might expect from the literature on skill-biased technological change. In all, we conclude that our estimations stand up to the series of robustness tests presented in this section.

5. Conclusion

This paper examined the evolution of employment and remuneration for detailed occupations on the German labour market. We used representative individual-level panel data for the period 1985-2008 to update evidence that the German occupational structure has polarised. We find that occupations situated around the 40th percentile of the earnings distribution in 1985 have lost, and high-paid occupations have gained employment shares. The lowest percentiles stagnated or recorded minor employment losses.

Next, we have shown that contrary to what one might expect from standard labour market models, this pattern of job polarisation is not matched by a symmetric evolution of occupational pay: the correlation between changes in employment and remuneration is extremely weak. We also provide new evidence that these trends have not been altered by the substantial labour market reforms that have been implemented in Germany since 2003.

Using panel data on the task content of occupations in Germany, we provided the first direct test for whether these long-run trends can be explained in a framework distinguishing between non-manual non-routine, non-manual routine, manual non-routine and manual routine tasks. We presented econometric evidence for task-biased technological change: the initial task content in 1985 explains a considerable proportion of the changes in the employment structure that occurred in the German economy between 1985 and 2008. The higher the share of routine jobs in an occupation in 1985, the more jobs have been lost to predominantly non-routine occupations, especially in manual occupations. Relatively high-paid non-manual non-routine occupations like engineers or managers have gained employment shares compared to non-manual routine occupations in which computers are typically assumed to be substitutes for routine tasks (e.g. office clerks, typists, bank tellers). The strongest employment losses are associated with high initial levels of the manual routine tasks that are predominantly carried out by occupations with below-median earnings (e.g. assemblers or machine operators). Contrary to the existing evidence for the U.S. and Britain, the upward bend in the lower tail of the wage distribution is not linked to a concentration of manual non-routine tasks: in the case of Germany, these tasks can be found at all levels of the wage structure. We argue that lower-tail employment polarisation is linked to job gains in a group of low-paid service occupations and show that these occupations carry out more diverse tasks than the predominantly manual routine blue-collar occupations that have lost employment shares.

While tasks explains a substantial part of the variation in employment, the evolution of pay rules is not consistently task-biased. By contrast, our results suggest that compositional changes such as increasing union membership and levels of formal education are significantly associated with long-run changes in hourly earnings.

We conclude that the trends documented in this paper cannot be accounted for by a simple demand shift: while our results suggest that employment is affected by what occupations actually do – manual or non-manual, routine or non-routine, manufacturing or service activities – the evolution of occupational pay does not appear to be task-biased and depends on compositional factors. This disconnection between employment and remuneration showcases the limitations of labour market models in which quantities and prices evolve symmetrically.

