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THE DYNAMICS OF TASK-BIASED TECHNOLOGICAL CHANGE : THE CASE OF OCCUPATIONS

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ABSTRACT:

This article uses detailed German household panel data to address important unresolved issues related to task-biased technological change. Implementing a task-based model of occupational employment and earnings, results show that the task composition of occupations in 1985 is significantly associated with relative employment changes and accounts at least partially for the job polarisation that occurred during the period 1985-2008. By contrast, initial task content is not related to observed trends in remuneration. We also contribute to a central, but so far under-researched aspect of task-biased employment changes, namely their dynamics over time. We show that task-biased employment effects can take more than a decade to materialize, differ across task categories, and be preceded by movements in the opposite direction. These findings have important ramifications for research in this field, for instance by underlining the necessity to work with sufficiently long observation periods and to pay closer attention to infra-period evolutions.

JEL CLASSIFICATION: J21, J24, J31.

KEYWORDS: Polarisation, Technological change, Pay rules, Occupations, Inequality, Tasks.

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INTRODUCTION

An accurate understanding of changes in relative employment and earnings of occupations is vital for sound economic policy, especially for correctly anticipating future skill needs and job opportunities. This paper contributes new insights on occupational dynamics by exploring to what extent technological change accounts for short- and medium-term developments of the occupational structure of employment and remuneration.

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 labour demand and supply (cf. Autor, Levy and Murnane, 2003; Spitz-Oener, 2006; Antonczyk, Fitzenberger, and Leuschner, 2009; Gathmann and Schönberg, 2010). In a nutshell, the rationale for looking at the task content of jobs is that this approach allows to better grasp what occupations actually do, i.e. to differentiate occupations according to the specific labour services they perform and the types of technologies they use.

In this paper, we focus on the "extensive" margin of task-biased dynamics and examine the relationship between the task composition of detailed occupations in year *t* and the evolution of relative employment and earnings over the period *t+x*. Previous work by Goos, Manning, and Salomons (2009) provides evidence for a link between an occupation's initial task composition and relative employment changes in a panel of European countries. The aim of our study is to address a range of unresolved issues related to the extensive margin of task-biased technological change. First, the empirical data by Goos, Manning and, Salomons (2009) analyse the relation between occupational task content (measured with data from the United States) and the evolution of occupational employment (using pooled occupation-level data from a set of European countries). This may be problematic if occupational tasks differ in the United States and Europe, or if European countries are heterogeneous with respect to the incidence of task-biased technological change. Focusing on the case of Germany, we avoid these problems by drawing on the same dataset for measuring the task content and the evolution of employment and remuneration of occupations. Second, we provide a first direct test whether task-biased technological change affects the relative employment and remuneration of occupations symmetrically. Contrary to the case of the United States, where trends towards employment polarisation appear to be accompanied by polarised changes in wages (Autor and Dorn, 2007), exploratory evidence from the UK and Germany suggests that the observed upward twist at the lower tail of the employment distribution is not accompanied with a corresponding increase in earnings (Goos and Manning, 2007; Dustmann, Ludsteck, and Schönberg, 2009). Our study tests directly and with the same dataset whether the evolution of employment and remuneration is similarly affected by the initial task composition or not. Finally, we contribute to the existing literature by documenting a central, but so far under-researched aspect of task-biased technological changes of the occupational structure, namely the dynamics of extensive changes over time. In particular, we show that employment effects are not immediate: task-biased technological change can take more than a decade to materialize and be preceded by periods of movements in the opposite direction. These findings have important ramifications for empirical research in this field, for instance by underlining the necessity to work with sufficiently long observation periods and to pay closer attention to infra-period evolutions.

The paper is structured as follows. The first section briefly summarizes the theoretical and empirical literature using task-based approaches to occupational change. We will heavily draw on this literature to construct a typology of tasks and to formulate predictions as to the effect of different task types on employment shares and relative earnings. The second section presents the data we use in this paper: a representative household panel from Germany covering the period 1985-2008, and then describes the operationalization of task types with this data. The thirth section analyses the impact of an occupation's task content in 1985 on its evolution until 2008. We focus on three aspects: (a) the link between initial task content and changes in employment shares over time; (b) the link between initial task content and changes in the occupation's hourly median wage; and (c) the relationship between task-biased technological change and labour market polarisation. Taken together, our results provide first direct evidence that task-biased technological change accounts at least partially for job polarisation in Germany. The final section concludes.

1. Literature Review and Theoretical Framework

During the 1990s, the literature on changes in occupational employment and remuneration emphasised relative demand for skill as explanation for rising earnings inequality in the United States and elsewhere (Lemieux, 2008). From the early 2000s onwards, a series of influential papers investigated the relationship between technology and job tasks (Autor, Levy, and Murnane, 2003; Spitz-Oener, 2006; Autor, Katz, and Kearny, 2006; Autor and Dorn, 2009). This new perspective is based on the proposition that the way in which occupations are affected by new technologies depends to a large extent on the tasks that they perform, arguing that technological change is not only skill- but also task-biased. The basic idea developed by Autor, Levy, and Murnane (2003) (hereafter referred to as ALM) 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).

Building on the basic distinction between routine and non-routine tasks, the ALM framework defines a typology of five task categories: 1) non-routine analytic, 2) non-routine interactive, 3) non-routine manual, 4) routine cognitive, and 5) routine manual tasks. Historically, routine manual 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 routine manual jobs is not clear-cut. Whereas routine manual 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 routine manual jobs may therefore depend on the sector of activity (e.g. manufacturing versus services).

Next, the massive diffusion of personal computers at the workplace has created substitution possibilities for routine cognitive jobs that typically carry out tasks involving repetitive forms of information-processing. As a consequence, occupations hired for predominantly routine cognitive tasks are considered by ALM to be substitutes for computers: this is the case for clerical occupations such as telephone switchboard operators or typists. By contrast, the spread of the same technologies is thought to be beneficial for high-paid occupations with non-routine tasks requiring creative problem-solving. Examples of occupations with predominantly non-routine non-manual 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, workers with predominantly non-routine manual tasks can be found in 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 non-routine manual 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 non-routine manual 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).

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.

The ALM framework has been used by a series of studies on workplace tasks. Autor and Dorn (2009) use US data on tasks to explain changes in the structure of local labour markets, including a relative decrease in the demand for routine tasks in clerical or production jobs that can be automated or outsourced and a relative increase in low-skill in-person service jobs that cannot be easily replaced with technology. Goos and Manning (2007) expand on the ALM model and look at the relation between the median wage of occupations and their task content. Using ALM's task data for the US, they show that 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 the polarisation of occupational employment that occurred in Great Britain during the period 1979-1999.

As for Germany, Spitz-Oener (2006) measures the incidence of the five ALM task categories and finds a decrease (increase) in routine (non-routine) task input between 1979 and 1998/99. In addition, differences in task input are shown to explain some of the inter-occupational variation in relative skill demand. Antonczyk, Fitzenberger, and Leuschner (2009) exploit an update of the task data used by Spitz-Oener (2006) to investigate the link between the evolution of occupational task input and remuneration between 1999 and 2006. Their findings indicate that changes in tasks contribute to "reducing (increasing) wage inequality at the top (bottom) of the wage distribution" (ibid., p. 21).

In general, task-biased technological change might lead to two complementary but nevertheless distinguishable effects. First, technology may provoke relative losses (gains) in the employment and remuneration of occupations carrying out routine (non-routine) tasks. This is the "extensive" dimension of task-biased changes. Second, technology may modify the composition of job tasks within occupations by increasing the incidence of non-routine relative to routine tasks (the "intensive" dimension). In this paper, we focus on the first effect and examine the link between task inputs of occupation i in year t and changes in the employment share and median wage of the same occupation between t and $t+x$. Here, the initial task input is interpreted as a propensity for occupation i to be either a substitute or a complement for new technologies implemented during the period x. In a nutshell, the ALM hypothesis of task-biased technological change predicts increasing employment and earnings for jobs with high initial levels of non-routine non-manual tasks and decreasing employment and earnings for occupations that initially carry out routine tasks. Whether jobs that are non-routine manual in year t fare better or worse in $t+x$ depends on the impact of technological change on the labour supply, as displaced labour might shift from routine to non-routine manual jobs. Empirical evidence for these hypotheses on the extensive dimension of task-biased technological change can be found in Goos, Manning, and Salomons (2009). In a regression controlling for the off-shoreability and educational composition of occupations, they find that changes in occupational employment between 1993 and 2006 are positively correlated with the importance of abstract and service tasks, but negatively correlated with routine tasks. Although quite compelling, the analysis in Goos, Manning, and Salomons (2009) is limited by the use of pooled occupation-level data from different European countries - a procedure likely to hide important intra-European diversity in the incidence and dynamics of task-biased occupational change. Another issue is that their dependent and independent variables are not measured on the same labour market: while the data on occupational employment stems from European household panels, the information on tasks is derived from the US source also used by ALM. While the workplace design is arguably relatively similar in the United States and Europe - or across European labour markets -, this procedure relies on the strong assumption that occupations are directly comparable across countries with respect to their task content.

One of the contributions of this paper is to provide a similar test as in Goos, Manning, and Salomons (2009) with representative panel data on tasks, employment, and earnings that are collected from the same sample. In addition, we document a hitherto neglected aspect of task-biased technological change, namely that the length of $t+x$ is central to the underlying phenomenon. By and large, existing empirical studies examine the intensive or extensive margins of task-biased technological change only between two points in time: for instance, ALM mainly mostly focus on $x = 10$; Spitz-Oener (2006) on $x = 6$ and $x = 19$; Goos, Manning, and Salomons (2009) use $x = 13$; Antonczyk, Fitzenberger, and Leuschner (2009) $x = 7$. This limitation is arguably due to the use of cross-sectional datasets that are collected in intervals of several years.