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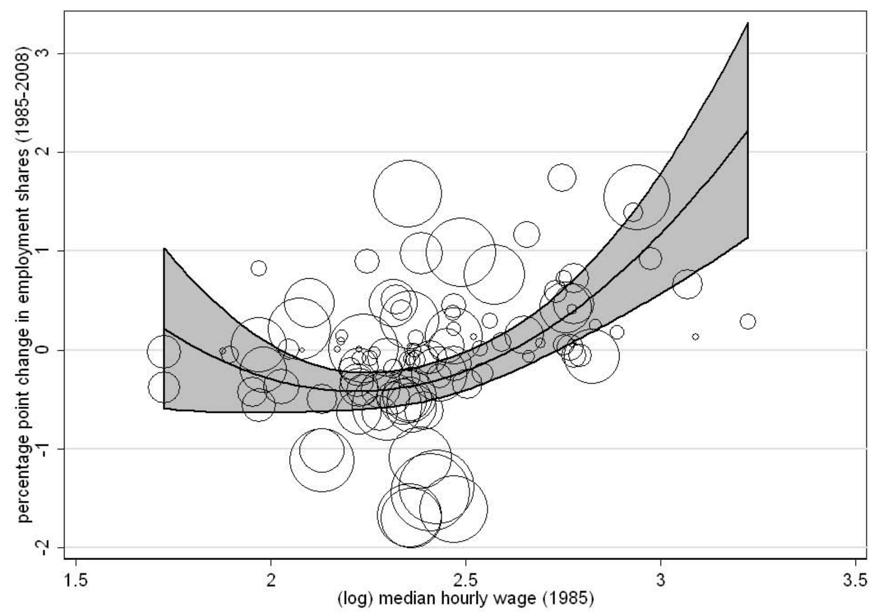
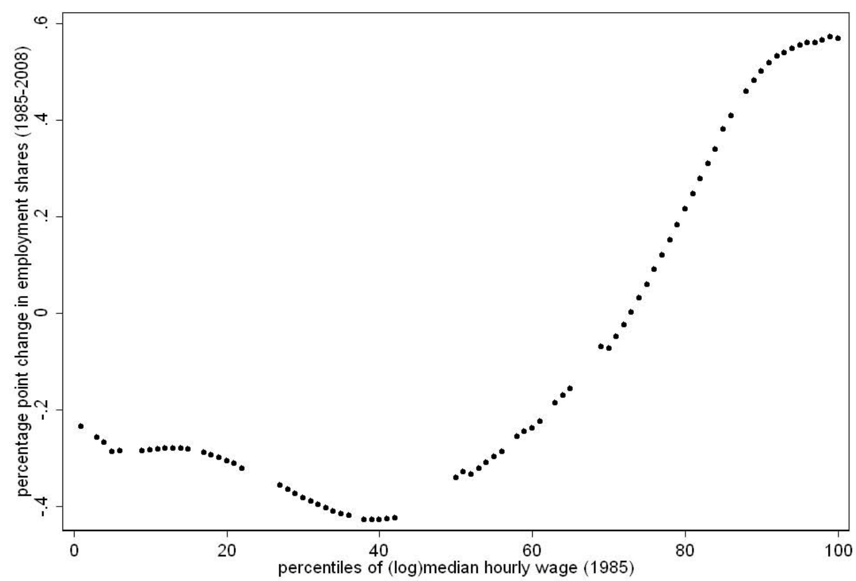
Figure 1: Evolution of employment shares in West Germany (1985-2008), occupations ranked by initial median hourly wage



(a) Scatter plot and prediction curve of occupations weighted by 1985 employment shares



(b) Occupations grouped in percentiles

Notes:
Data source: SOEP (ISCO 88 3-digit occupations), earnings are CPI-deflated. Shares based on hours worked in occupations. Each circle in panel (a) represents an ISCO 88 3-digit occupation, curves are quadratic prediction plots and 95% confidence intervals. The curve in panel (b) is a locally weighted non-parametric smoothing regression (bandwith = 0.8).

Table 1: Regression analysis of hourly earnings and employment

Period	1985-1989	985-1995	1985-2001	1985-2008
(a) DEPENDENT VARIABLE: change in employment share (measured by head counts)				
(log) initial median hourly wage	0.15	-2.75	-6.33**	-10.35**
	(1.08)	(2.21)	(3.06)	(4.14)
sq. (log) initial median hourly wage	-0.08	0.62	1.42**	2.28***
	(0.23)	(0.46)	(0.61)	(0.84)
constant	0.09	3.02	6.48*	11.36**
	(1.26)	(2.66)	(3.79)	(4.99)
Adj. R-squared	0.04	0.02	0.07	0.10
F	2.14	1.23	5.34	6.88
N	107	105	104	106
(b) DEPENDENT VARIABLE: change in employment share (measured by working hours)				
(log) initial median hourly wage	0.64	-1.72	-4.84*	-8.47**
	(1.14)	(1.92)	(2.63)	(3.80)
sq. (log) initial median hourly wage	-0.18	0.42	1.19**	1.98**
	(0.25)	(0.42)	(0.55)	(0.79)
constant	-0.50	1.66	4.62	8.63*
	(1.30)	(2.19)	(3.10)	(4.47)
Adj. R-squared	0.05	0.03	0.13	0.14
F	1.46	0.99	6.13	7.98
N	107	105	104	106
(c) DEPENDENT VARIABLE: change in (log) median hourly wage				
(log) initial median hourly wage	0.05	-0.68	-0.02	0.54
	(0.44)	(0.71)	(0.72)	(0.88)
sq. (log) initial median hourly wage	-0.02	0.12	-0.01	-0.15
	(0.09)	(0.15)	(0.15)	(0.18)
constant	0.11	1.10	0.31	-0.31
	(0.56)	(0.87)	(0.89)	(1.09)
Adj. R-squared	0.01	0.05	0.02	0.05
F	1.57	1.92	1.85	5.29
N	107	105	104	106
(d) DEPENDENT VARIABLE: change in employment share (measured by working hours)				
change in (log) median hourly wage	-0.18	-1.06***	-0.83	-0.39
	(0.28)	(0.34)	(0.57)	(0.51)
constant	0.00	0.20**	0.07	-0.14
	(0.06)	(0.10)	(0.18)	(0.15)
Adj. R-squared	-0.01	0.05	0.01	-0.00
F	0.43	9.45	2.14	0.59
N	107	105	104	106

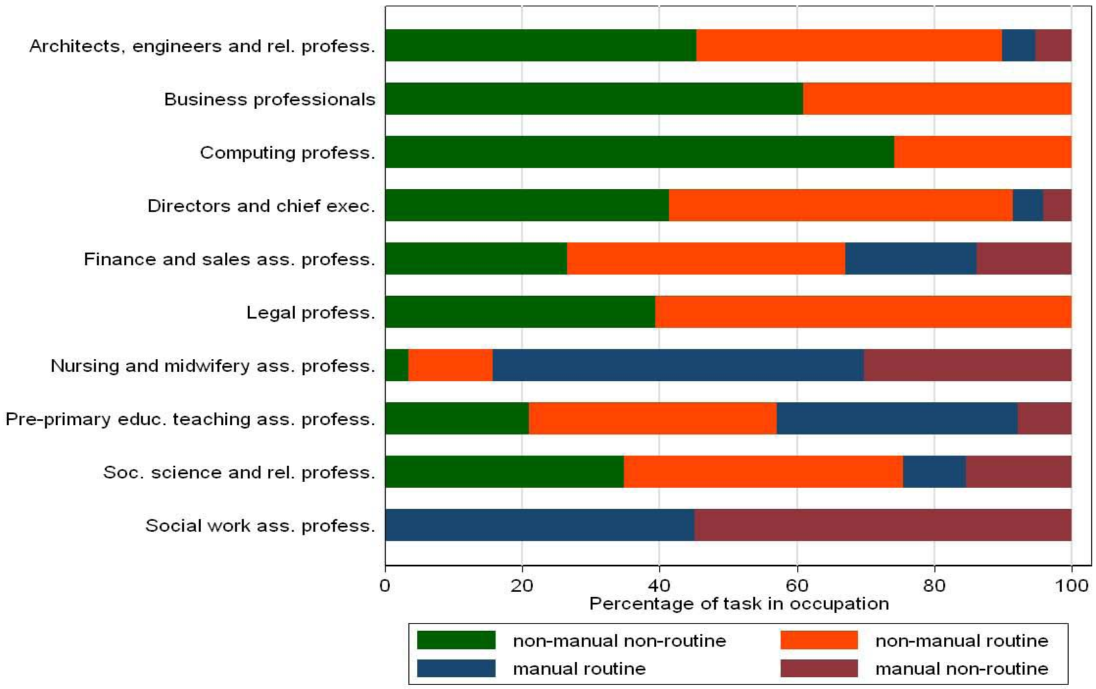
Notes:
Data source: SOEP (ISCO 88 3-digit occupations, West Germany).
Significance levels: * p<.10, ** p<.05, *** p<.01. Robust standard errors between brackets.