By contrast, we estimate the effect of the initial task content for values of x from *1* up to *23*, i.e. we explore the *dynamics* of (extensive) task-biased technological change over time. The economic rationale for varying the length of x is that task-biased changes might need some time to materialise: not all firms adopt new technologies immediately, and even firms that do so might undergo a transition period in which the employment structure is modified gradually. Take, for example, the substitution of secretarial staff with computer-based information-processing. A firm that decides to implement such a substitution will typically experience significant organisational restructuring: some or all of the secretaries have to be laid off or retrained; the firm has to hire IT professionals for the implementation and maintenance of the new technology; managerial and clerical staff has to be trained in the use of the new technologies, etc. Importantly, the dynamics of employment and earnings might vary across task types. For instance, we expect that it takes longer to develop technologies that substitute for routine than for non-routine tasks. Indeed, our results indicate that the length of x matters: most employment effects are only observed after a transition period of 10 years, and for some task types it may take up to 15 years until significant changes in the occupational employment distribution start to emerge.

2. Data and Operationalisation of Task Categories

2.1. 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 annual wave of the panel was collected in 1984, the latest available in 2008. 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, Frick, and Schupp (2007).

Several filters have been applied to the raw SOEP data. First, since we focus on the evolution of employment and earnings, all individuals that are not employed at the time of the interview have been dropped. This step eliminates around 50 per cent 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 per cent 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 148,114 individual-year observations. Detailed information on specific SOEP variables will be provided below.

2.2. TASK CATEGORIES IN THE SOEP

Task data in both ALM and Goos, Manning, and Salamons (2009) is based on the same source, namely the task definitions in the US Dictionary of Occupational Titles (DOT). The 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 types of tasks that might be relevant for the impact of technology on employment and earnings. Both subjective and objective strategies to measure the task content of occupations have advantages and disadvantages (Spitz-Oener, 2006). The administrative evaluation of jobs in the 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 diversified may depend on her personal experience in other jobs, something that is by definition unequally distributed among respondents. 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: 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.

Compared to other datasets with subjective task data for Germany, the information on tasks and workplace characteristics in the SOEP is relatively less detailed. The Qualification and Career Survey (QCS)[1], a dataset with similar sample size collected jointly by the Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment (IAB) and that has been used in a range of studies (e.g. Spitz-Oener, 2006; Dustmann, Ludsteck, and Schönberg, 2009; Antonczyk, Fitzenberger, and Leuschner, 2009), contains very narrow definitions of skill requirements, job tasks, and workplace characteristics. In practice, however, empirical analyses aggregate this information into four or five broad task categories. The advantage of the SOEP data is that it allows to link the information on the initial task content of occupations to year-to-year changes in employment

1 In German "Qualifikation und Berufsverlau".

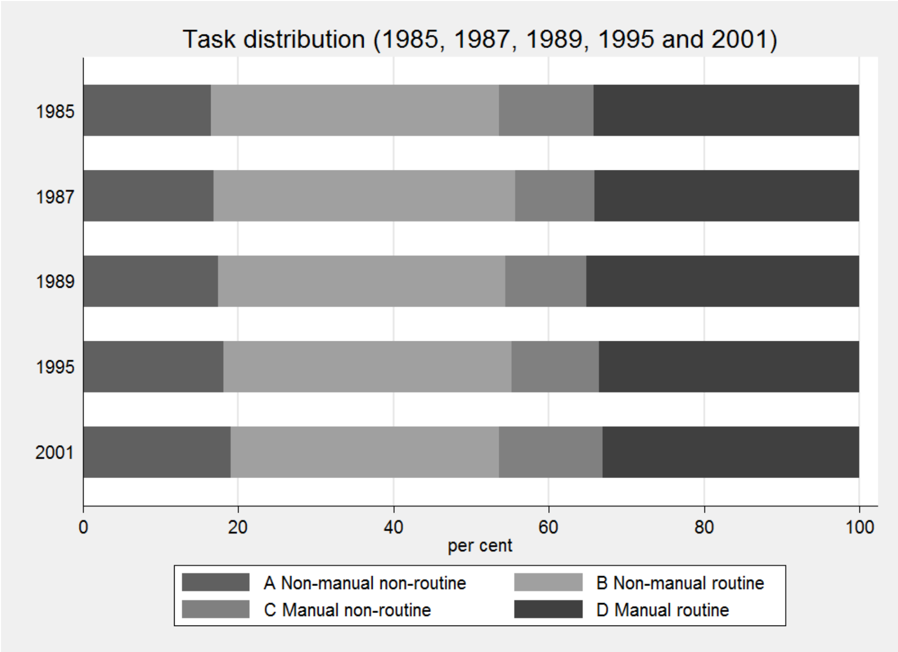
and remuneration, while the QCS is only compiled in intervals of 5-6 years. While it is of course possible to merge the (detailed) task data from the QCS with another source of annual data on occupations (as done by Gathmann and Schönberg, 2010), the fact that the SOEP contains both initial task data and annual changes in the employment, earnings, and socio-demographic composition of occupations allows us to avoid the statistical imprecision that inevitably arises from merging datasets with different sample designs.

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 workplace 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?". In our baseline model, 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 probably reflected by 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. Combing both dimensions, we then classified individuals according to their subjective job assessments as working in either 1) non-routine non-manual, 2) routine non-manual, 3) non-routine manual, or 4) routine manual employments.

Figure 1 presents the evolution of employment shares for these four task categories in our final sample of individuals. The observed trends are broadly in line with the ALM hypothesis on the intensive margin of task-biased technological change: non-routine non-manual jobs display constantly increasing employment shares from 16.5 per cent in 1985 to 19.0 per cent in 2001, while the share of individuals with routine non-manual jobs has decreased by 2.5 percentage points. The proportion of manual routine jobs has remained roughly constant. Overall, the evolution of the aggregate task distribution is relatively stable and the changes are somewhat smaller compared to cross-sectional data for Germany (cf. Spitz-Oehner, 2006).

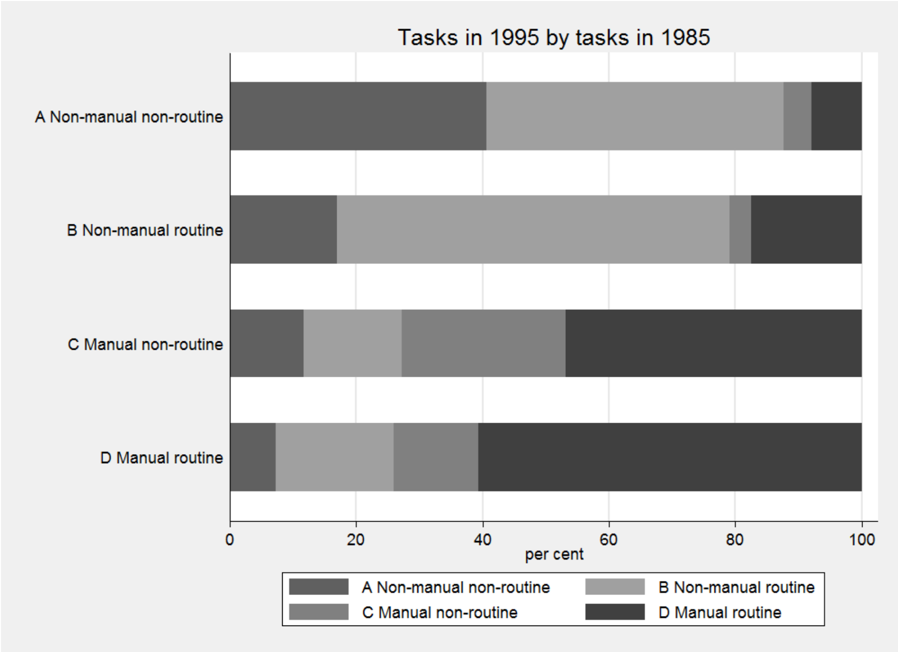
FIGURE 1. EVOLUTION OF EMPLOYMENT SHARES OF TASK CATEGORIES OVER TIME



Data source: SOEP.

Although the focus of this paper lies on the extensive margin - i.e. the link between the initial task distribution and subsequent changes in employment and earning -, it should be noted that the relative stability of the task distribution in Figure 1 masks substantial switching between task categories. To illustrate this, Figure 2 shows the distribution of individuals across task categories in 1995 according to their self-declared task category in 1985. While more than 60 per cent of individuals classified in 1985 as routine manual still remained in this category in 1995, only 26 per cent of individuals in non-routine manual jobs have worked in this category in 1985 and 1995.

FIGURE 2. DISTRIBUTION OF INDIVIDUALS BY TASK CATEGORIES IN 1995 ACCORDING TO TASK CATEGORIES IN 1985



Data source: SOEP.

The aggregation of individual-level information allows to compute task profiles of detailed occupations. We have used ISCO88 three-digit occupations that are consistently available in the SOEP for the entire period from 1985 until 2008. Figure 3 shows the task profiles of occupations according to which task type predominated in 1985. Among the occupations with the highest share of non-routine non-manual tasks (Figure 3a), we mostly find professionals and managers, but also some teaching occupations. This is in line with the idea that non-routine non-manual tasks are carried out by high-wage white-collar occupations that are hired for complex problem-solving and cognitively demanding jobs. Next, clerical occupations dominate among ISCO three-digit groups with the highest levels of routine non-manual tasks (Figure 3b). This contrasts with the variety of occupations with a high share of non-routine manual tasks (Figure 3c): this group contains not only professionals from the medial or social sector, but also blue-collar occupations such as foremen or high-skilled operators. Finally, almost all occupations with a high initial share of routine manual tasks are blue-collar occupations (Figure 3d).

FIGURE 3. TASK PROFILE OF ISCO88 THREE-DIGIT OCCUPATIONS

Fig 3a

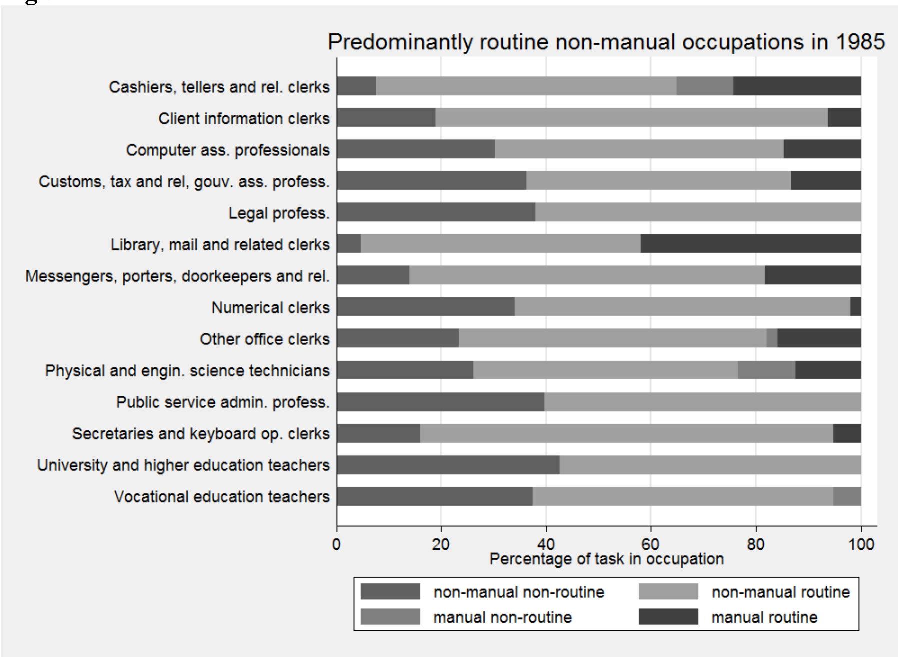


Fig 3b

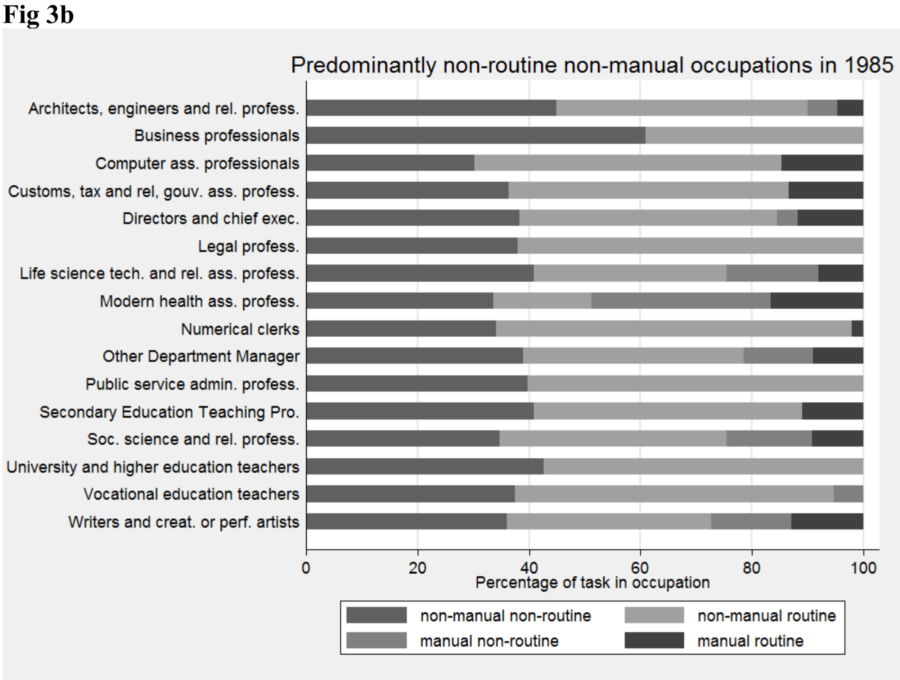


Fig 3c

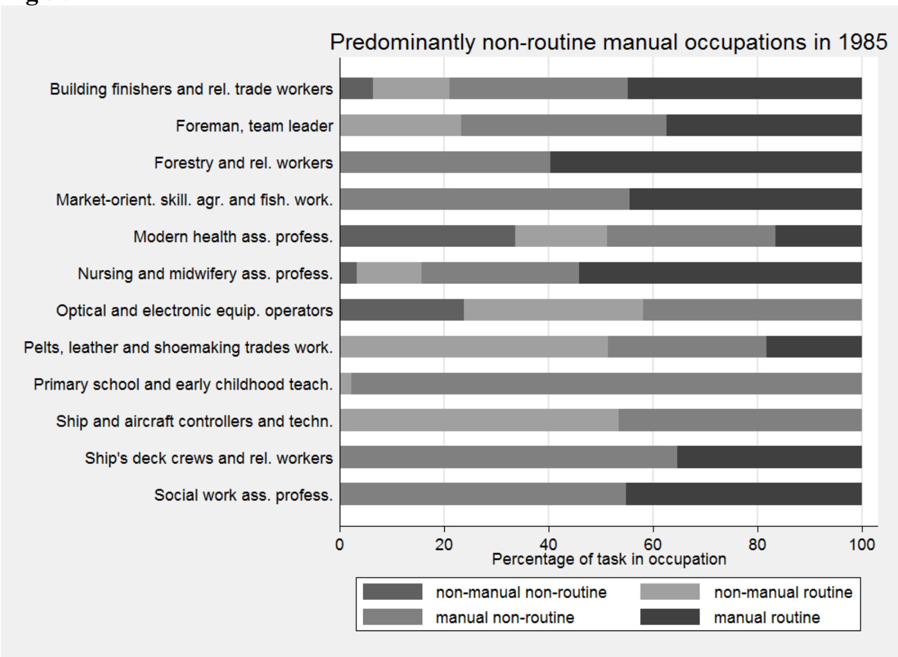
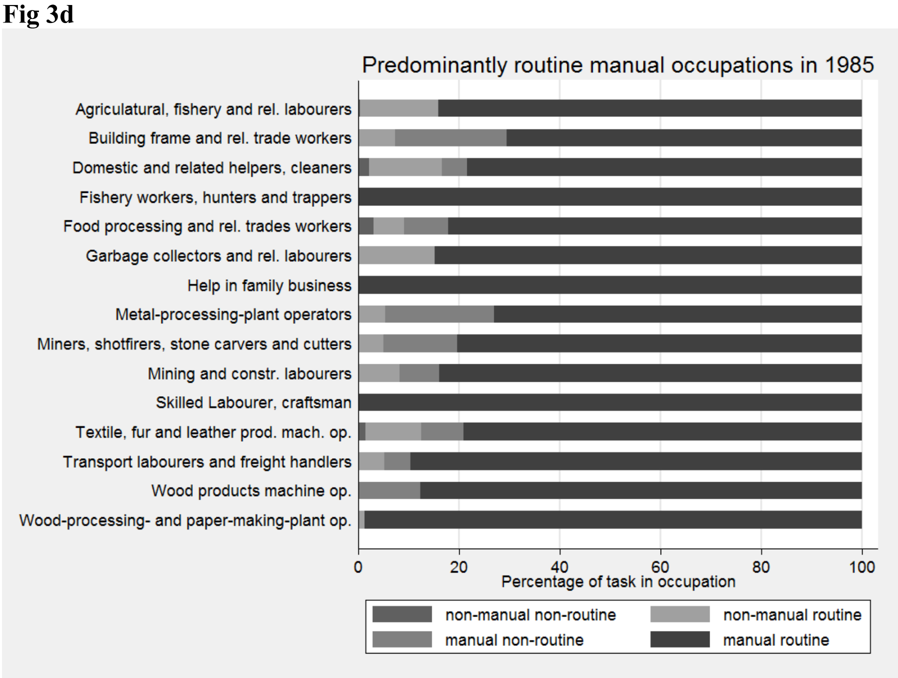


Fig 3d



Data source: SOEP.

It should be noted that Figure 3 not only allows to characterize broad occupations according to predominant task types. The occupational task profiles also illustrate the considerable diversity within occupational categories, even if measured at the detailed three-digit level. As a consequence, it would be misleading to refer to occupations as being exclusively non-routine non-manual or exclusively routine manual; in practice, all task types can be found in most occupations.

3. Regression Analysis

3.1. Evolution of the employment structure

In order to test formally whether changes in occupational employment and remuneration can be accounted for by the propensity of occupations to be substitutes or complements for new technological at the workplace, we formulate the following model:

$$\Delta\left(EMPLOYMENT\right)_{i,t+x} = \alpha + \sum_{k=1}^{3} \beta_k \left(TASKS\right)_{k,i,t} + \sum_{l=1}^{7} \sigma_l \, \Delta X_{l,i,t+x} + \varepsilon_{i,t+x} \quad (1)$$

The dependent variable in Equation (1) is the change in the share of occupation *i* in total employment between *t* and *t+x*. The main explanatory variable is the proportion of task type *k* in occupation *i* at *t*. The variables $TASKS_k$ are therefore the proportions of non-routine non-manual, routine non-manual, non-routine manual, and routine manual jobs in each occupation. If technological change affects the evolution of occupational employment differently according to their respective initial task content, we would expect that the initial share of manual and non-manual routine tasks at *t* has a negative and the share of non-manual non-routine tasks a positive impact on relative employment changes.