Table 2: Share in total hours worked according to task categories

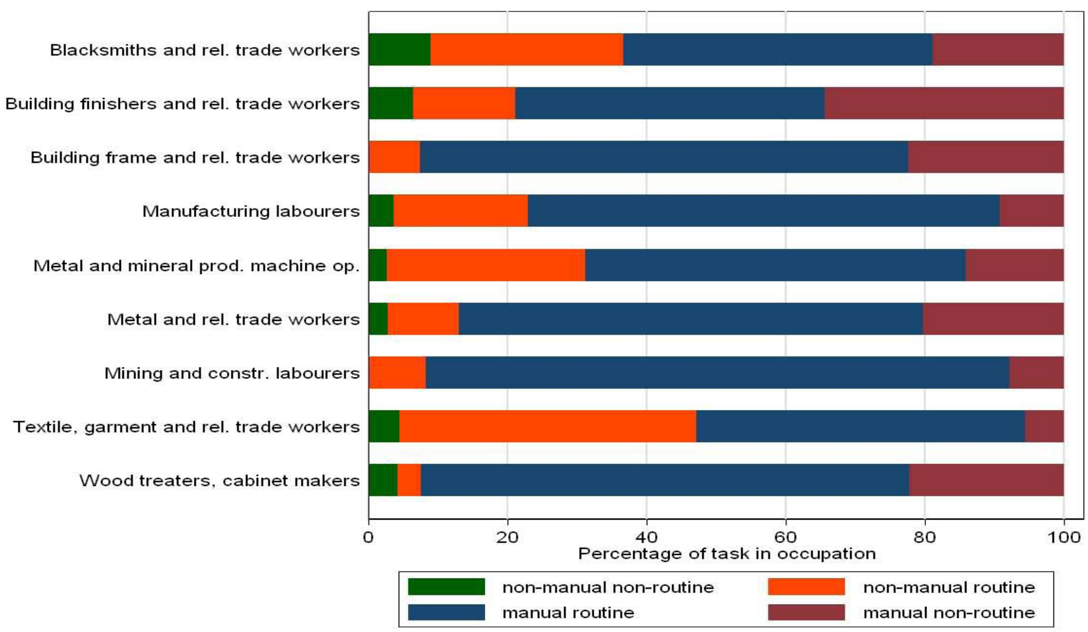
	1985	1989	1995	2001
Non-manual non-routine	17.33	17.63	18.87	19.35
Non-manual routine	37.89	37.12	37.96	35.02
Manual non-routine	32.89	34.85	32.51	32.92
Manual routine	11.89	10.40	10.66	12.71

Notes:
Data source: SOEP.
Shares refer to West Germany.
For definition of task categories see text.