A change in occupational employment can either be the result of demand shifts (e.g. technological change, trade, changes in public employment) or supply shifts (e.g. expansion of formal education, female labour force participation, increasing average seniority). To isolate the impact of the occupation's 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+x*. In our baseline specification, the vector of control variables *X* contains the following information: the proportion of women; the proportion of foreigners, where foreigners are defined as workers with a non-German nationality; the average job tenure in the occupation; the average age in the occupation; the educational composition of the occupation, measured in three levels using the ISCED classification of educational attainment (low = ISCED level 0, 1 and 2; medium = ISCED level 3 and 4; high = ISCED level 5 and 6, see CEDEFOP, 2010); and the share of individuals in the occupation that work for a public employer.

Descriptive statistics for all variables are presented in Table 1. The secular trends evidenced in the literature appear also in our data: the average proportion of women increased by 10 percentage points between 1985 and 2008, and the average age rose from 39 to 42 years. As a consequence of substantial educational expansion in Germany, medium and high levels of education increased to the expense of low-level education.

TABLE 1. DESCRIPTIVE STATISTICS FOR OCCUPATIONS

	1985	1995	2001	2008
Weekly working hours	40.68	38.89	39.15	39.15
	(4.61)	(5.17)	(5.91)	(5.82)
Share in total working hours	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Median hourly wage (2005 Euros)	11.13	13.54	14.04	14.08
	(2.91)	(3.61)	(3.70)	(3.86)
Non-routine non-manual	0.15	0.16	0.19	-
	(0.14)	(0.16)	(0.16)	
Routine non-manual	0.34	0.33	0.34	-
	(0.21)	(0.21)	(0.19)	
Non-routine manual	0.13	0.12	0.13	-
	(0.11)	(0.11)	(0.11)	
Routine manual	0.37	0.38	0.33	-
	(0.25)	(0.27)	(0.25)	
Gender ratio	0.33	0.36	0.39	0.43
	(0.30)	(0.31)	(0.30)	(0.28)
Foreigners	0.09	0.12	0.11	0.08
	(0.10)	(0.11)	(0.09)	(0.08)
Tenure	10.8	10.45	10.56	11.08
	(3.18)	(3.33)	(3.51)	(3.56)
Age	38.52	39.60	40.72	42.14
	(3.18)	(3.67)	(3.12)	(3.21)
Low education	0.26	0.22	0.16	0.11
	(0.18)	(0.16)	(0.14)	(0.11)
Medium education	0.54	0.56	0.56	0.55
	(0.22)	(0.22)	(0.23)	(0.26)
High education	0.19	0.22	0.28	0.34
	(0.22)	(0.26)	(0.28)	(0.30)
Public employment	0.25	0.24	0.24	0.25
	(0.29)	(0.28)	(0.28)	(0.30)
Occupations	107	111	112	112
Observations per occupation	39.81	41.09	64.51	56.42
	(42.27)	(47.24)	(73.0)	(62.8)

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 for the years 1985, 1987, 1989, 1995 and 2001. Gross earnings are CPI adjusted (base = 2005).

We estimated Equation (1) by weighting each occupation by its initial employment share to ensure that results are not biased towards small occupations (see Goos and Manning, 2007). In our baseline model, the starting year is $t = 1985$ and we let x vary from 1 until 23, i.e. for each year from 1986 until 2008 we obtain an employment coefficient for each variable in the model.

The reference categories are "routine non-manual tasks" and "low education". As a consequence, the correct interpretation of the estimated task coefficients has to take into account the relationship between routine non-manual tasks, on the one hand, and employment and earnings on the other hand. Table 2 lists the pairwise correlations between initial task shares and changes in employment and remuneration, as well as the Bonferroni-adjusted significance of these correlations. Throughout almost the entire observation period, the pairwise correlations between employment changes and the initial share of routine non-manual tasks are positive and (since 1996) statistically significant. Due to this positive pairwise correlation, a negative value for the task coefficients in Equation (1) does not necessarily reflect a decrease in employment shares but merely a negative impact with respect to the category of routine non-manual tasks.

TABLE 2. PAIRWISE CORRELATIONS BETWEEN OCCUPATION'S TASK SHARES IN 1985 AND CHANGES IN EMPLOYMENT SHARES AND MEDIAN HOURLY EARNINGS (1985-2008)

	Employment shares				Median hourly earnings			
	Non-routine non-manual	Routine non-manual	Non-routine manual	Routine manual	Non-routine non-manual	Routine non-manual	Non-routine manual	Routine manual
1986	0,1193	0.3066*	-0,1004	-0.2777*	0,0112	-0,0068	-0,0996	0,0437
1987	0,0712	0,2372	-0,1362	-0,1772	0,0353	0,0434	-0,0296	-0,0319
1988	0,157	0.3750*	-0.3277*	-0.2532*	0,0534	0,0401	-0,1569	0,0057
1989	-0,1422	-0,1982	0,2183	0,1497	-0,0741	-0,0174	-0,1032	0,096
1990	-0,0351	0,006	-0,0259	0,0273	-0,0761	-0,1417	0,0674	0,1276
1991	0,1095	-0,039	0,1863	-0,1014	0,0067	-0,0408	-0,002	0,0295
1992	0.2830*	0,2201	0,0209	-0.3382*	0,03	0,1192	-0,0806	-0,0704
1993	0.2643*	0,2081	0,0231	-0.3205*	0,0132	0,0381	-0,0559	-0,0142
1994	0.3880*	0,2356	0,0301	-0.4136*	0,023	0,0302	0,0075	-0,0373
1995	0.4214*	0,2051	0,0001	-0.3951*	-0,0569	0,0042	-0,0208	0,036
1996	0.4887*	0.2663*	-0,0774	-0.4519*	0,0109	0,0348	-0,0034	-0,0362
1997	0.5085*	0.3560*	-0,1449	-0.5061*	-0,195	-0,1281	0,0323	0,2005
1998	0.5849*	0.3643*	-0,1696	-0.5458*	-0,1214	0,0701	-0,0357	0,0277
1999	0.6271*	0.4261*	-0,2303	-0.5949*	-0,0198	0,0315	0,0337	-0,0287
2000	0.5861*	0.4710*	-0.2663*	-0.5937*	0,0195	0,0087	0,0682	-0,0474
2001	0.5963*	0.4791*	-0.2864*	-0.5984*	-0,0692	-0,0294	0,0375	0,0476
2002	0.7429*	0.5550*	-0.4170*	-0.6924*	0,0271	-0,02	0,0494	-0,0195
2003	0.7339*	0.5534*	-0.4173*	-0.6857*	-0,0867	-0,1162	0,1001	0,0994
2004	0.6850*	0.5617*	-0.3811*	-0.6792*	-0,0045	-0,0596	0,1068	0,0086
2005	0.6873*	0.5535*	-0.3779*	-0.6752*	-0,0183	-0,0802	0,2039	-0,0098
2006	0.6968*	0.5361*	-0.3743*	-0.6664*	0,0398	0,0196	0,049	-0,0521
2007	0.6974*	0.5283*	-0.4098*	-0.6471*	0,0394	0,0376	0,0783	-0,0883
2008	0.6891*	0.5266*	-0.4042*	-0.6433*	-0,0225	0,0087	0,1797	-0,0692

Notes : Pair-wise Bonferroni-adjusted correlations for occupations; stars indicate whether the correlation is significant at the 10 per cent level.

Regression results for Equation (1) are reported in Table 3. While the model has a reasonably good fit throughout the entire period, the adjusted coefficient of determination increases from an average of 11.2 per cent for the decade 1985-1995 to an average of 44.9 per cent for the period 1995-2008.

TABLE 3. REGRESSION RESULTS FOR BASELINE MODEL. DEPENDENT VARIABLE: CHANGE IN EMPLOYMENT SHARE OF OCCUPATION BETWEEN *1985* AND *1985 + x*

	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Non-routine non-manual	-0.38**	-0.43	-0.44	-0.03	-0.3	0.56	0.3	0.15	0.64	1.12*	1.30**	1.3	1.90***	1.70**	1.63**	1.98**	3.12***	3.15***	2.43**	2.47**	2.95**	3.16***	3.04***
	(0.18)	(0.27)	(0.27)	(0.42)	(0.35)	(0.39)	(0.35)	(0.39)	(0.40)	(0.58)	(0.60)	(0.79)	(0.66)	(0.70)	(0.80)	(0.82)	(1.13)	(1.11)	(1.21)	(1.23)	(1.21)	(1.03)	(0.96)
Non-routine manual	-0.05	-0.23	-0.59**	0.38	-0.14	0.75**	0.49	0.56	0.79	0.82*	0.63*	0.41	0.48	0.26	0.06	0.09	-0.68	-0.76	-0.57	-0.63	-0.46	-1.07	-0.85
	(0.15)	(0.23)	(0.29)	(0.31)	(0.23)	(0.32)	(0.39)	(0.47)	(0.50)	(0.46)	(0.37)	(0.51)	(0.48)	(0.46)	(0.56)	(0.72)	(0.86)	(0.77)	(0.81)	(0.91)	(0.81)	(1.16)	(1.07)
Routine manual	-0.35***	-0.31*	-0.33**	0.05	-0.12	0.01	-0.38*	-0.50*	-0.41	-0.29	-0.43	-0.71	-0.57	-0.66	-1.01*	-1.04*	-1.07*	-1.01*	-1.59**	-1.37**	-1.35**	-0.94*	-1.10**
	(0.11)	(0.16)	(0.17)	(0.19)	(0.21)	(0.24)	(0.21)	(0.29)	(0.27)	(0.32)	(0.32)	(0.50)	(0.39)	(0.40)	(0.53)	(0.53)	(0.55)	(0.55)	(0.71)	(0.68)	(0.64)	(0.57)	(0.54)
Δ gender ratio	-0.25	0.12	-0.28	-0.63**	-0.04	-0.42	-0.51*	-0.15	-0.77*	-0.35	-0.57	-1.40***	-0.98*	-0.34	-1.16*	-1.91**	-0.35	-0.25	-0.77	-0.55	-1.23	-0.4	-0.31
	(0.17)	(0.26)	(0.25)	(0.29)	(0.22)	(0.30)	(0.31)	(0.34)	(0.42)	(0.39)	(0.38)	(0.48)	(0.51)	(0.32)	(0.66)	(0.74)	(0.75)	(0.60)	(0.67)	(0.65)	(0.76)	(0.56)	(0.67)
Δ foreigners	0.72*	0.41	0.6	0.34	0.33	-0.12	-0.15	0.09	-0.88*	-0.34	0.52	-0.16	0.3	0.64	-0.79	-0.05	-0.49	-0.54	-0.69	-0.33	0.27	-0.15	0.96
	(0.38)	(0.56)	(0.41)	(0.30)	(0.40)	(0.43)	(0.49)	(0.60)	(0.47)	(0.61)	(0.44)	(0.84)	(0.45)	(0.45)	(0.69)	(0.82)	(0.81)	(0.73)	(0.85)	(0.77)	(0.81)	(0.75)	(0.77)
Δ (mean) tenure	0.02	-0.02	-0.03*	-0.02	-0.02	-0.02	-0.01	-0.01	0	-0.01	-0.02	-0.04*	-0.02	-0.03*	-0.05**	-0.05*	-0.03	-0.02	-0.04	-0.02	-0.02	-0.05	-0.04
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Δ (mean) age	-0.03*	0	0	0	0.01	0.02	0	0.01	-0.02	-0.02	-0.02	0.01	0	0.01	0	0.01	-0.02	-0.01	0	-0.01	-0.02	0	-0.02
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Δ medium education	0.01	0.32	0.19	0.17	0.42	-0.18	-0.14	-0.12	-0.06	-0.06	0.09	0.31	0.03	0.11	0.41	0.35	0.89	1.12*	1	0.33	0.72	0.41	0.54
	(0.22)	(0.35)	(0.21)	(0.35)	(0.41)	(0.27)	(0.34)	(0.39)	(0.35)	(0.41)	(0.38)	(0.33)	(0.46)	(0.48)	(0.56)	(0.48)	(0.59)	(0.62)	(0.67)	(0.67)	(0.72)	(0.48)	(0.54)
Δ high education	0.17	0.49	0.21	0.22	0.47	-0.48	-0.73*	0.08	-0.34	-0.25	-0.19	-0.53	-0.11	0.04	-0.48	-0.62	-0.28	-0.16	-0.54	-0.87	-0.71	-0.66	-0.83
	(0.33)	(0.41)	(0.28)	(0.45)	(0.46)	(0.34)	(0.40)	(0.46)	(0.39)	(0.34)	(0.36)	(0.41)	(0.53)	(0.43)	(0.66)	(0.61)	(0.78)	(0.72)	(0.70)	(0.75)	(0.77)	(0.73)	(0.83)
Δ public employment	-0.45*	-0.77**	-0.76***	-1.03***	-1.05***	0.12	0.09	0.09	0.34	-0.02	0.06	0.47	0.15	0.43	0.26	0.04	0.13	-0.1	0.52	0.33	-0.03	-0.5	-0.52
	(0.26)	(0.37)	(0.25)	(0.33)	(0.33)	(0.27)	(0.35)	(0.35)	(0.38)	(0.44)	(0.37)	(0.37)	(0.38)	(0.38)	(0.44)	(0.40)	(0.47)	(0.50)	(0.59)	(0.58)	(0.57)	(0.57)	(0.52)
Constant	0.21**	0.20*	0.25*	-0.08	0.08	-0.17	0.06	0.09	0.07	-0.12	-0.12	0.02	-0.21	-0.12	0.09	0	-0.13	-0.2	0.2	0.13	0	-0.25	-0.17
	(0.08)	(0.12)	(0.13)	(0.13)	(0.14)	(0.17)	(0.15)	(0.19)	(0.19)	(0.23)	(0.21)	(0.35)	(0.27)	(0.29)	(0.36)	(0.37)	(0.38)	(0.39)	(0.52)	(0.51)	(0.47)	(0.39)	(0.39)
R-squared	0.13	0.08	0.21	0.1	0.05	0.04	0.09	0.04	0.2	0.18	0.26	0.31	0.34	0.39	0.4	0.43	0.57	0.56	0.52	0.49	0.52	0.51	0.54
F	3.28	1.95	2.43	2.25	1.44	1.52	1.92	1.57	5.16	2.39	2.65	3.14	4.05	4.39	4.48	4.46	6.93	7.81	5.8	4.92	4.94	7.99	7.68
Number of occupations	106	106	105	107	107	106	105	102	98	105	104	105	106	105	106	104	103	105	104	104	106	106	106
Prob > F for equality of coefficienbts																							
Non-routine non-manual = non-routine manual	0.05	0.45	0.64	0.34	0.62	0.61	0.66	0.40	0.78	0.65	0.26	0.18	0.03	0.02	0.03	0.03	0.00	0.00	0.01	0.01	0.00	0.00	0.00
Non-routine non-manual = manual routine	0.85	0.52	0.50	0.80	0.50	0.04	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Non-routine manual = manual routine	0.04	0.76	0.41	0.31	0.96	0.04	0.04	0.02	0.02	0.04	0.03	0.04	0.06	0.06	0.13	0.20	0.70	0.78	0.25	0.45	0.34	0.92	0.83

Notes:

Date source: SOEP (ISCO 88 three-digit occupations in West Germany).

Reference categories are "routine non-manual tasks“ and "low education". For definitions see text.

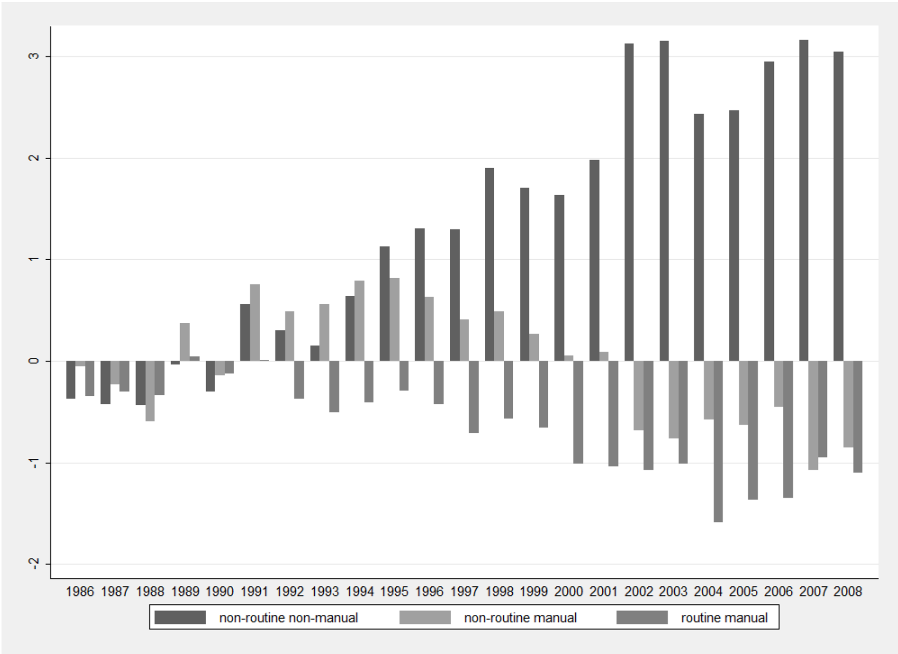
Significance levels: * p<.10, ** p<.05, *** p<.01. Robust standard errors between brackets.

The estimated coefficients reveal a dynamic pattern of employment effects. Except for the very first year, the impact of the initial share of non-routine non-manual tasks is not significantly different from the reference category during the first ten years after 1985. From the early 1990 onwards, however, the coefficient becomes positive and increases in magnitude; the difference between non-routine and routine non-manual tasks becomes statistically significant after 1995.

This contrasts with the dynamics of the coefficients for routine manual tasks: the correlation with changes in employment shares becomes increasingly negative from the early 1990 onwards (see Table 2), and the difference with respect to the reference category is significant for the years 1986-87, 1992-93, and after 2000 (see Table 3). A strongly significant difference between non-routine non-manual and routine manual tasks already appears from 1991 onwards (see F test for equality of regression coefficients at the bottom of Table 3).

The most striking development is the relationship between employment changes and the initial share of non-routine manual tasks in an occupation. Relative to the reference category (i.e. routine non-manual tasks), the coefficient is positive throughout the 1990s, but then becomes increasingly negative in the 2000s. Indeed, the difference between non-manual and manual non-routine tasks becomes significant after 1998, while the difference between routine and non-routine manual tasks is only significant between 1991 and 2000 (see bottom of Table 3). Figure 4 depicts the dynamics of all task coefficients and illustrates the hump-shaped pattern for non-routine manual tasks along with the relatively monotonous evolution of the employment coefficients of non-routine non-manual and routine manual tasks.

FIGURE 4. ESTIMATED EMPLOYMENT COEFFICIENTS FOR INITIAL TASK COMPOSITIONS



Notes: Data source: SOEP. Figure shows estimated coefficients measuring the relationship between the shares of different task categories in occupation in 1985 and changes in occupational employment shares between 1985 and 1985+x. Model controls for within-occupation changes in gender ratio, proportion of foreigners, average age and seniority, educational composition and share of public employment. Reference category: routine non-manual tasks.