Figure 2: Initial task composition of selected occupations



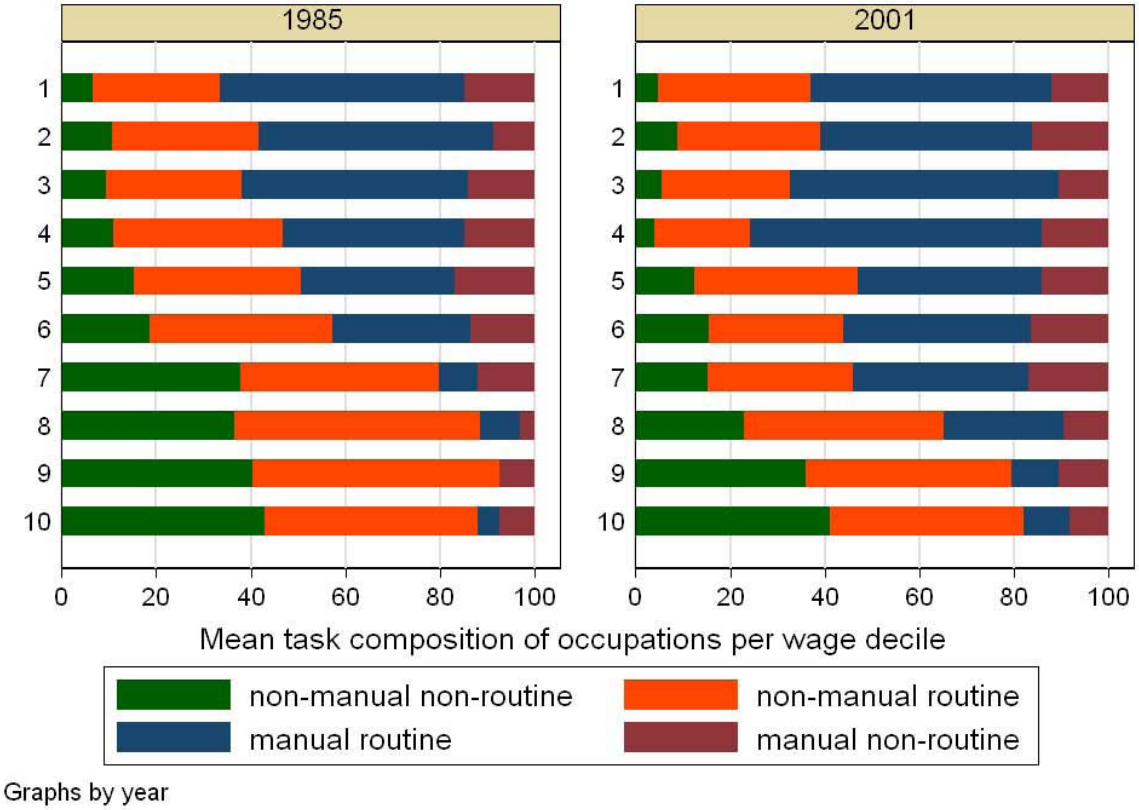
(a) Ten occupations with highest increase in employment share (1985-2008)



(b) Ten occupations with highest decrease in employment share (1985-2008)

Notes:
Data source: SOEP (ISCO 88 3-digit occupations, West Germany).
For definition of task categories see text.
Employment measured by hours worked, task compositions refer to 1985.

Figure 3: Task composition of wage deciles in 1985 and 2001



Notes:
Data Source: SOEP (West Germany).
For definition of task categories see text.
Figure shows the average task composition of ISCO 88 3-digit occupations, grouped by wage deciles according to their median hourly wage in 1985 and 2001.

Table 3: Descriptive statistics for occupations

	1985		Δ 1985-2008	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Weekly working hours	40.64	4.64	-1.75	4.13
Share in total working hours	0.01	0.01	0.00	0.01
Median hourly wage	11.13	2.90	1.57	2.38
Non-manual non-routine	0.15	0.15	-	-
Non-manual routine	0.34	0.21	-	-
Manual non-routine	0.13	0.11	-	-
Manual routine	0.37	0.26	-	-
Temporary contracts	0.10	0.08	0.01	0.20
Union members	0.29	0.17	-0.07	0.12
Gender ratio	0.33	0.30	0.07	0.13
Foreigners	0.09	0.10	0.03	0.08
(Mean) Tenure	10.77	3.21	0.88	3.78
Low education	0.26	0.18	-0.08	0.13
Medium education	0.54	0.23	0.07	0.17
High education	0.20	0.27	0.01	0.15
Occupations	107		106	
Observations per occupation	38.86	41.38	38.86	41.39

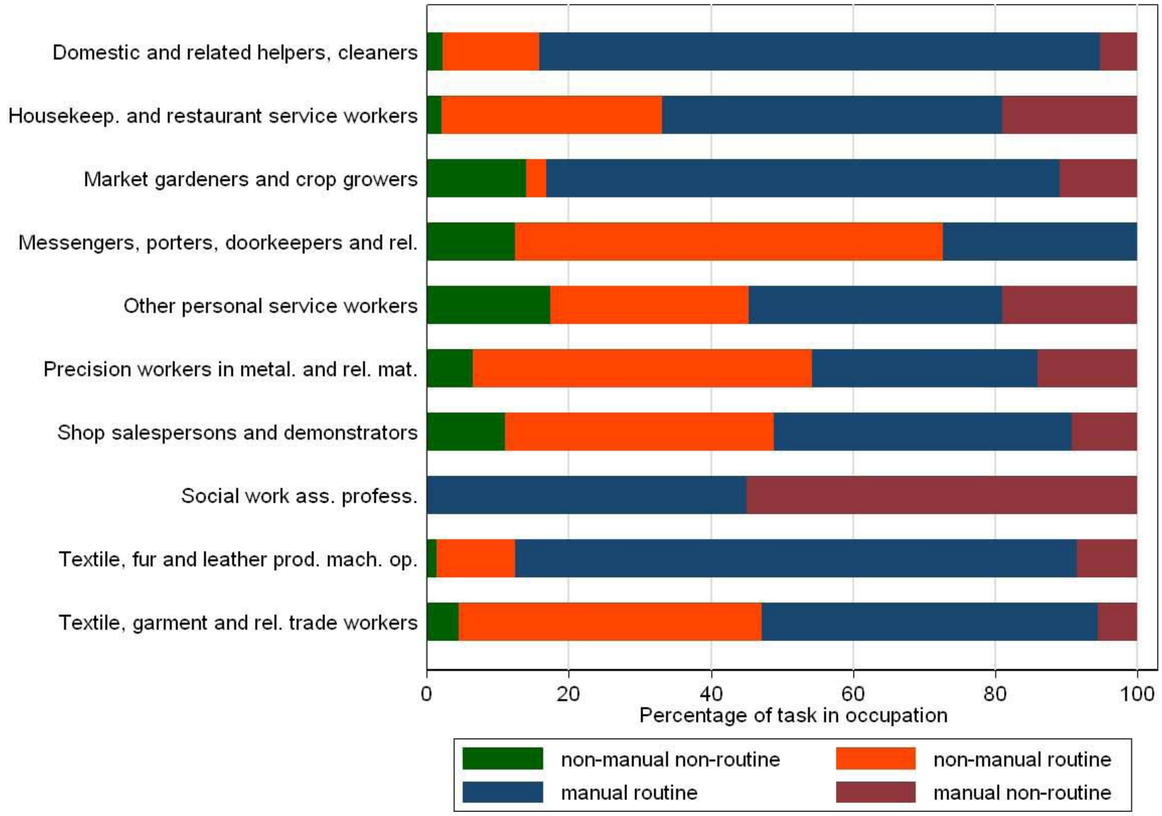
Notes:
Date source: SOEP (ISCO 88 3-digit occupations in West Germany).
For definition of task categories see text. The SOEP contains information on tasks fort he years 1985, 1987, 1989, 1995 and 2001.

Table 4: Regression results for baseline model

	Δ employment share			Δ median hourly wage		
	1985-1995	1985-2001	1985-2008	1985-1995	1985-2001	1985-2008
Non-manual non-routine	1.57***	2.81***	2.93***	-0.03	-0.02	0.04
	(0.47)	(0.52)	(0.54)	(0.09)	(0.10)	(0.14)
Non-manual routine	0.52	1.02**	0.88*	0.05	0.04	0.19**
	(0.37)	(0.51)	(0.49)	(0.07)	(0.07)	(0.09)
Manual non-routine	1.10**	0.97	-0.39	-0.04	0.07	0.58***
	(0.54)	(0.77)	(0.92)	(0.12)	(0.15)	(0.20)
Δ temporary contracts	0.45	-0.73	-0.26	-0.27	-0.32*	-0.05
	(0.56)	(0.73)	(0.52)	(0.17)	(0.16)	(0.23)
Δ union members	0.01	0.95	1.96***	0.08	0.27**	0.28**
	(0.45)	(0.63)	(0.57)	(0.10)	(0.11)	(0.12)
Δ gender ratio	-0.55	-1.76***	-0.41	-0.25*	-0.18	-0.04
	(0.37)	(0.66)	(0.56)	(0.13)	(0.12)	(0.20)
Δ foreigners	-0.70	0.20	1.92***	0.07	0.10	-0.16
	(0.66)	(0.82)	(0.62)	(0.16)	(0.14)	(0.19)
Δ (mean) tenure	-0.02	-0.04**	-0.05***	-0.01	0.00	0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Δ medium education	-0.00	0.13	-0.17	-0.04	-0.03	0.03
	(0.43)	(0.41)	(0.45)	(0.10)	(0.09)	(0.14)
Δ high education	0.06	-0.53	-0.73	0.10	0.15	0.44***
	(0.36)	(0.61)	(0.77)	(0.12)	(0.12)	(0.15)
Constant	-0.50***	-0.90***	-0.69**	0.19***	0.19***	0.01
	(0.16)	(0.25)	(0.24)	(0.03)	(0.04)	(0.06)
Adj. R-squared	0.23	0.44	0.53	0.02	0.09	0.21
F	2.90	4.81	6.75	0.82	1.65	4.54
N	104	104	106	104	104	106