The pattern of employment changes depicted in Figure 4 is robust to a series of robustness tests that cannot be reported here for space reasons (each robustness test produces 23 annual coefficients for each task category and each control variable). We notably experimented with alternative specifications of Equation (1), for instance by including the initial educational composition or average age of each occupation among the control variables. We also tested whether the starting year affects the observed dynamics and estimated Equation (1) for $t = 1987$ and $t = 1989$. Next, we restricted the regression only to those occupations for which we possess at least 5 (10) observations (depending on the year, this reduces the sample by around 10 (20) occupations). Finally, we also checked the robustness of our results to alternative definitions of our task categories. Indeed, the fact that each question on job characteristics allows for nuanced answers (for instance, individuals can fully, partially, or not at all agree with the statement that their job is physically demanding) gives rise to many alternative operationalisations of the four task categories. None of these robustness tests does, however, affect the overall pattern and significance of the link between employment changes and initial tasks described above.

3.2. CHANGES IN THE WAGE STRUCTURE

It is straightforward to turn Equation (1) into a model of changes in the occupational wage structure. In this section, we present estimation results using the change in the logarithm of the median hourly wage of occupation *i* as dependant variable. A thus modified estimation of Equation (1) contributes to the literature on task-biased occupational changes as the first direct test for whether task-biased technological change affects employment and pay rules in the same direction. In fact, it is unclear whether task-biased technological change affects employment and wages symmetrically: existing evidence suggests that in the 1990s US wages and employment covary (Autor and Dorn, 2009), while the remuneration of "lousy jobs" in the UK and Germany seems to have deteriorated despite positive demand shocks (Goos and Manning, 2007; Dustmann, Ludsteck, and Schönberg 2009; Antonczyk, Fitzenberger, and Leuschner, 2009). A disconnection between the evolution of employment shares and wages may be due to the above-mentioned supply-side effects (displaced routine workers turn to the 'lousy' but growing occupations with non-routine manual tasks), but Goos and Manning (2007) also cite institutional factors such a falling unionisation and lower minimum wages to account for this phenomenon. Institutional factors that may have affected the evolution of low-wage occupations in Germany are the decrease of the coverage of collective bargaining, the extensive use of opening clauses in collective bargaining agreements (Seifert and Massa-Wirth, 2005), and the so-called Hartz reforms that aimed to increase the pressure on unemployed individuals to enter available jobs (Jacobi and Kluve, 2006).

Our data allows to directly address the question whether the hypothesised demand shifts away from predominantly routine and/or manual (and towards non-routine and/or non-manual) occupations have a corresponding downward (upward) effect on pay rules.

TABLE 4. REGRESSION RESULTS FOR BASELINE MODEL. DEPENDENT VARIABLE: CHANGE IN THE LOGARITHM OF OCCUPATIONAL MEDIAN WAGE BETWEEN *1985* AND *1985 + X*

	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Non-routine non-manual	0.05	0	0.06	-0.01	0.11	0.14	0.01	-0.03	0.01	-0.01	-0.03	-0.02	-0.23	-0.03	-0.02	-0.02	0.13	0.06	0.05	0.05	0.05	-0.05	-0.11
	(0.10)	(0.11)	(0.14)	(0.10)	(0.10)	(0.10)	(0.13)	(0.13)	(0.13)	(0.12)	(0.15)	(0.16)	(0.16)	(0.14)	(0.12)	(0.15)	(0.18)	(0.14)	(0.12)	(0.15)	(0.16)	(0.17)	(0.19)
Non-routine manual	-0.07	0.02	-0.16	-0.16	0.06	0.01	-0.03	-0.05	0.06	-0.03	0.05	-0.03	-0.05	0.09	0.07	0.03	0.23**	0.09	0.15	0.28***	0.13	0.22	0.30**
	(0.12)	(0.07)	(0.15)	(0.12)	(0.08)	(0.08)	(0.10)	(0.11)	(0.09)	(0.09)	(0.13)	(0.11)	(0.11)	(0.10)	(0.10)	(0.12)	(0.11)	(0.14)	(0.14)	(0.10)	(0.14)	(0.13)	(0.15)
Routine manual	0.07	-0.03	0.06	0.04	0.09*	0.06	-0.05	-0.03	-0.04	-0.04	-0.02	0.06	-0.11	-0.09	-0.05	-0.03	0.01	0.04	0	-0.06	-0.04	-0.18**	-0.16*
	(0.06)	(0.07)	(0.07)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)	(0.09)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.10)	(0.08)	(0.09)
Δ gender ratio	-0.47*	-0.28**	-0.25	-0.30***	-0.17	-0.29***	-0.28**	-0.11	-0.02	-0.39***	-0.12	-0.14	0.02	-0.18*	-0.19	-0.25*	-0.1	-0.22*	-0.11	-0.14	-0.23	-0.21	-0.04
	(0.28)	(0.13)	(0.19)	(0.11)	(0.13)	(0.08)	(0.11)	(0.14)	(0.12)	(0.10)	(0.11)	(0.12)	(0.13)	(0.10)	(0.14)	(0.14)	(0.16)	(0.12)	(0.14)	(0.13)	(0.17)	(0.16)	(0.18)
Δ foreigners	0.24	0.57	0.06	0.32**	0.2	0.2	0.15	0.03	0.14	-0.05	-0.60**	0.32*	0.24*	0.25**	-0.03	0.02	-0.21	-0.18	-0.14	-0.13	0.25*	-0.21	-0.06
	(0.30)	(0.38)	(0.16)	(0.15)	(0.15)	(0.13)	(0.14)	(0.14)	(0.15)	(0.17)	(0.28)	(0.18)	(0.14)	(0.13)	(0.10)	(0.13)	(0.26)	(0.11)	(0.15)	(0.14)	(0.15)	(0.14)	(0.21)
Δ (mean) tenure	0.01	0	-0.01	0	0.01	0	0.01	0	0	-0.01**	0	0	0	0	0	0	0.01	0	0	0.01	0.02*	0.01	0
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Δ (mean) age	0.01	0	0.01	0.01*	0	0	0	0	0.01*	0.01***	0.01**	0.01***	0.01*	0	0.01**	0.01*	0	0	0.01**	0.01	-0.01	0.01	0
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Δ medium education	-0.07	0.24*	-0.04	0.12	0.16	0.07	-0.03	-0.02	0.06	0.12	0.08	0.06	0.17*	0.20*	-0.06	0.01	0.15	-0.04	-0.07	0.05	0.02	0.1	0.09
	(0.24)	(0.14)	(0.13)	(0.10)	(0.12)	(0.08)	(0.16)	(0.12)	(0.08)	(0.08)	(0.11)	(0.12)	(0.09)	(0.10)	(0.08)	(0.09)	(0.13)	(0.13)	(0.10)	(0.11)	(0.11)	(0.12)	(0.15)
Δ high education	0.29	0.2	0.24	0.24	0.36**	0.15	0.12	0.15	0.17	0.06	0.17	0.03	0.19	0.27**	0.17	0.15	0.41**	-0.02	0.18	0.27*	0.40***	0.27*	0.38**
	(0.54)	(0.26)	(0.19)	(0.15)	(0.17)	(0.09)	(0.22)	(0.16)	(0.15)	(0.09)	(0.13)	(0.12)	(0.12)	(0.13)	(0.10)	(0.12)	(0.17)	(0.14)	(0.15)	(0.14)	(0.14)	(0.14)	(0.16)
Δ public employment	0.37*	0.07	0.06	0.14	0.33**	0.32***	0.39***	0.17	0.2	0.01	0.32***	0.23**	0.16*	0.15	0.07	0.11	0.08	0.1	0.11	0.09	-0.09	0.18	0.2
	(0.21)	(0.19)	(0.16)	(0.12)	(0.14)	(0.12)	(0.14)	(0.14)	(0.13)	(0.10)	(0.10)	(0.09)	(0.09)	(0.10)	(0.06)	(0.09)	(0.10)	(0.09)	(0.11)	(0.11)	(0.15)	(0.13)	(0.13)
Constant	0.01	0.07*	0.08*	0.11***	0.08**	0.09**	0.18***	0.20***	0.17***	0.20***	0.23***	0.16**	0.23***	0.21***	0.20***	0.20***	0.12	0.21***	0.15***	0.16**	0.16**	0.19***	0.17**
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.07)	(0.06)	(0.05)	(0.06)	(0.08)	(0.07)	(0.08)
R-squared	0.08	0.03	-0.02	0.14	0.06	0.14	0.2	-0.03	0.01	0.1	0.25	0.14	0.06	0.05	0.09	0.06	0.13	0.08	0.16	0.14	0.16	0.18	0.14
F	1.4	1.45	0.81	3.27	2.1	4.03	2.92	0.66	1.17	2.68	3.33	2.76	2.06	1.4	2.37	1.62	2.27	2.69	2.09	2.9	2.54	3.15	2.67
Number of occupations	106	106	105	107	107	106	105	102	98	105	104	105	106	105	106	104	103	105	104	104	106	106	106
Prob > F for equality of coefficienbts																							
Non-routine non-manual = non-routine manual	0.41	0.87	0.20	0.32	0.69	0.21	0.80	0.89	0.70	0.90	0.64	0.94	0.24	0.41	0.53	0.76	0.56	0.86	0.55	0.13	0.68	0.08	0.03
Non-routine non-manual = manual routine	0.80	0.63	0.97	0.41	0.85	0.19	0.53	1.00	0.56	0.73	0.93	0.41	0.25	0.55	0.61	0.91	0.32	0.89	0.60	0.31	0.45	0.37	0.77
Non-routine manual = manual routine	0.34	0.65	0.20	0.16	0.74	0.60	0.90	0.87	0.40	0.92	0.69	0.53	0.66	0.15	0.33	0.68	0.09	0.80	0.40	0.01	0.40	0.02	0.02

Notes:

Date source: SOEP (ISCO 88 three-digit occupations in West Germany).

Reference categories are "routine non-manual tasks“ and "low education". For definitions see text.

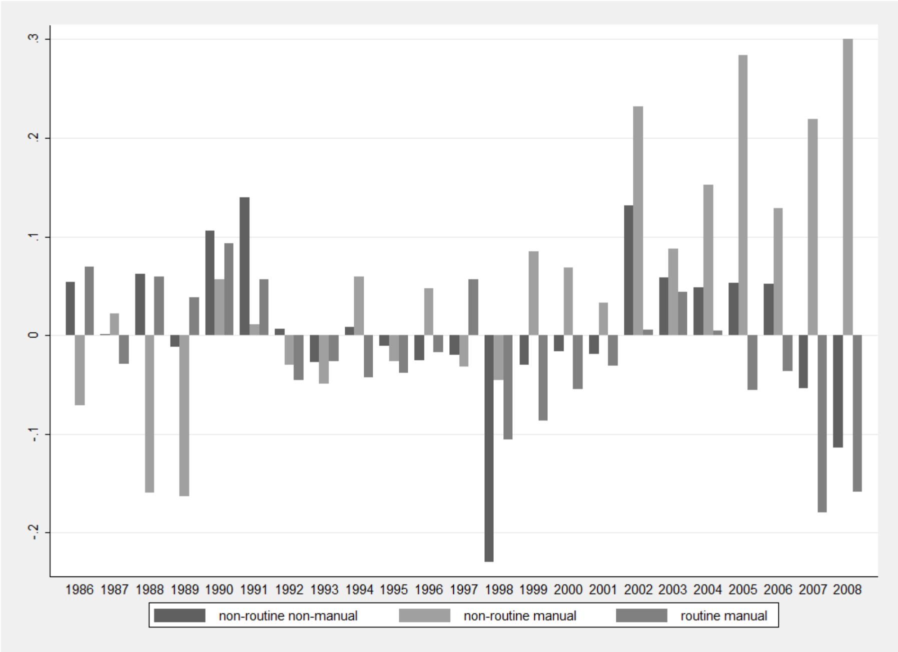
Significance levels: * p<.10, ** p<.05, *** p<.01. Robust standard errors between brackets.

Table 4 shows the estimated wage coefficients for the years 1986-2008.[2] Compared to the results for employment changes, the model provides far less explanatory power: the adjusted coefficient of correlation averages 7.1 per cent for the decade 1985-1995 and is only 5.5 percentage points higher for the years 1996-2008. Also the pattern of significance of individual explanatory variables differs; while the task variables are strongly associated with medium- and long-run changes in the occupational employment structure, we find no systematic correlation between initial tasks and the evolution of occupational earnings (see Figure 5). The few significant coefficients suggest a positive wage effect of the initial share of non-routine manual jobs in 2002, 2005, and 2008. In addition to the relatively erratic and mostly non-significant coefficients of the other task variables, this is also evidence against a symmetric impact of task-biased technological change given that we do not observe a corresponding positive employment effect for non-routine manual tasks during the 2000s.

Compositional changes within occupations are more important in the wage equation (see table 4). A rising share of women in an occupation is associated with significant decreases in the median wage, while rises in the average age and shares of highly educated workers are positively related to occupational earnings. Again, these results stand up to the list of robustness tests mentioned in the previous section.

2 The interpretation of coefficients in Table 4 is straightforward. Contrary to the case of changes in employment shares, there is not significant pairwise correlation between the reference category (routine non-manual tasks) and the evolutions of hourly earnings (see Table 2).

FIGURE 5. ESTIMATED WAGE COEFFICIENTS FOR INITIAL TASK COMPOSITIONS



Notes: Data source: SOEP. Figure shows estimated coefficients measuring the relationship between the shares of different task categories in occupation in 1985 and changes in the logarithm of occupational median wage between 1985 and 1985+x. Model controls for within-occupation changes in gender ratio, proportion of foreigners, average age and seniority, educational composition and share of public employment. Reference category: routine non-manual tasks.

3.3. A TASK-BASED EXPLANATION OF POLARISATION?

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 (Katz and Autor, 1999), we see mounting evidence that some low-wage occupations are also expanding in the US, Britain, and a range of European countries (see Goos, Manning and, Salomons, 2009; CEDEFOP, 2010). Goos and Manning (2007) refer to this phenomenon as "job polarisation". We complete our analysis by showing how the observed pattern of task-biased changes in occupational employment relates to the phenomenon of polarisation.

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

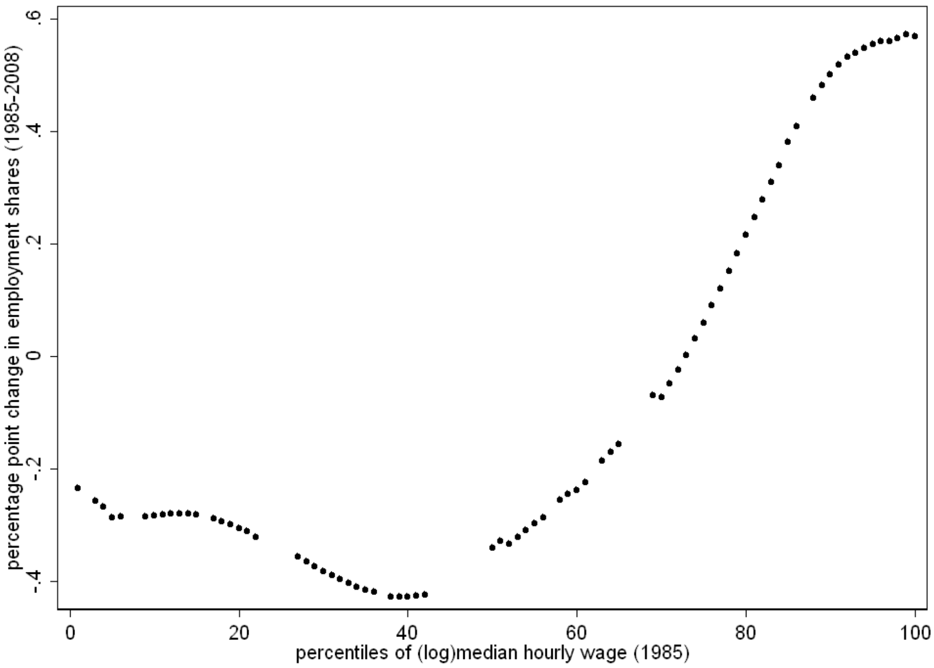
(Antonczyk, DeLeire, and Fitzenberger, 2010). Yet others analyse polarisation in terms of initial skill levels and operationalize skills through average years of schooling (Autor, Katz, and Kearney, 2006) or by proxying skills through wage premia (Spitz-Oener, 2006). In general, the issue of what constitutes "job quality" appears to be particularly thorny for the case of service jobs (Gadrey, 1996; 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*, then employment (wage) polarisation between *t* and *t+x* 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*. Given that empirical studies typically conclude that factors like off-shoring, out-sourcing, and international trade play a subordinate role for the overall evolution of the occupational employment structure as a whole (see Freeman, 2004; Goos, Manning, and Salomons, 2009), the task composition of occupations is increasingly regarded as a driving force of polarisation.

Existing evidence on polarisation in Germany has concentrated on the 1980s and 1990s (see Spitz-Oener, 2006; Dustmann, Ludsteck, and Schönberg, 2009), and more recent studies cover only short periods (Antonczyk, Fitzenberger, and Leuschner (2009) analyse wage polarisation between 1999 and 2006) or exclude the years after 2004 (Antonczyk, DeLeire, and Fitzenberger, 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. Crucially, to our knowledge none of the existing studies has tested directly whether occupational task content is linked to the job polarisation that occurred in Germany.

Our sample suggests that the German occupational employment structure has polarised during the period 1985-2008. To see this, we chart changes in employment shares[3] against the percentiles of the initial earnings distribution as proposed by Dustmann, Ludsteck, and Schönberg (2009). The resulting graph reveals a similar pattern of polarisation than the one found by previous studies for the 1980s and 1990s, with top-income occupations enjoying considerable employment gains and a hollowing out of middling occupations (Figure 6). 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 corroborates and updates other studies with German data and suggests that polarisation is a robust and continuing process in Germany.

3 In this section, we follow the convention to measure employment shares with headcounts in each occupation. The shape of the graphs does not change substantially if actual hours worked are used as employment measure.

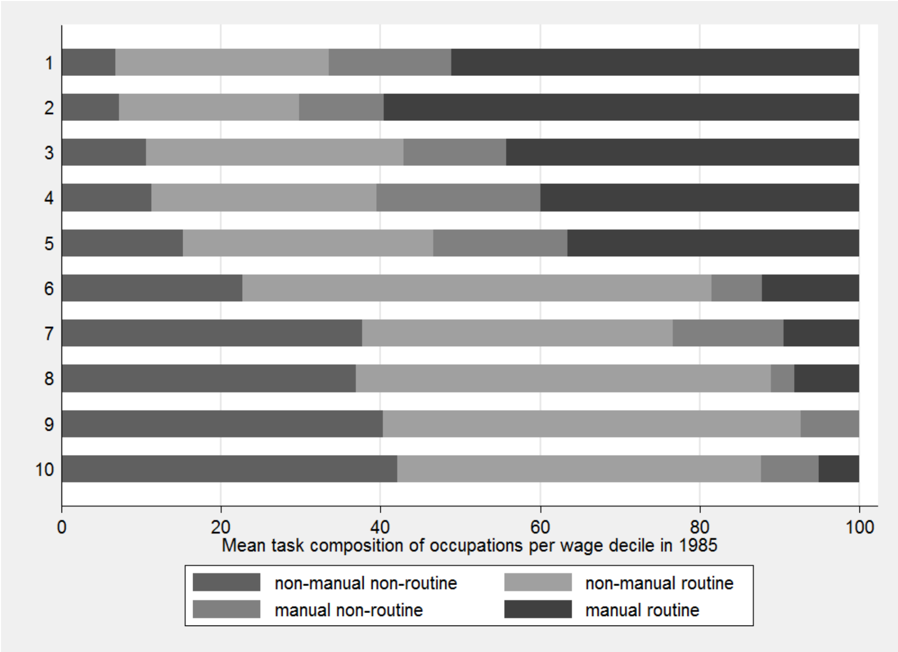
FIGURE 6. EVOLUTION OF EMPLOYMENT SHARES (1985-2008), OCCUPATIONS GROUPED IN PERCENTILES



Notes: Data source: SOEP (ISCO88 three-digit occupations), earnings are CPI-deflated. Shares based on hours worked in occupations. The curve is a locally weighted non-parametric smoothing regression (bandwith = 0.8).