Notes:
Date source: SOEP (ISCO 88 3-digit occupations in West Germany).
Reference categories are "manual routine tasks“ and "low education". For definitions see text.
Significance levels: * p<.10, ** p<.05, *** p<.01. Robust standard errors between brackets.

Figure 4: task composition of low-wage occupations



Notes:
Date source: SOEP (ISCO 88 3-digit occupations in West Germany). For definition of task categories see text.
Figure shows 1985 task compositions of ten ISCO 88 3-digit occupations with the lowest hourly median wage in 1985.

Table 5: Regressions results for robustness tests

	Δ employment share			Δ median hourly wage		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Non-manual non-routine	2.60***	2.67***	2.81***	-0.03	0.03	0.26
	(0.52)	(0.54)	(0.79)	(0.09)	(0.14)	(0.18)
Non-manual routine	1.43**	0.84	1.06**	0.14	0.20**	0.18*
	(0.55)	(0.52)	(0.50)	(0.10)	(0.09)	(0.10)
Manual non-routine	0.81	-0.67	-0.12	0.50**	0.59***	0.63***
	(1.00)	(1.06)	(0.85)	(0.20)	(0.20)	(0.21)
Δ temporary contracts	0.02	-0.30	-0.34	-0.02	-0.02	-0.08
	(0.72)	(0.59)	(0.53)	(0.20)	(0.22)	(0.24)
Δ union members	1.49***	2.10***	2.00***	0.29**	0.28**	0.30**
	(0.51)	(0.57)	(0.60)	(0.14)	(0.12)	(0.12)
Δ gender ratio	0.05	-0.48	-0.65	0.09	-0.04	-0.00
	(0.54)	(0.57)	(0.61)	(0.15)	(0.20)	(0.20)
Δ foreigners	1.47*	2.41***	2.17***	-0.13	-0.19	-0.20
	(0.81)	(0.71)	(0.62)	(0.17)	(0.18)	(0.19)
Δ (mean) tenure	-0.05*	-0.05***	-0.05***	0.01**	0.01	0.01
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Δ medium education	-0.75	-0.01	-0.91	0.05	0.02	0.07
	(0.48)	(0.54)	(0.57)	(0.13)	(0.13)	(0.17)
(Initial) medium education			-0.99*			0.05
			(0.57)			(0.11)
Δ high education	-1.10	-0.60	-1.12	0.55***	0.41***	0.30
	(0.90)	(0.81)	(0.83)	(0.14)	(0.14)	(0.18)
(Initial) high education			-0.50			-0.15
			(0.67)			(0.12)
Adj. R-squared	0.47	0.50	0.54	0.22	0.21	0.23
F	5.67	7.22	6.29	6.78	4.29	4.82
N	109	106	106	108	106	106

Notes:
Date source: SOEP (ISCO 88 3-digit occupations in West Germany). For definition of models see text.
Reference categories are "manual routine tasks“ and "low education". For definitions see text.
Significance levels: * p<.10, ** p<.05, *** p<.01. Robust standard errors between brackets.