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. Figure 7 shows the task composition of wage deciles according to the median wage of three-digit occupations in 1985. 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 top two deciles in 1985 was higher than 40 per cent. By contrast, the proportion of manual routine tasks is larger in occupations whose median wage is situated in the lower deciles. Interestingly, the proportion of non-routine manual tasks appears to be more broadly distributed, with a proportion of around 10 per cent in most deciles. This peculiar distribution of non-routine manual tasks is similar to the findings by Goos and Manning (2007) for the US, where as much as 33 per cent of occupations in the upper tercile require non-routine manual skills. In addition, it confirms the diversity of predominantly routine non-manual occupations that is visible in Figure 3c.

FIGURE 7. TASK COMPOSITION OF WAGE DECILES IN 1985

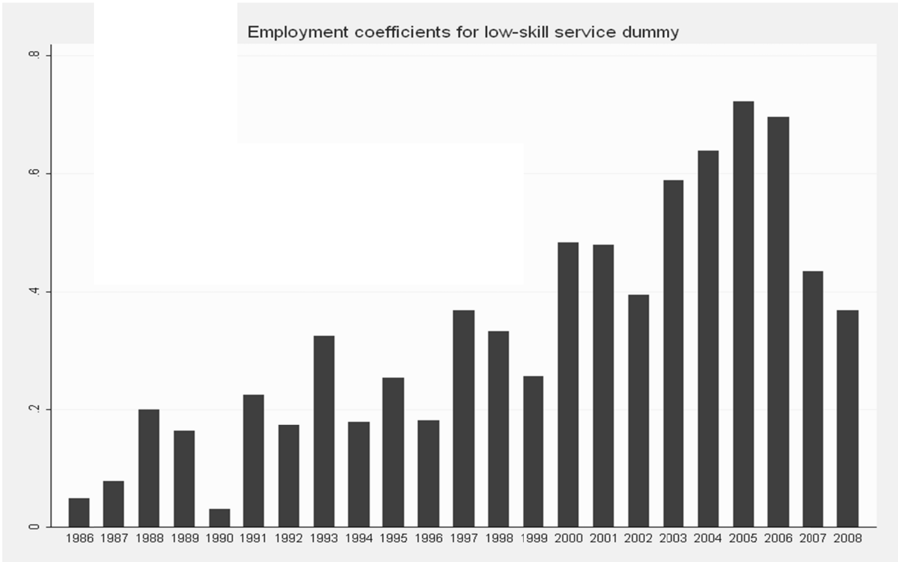


Notes: Data Source: SOEP. For definition of task categories see text. Figure shows the average task composition of ISCO88 three-digit occupations, grouped by wage deciles according to their median hourly wage in 1985.

Is it possible to reconcile (a) the distribution of tasks in the occupational wage distribution, (b) our evidence for significant relations between initial task content and employment changes, and (c) the labour market polarisation shown in Figure 6? The answer is: yes, except for the small upward twist at the lower tail of the earnings distribution. Relatively high-paid non-routine non-manual occupations like engineers or managers have gained employment shares compared to routine non-manual occupations in which computers are typically assumed to be substitutes for routine tasks (e.g. office clerks, typists, bank tellers). This is in line with the observation that employment gains are strongest at the top of the occupational wage structure and decrease in the third quartile (see Figure 6). The strongest employment losses are associated with high initial levels of the routine manual tasks that are predominantly carried out by occupations with below-median earnings (e.g. assemblers or machine operators).

As for the upward twist in lower-tail employment, different authors have attributed this evolution to "a single proximate cause - rising employment and wages in low-education, in-person service occupations" (Autor and Dorn, 2009). Given that our four task categories do not isolate these occupations, we have created a dummy variable that reflects whether the occupation at hand corresponds to this criteria. The list of ISCO88 three-digit occupations that we classified as low-education, in-person service occupations is provided in Appendix A. We then re-estimated Equation (1) including the service dummy. While the coefficients for the task categories and other control variables are robust to this modification, the service dummy fits well with the observed increase in lower-tail employment: the corresponding employment coefficient is positive and increasing througout most of the observation period and statistically significant for all years after 1997 (the evolution of the employment coefficient for the service dummy is shown in Figure 8). Combined with the positive (negative) employment coefficient for non-routine non-manual (routine manual) tasks, this completes our account of polarisation during the period 1985 and 2008 in Germany.

FIGURE 8. EMPLOYMENT COEFFICIENTS FOR LOW-SKILL SERVICE DUMMY



Notes: Data source: SOEP. Figure shows estimated coefficients measuring the relationship between a task dummy for low-education, in-person service occupations and changes in occupational employment shares between 1985 and t*. Model controls for initial task compositions and within-occupation changes in gender ratio, proportion of foreigners, average age and seniority, educational composition and share of public employment.

CONCLUSION

The empirical results presented in this paper document that a significant proportion of medium-term employment changes in Germany can be accounted for by distinguishing occupations according to a typology of tasks: occupations that predominantly carried out routine manual tasks in 1985 have lost relative employment shares, while mostly non-routine non-manual occupations have increased their weight in the employment structure. However, these two effects did not materialize before the mid-1990s, thereby emphasising the hitherto neglected dynamics of task-biased technological change. The singular relationship between non-routine manual tasks and employment changes underlines best why dynamics matter: after a decade of growth in relative employment shares, the relationship turned around in the early 2000s. An intuitive explanation for this evolution is that it took longer for technological change to substitute for non-routine than for routine manual workers, but that after 15 years negative employment effects eventually also started to affect occupations whose tasks were initially predominantly non-routine and manual. These findings have important ramifications for empirical research in this field, for instance by underlining the necessity to work with sufficiently long observation periods and to pay closer attention to infra-period evolutions.

A second issue that we addressed is the question whether the extensive margin of task-biased technological change affects occupational employment and earnings symmetrically, as suggested by a demand shock to a simple supply and demand model. Our results indicate that the link between tasks and employment changes is much stronger than the link between tasks and wages; most wage coefficients behave rather erratically, and those that are significant do not point in the same direction as the employment changes. This lends empirical backing to suggestions that the impact of tasks on wages and employment might be disconnected.

Finally, we provide the first direct evidence that task-biased technological change accounts at least partially for job polarization in Germany: occupations that have gained relative employment shares due to their initial task composition are predominantly situated in the upper deciles of the wage structure, while negative employment effects are recorded for tasks that occur in the middle and lower part of the wage structure. To provide a complete account of polarization, we introduced a dummy for low-education, in-person service occupations. The significantly positive employment effect of this dummy fits well to the observed upward twist in the lower tail of the employment distribution.

It is likely that the dynamics analysed in this paper are not only driven by technological factors, but also by Germany's specific socio-institutional setting. The speed and extent of the adoption of technologies that replace or complement different tasks might, for instance, depend on national firm cultures or the collective bargaining regime. One way to improve our understanding of the dynamics of task-biased technological change is therefore to compare the German dynamics presented in this paper with other labour markets that experienced similar shifts in the occupational employment structure.

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APPENDIX A. LIST OF LOW-EDUCATION, IN-PERSON SERVICE OCCUPATIONS AND DESCRIPTIVE STATISTICS FOR 1985

ISCO88 codes	Label	Median hourly wage	Education			Employment share
			Low	Medium	High	
512	HOUSEKEEPING AND RESTAURANT SERVICES WORKERS	7.14	0.43	0.53	0.04	0.02
513	PERSONAL CARE AND RELATED WORKERS	8.18	0.22	0.63	0.16	0.02
514	OTHER PERSONAL SERVICES WORKERS	5.63	0.39	0.54	0.08	0.01
516	PROTECTIVE SERVICES WORKERS	11.45	0.69	0.24	0.07	0.01
522	SHOP SALESPERSONS AND DEMONSTRATORS	7.96	0.27	0.70	0.02	0.03
913	DOMESTIC AND RELATED HELPERS, CLEANERS AND LAUNDERERS	7.13	0.72	0.25	0.03	0.02
914	BUILDING CARETAKERS, WINDOW AND RELATED CLEANERS	11.13	0.33	0.49	0.18	0.01
915	MESSENGERS, PORTERS, DOORKEEPERS AND RELATED WORKERS	7.74	0.51	0.48	0.01	0.00
916	GARBAGE COLLECTORS AND RELATED LABOURERS	10.55	0.61	0.39	0.00	0.00
	All low-education, in-person service occupations	8.18	0.42	0.51	0.07	0.11
	Other occupations	11.49	0.24	0.55	0.21	0.98

Notes: Gross median hourly earnings measured in CPI-adjusted Euros (base = 2005). Percentage do not sum up to 100 per cent due to rounding.