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Abstract:
This paper sheds light on how changes in the organization of work lead to wage inequality. We present a theoretical model in which workers with a wider span of competence (higher level of multitasking) earn a wage premium. Since abilities and opportunities to expand the span of competence are distributed unequally among workers across and within education groups, our theory explains (1) rising wage inequality between groups, (2) rising wage inequality within groups, and (3) the polarization of work and the decoupling of the income distribution. Using a rich German data set covering a 20-year period from 1986 to 2006, we provide empirical support for our model.

Keywords: wage inequality, tasks, multitasking, organizational change

JEL classification: J31, J24, L23

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1 Introduction

This paper provides a theoretical and empirical analysis that helps explain several important developments in wage inequality in terms of observed changes in the organization of work. The developments comprise the following empirical regularities: (i) rising wage inequality between skill groups, (ii) increasing within-group wage inequality, and (iii) the " polarization of work" (a reduction in the mass of middle-income earners) and the "decoupling of the earnings distribution" (with more inequality in the upper range of the wage distribution and less inequality in the lower range of this distribution).[1] We observe that many of the developments in the organization of work over the past two decades involve changes in workers' spans of competence, defined in terms of the breadth of their portfolios of tasks. In our empirical analysis we show that cross-section and time-series variations in workers' span of competence shed light on the above empirical regularities.

The paper is organized as follows. Section 2 provides some background and summarizes some relevant literature. Our theoretical analysis in Section 3 explains why the span of competence tends to rise with the skill level, defined in terms of education. In particular, higher-skilled workers are able to take advantage of more complementarities across tasks and thus they experience a rise in their productivity and wages, relative to lower-skilled workers. The resulting wage differential we call the "multitasking premium." We also show that, within education groups, differences in spans of competence (defined in terms of multitasking) can help account for a growing fraction of within-group inequality. Finally, we indicate how changes in multitasking spans can help explain why work has become polarized and the earning distribution has become decoupled over the past decade in several countries.

In Section 4, we construct a simple empirical measure of multitasking and then, using a rich data set of Germany covering 20 years from 1986 to 2006, we introduce some preliminary evidence indicating the growing importance of multitasking. In Section 5, we present wage regressions that provide evidence for the existence of a multitasking premium and find that it increases throughout the 20 years of our sample period. We also show that the level of multitasking can explain an increasing fraction of wage inequality within education groups.

[1] For papers discussing these regularities, see e.g. Autor et al. (2008); Dustmann et al. (2009); Lemieux (2006); Juhn et al. (1993); Autor et al. (2006); Goldin and Katz (2007).

2 Background

Large bodies of evidence testify to the significant changes in the organization of work that have taken place in many OECD countries over the past two decades (cf. NUTEK, 1999; Snower et al., 2009). Hierarchies have become flatter, decision-making has become more decentralized (Caroli and Van Reenen, 2001), team work has become important (OECD, 1999; Carstensen, 2001), job rotation and quality circles are more frequently used (Osterman, 2000). What many of these organizational changes have in common is that workers now perform broader sets of tasks, i.e. they have increased their spans of competence. A number of studies provide evidence that these organizational innovations have often gone hand in hand with technological innovations, such as ICT capital and versatile machines capable of producing a greater variety of customized products (cf. Brynjolfsson and Hitt, 2000; Bartel et al., 2007; Bresnahan et al., 2002; Aghion et al., 2002). Some authors also show that organizational change is complementary to skilled labour (Caroli and Van Reenen, 2001; Bresnahan et al., 2002; Bauer and Bender, 2004). The implications of this workplace transformation for individual wages have however remained largely unexplored thus far.

Earnings inequality has risen substantially in many advanced countries during the last three decades. In the US, wage inequality has grown strongly during the 1980s and the income distribution has started to polarize more recently (Goldin and Katz, 2007; Autor et al., 2006). Similar developments have been reported for the UK and have, to a lesser extent, also been observed in other developed countries such as Germany (e.g. Haskel and Slaughter, 2001; Goos and Manning, 2007; Dustmann et al., 2009). A major contributor to rising overall inequality is the educational wage differential (college premium), which has increased strongly since the 1980s in the US and since the 1990s in Germany (Autor et al., 2008; Dustmann et al., 2009). However, observable characteristics such as education or work experience have been found to explain at most half of the variation in wages so that the wage dispersion *within* these groups is at least as important a contributor to overall inequality as the variation *between* the groups (Juhn et al., 1993; Katz and Autor, 1999).

In the mainstream literature, the link between educational premia and wage premia is explained primarily through globalization, de-industrialization, and skill-biased technological change (SBTC), with the last playing a particularly prominent role. Each of these explanations is, to some degree, a "black box" comprising various economic phenomena, including multitasking. The contribution of this paper is thus not simply to be seen as a distinct alternative to these explanations, but also as a step towards getting into the black box. The various problems with the conventional explanations are well-known. With regard to the SBTC hypothesis, for example, Card and DiNardo (2002) have argued that, if SBTC caused the steep rise in US (and UK) earnings inequality during the 1980s, it is difficult to explain why it has failed to produce a similarly steep rise in the 1990s even though ICT capital continued to spread across the US and other advanced countries, and the spread may have even accelerated. They also report the development of several wage differentials (e.g. gender, race, age) which cannot be explained by the simple SBTC hypothesis. Furthermore, SBTC is often measured as a residual (such as a Solow residual), i.e. as a catch-all category for everything that cannot be explained by other measured variables (Snower, 1999). Some contributors have suggested that SBTC affects the wage structure primarily through organizational changes in the workplace (Caroli and Van Reenen, 2001; Bresnahan et al., 2002). Yet, while Levy and Murnane (2004) and Spitz-Oener (2006) have studied how technical change affects the task requirements of jobs, we are not aware of any study that has looked at how multitasking evolved and how it affects earnings.

The reasons for rising within-group inequality remain highly controversial as well. Juhn et al. (1993) suggest that rising within-group inequality reflects increasing returns to some type of skill other than years of schooling or experience. Some authors tried to capture unobserved ability by measures of cognitive skill (e.g. IQ), but were not successful in explaining increasing residual inequality well (Gould, 2005; Blau and Kahn, 2005). Hence, it is still an open question what constitutes these unobserved skills that seem to drive within-group inequality.

As noted, this paper explains how the rising multitasking premium can shed light on wage inequality between and within skill groups. The rise of multitasking is part of a broader set of changes in the organization of work that has swept through OECD countries over the past two decades. These organizational changes have been driven by improvements in ICT capital, the introduction of more versatile machinery, and the broadening of human capital across skills through education and training, all of which enable workers to exploit complementarities among wider groups of tasks (cf. Lindbeck and Snower, 1996, 2000). For example, the implementation of ICT capital reduces the cost of communication and facilitates communication processes. As a result, it becomes easier for co-workers to obtain information about each other's tasks, to take over each other's responsibilities, and to perform larger sets of tasks. Consequently, we would expect workers with wider spans of competence to earn a multitasking premium because they are able to exploit more complementarities among tasks. Our empirical analysis provides support for this claim.

3 A Theoretical Model of the Span of Competence

We now present a theoretical model that shows how exogenous changes such as the improvements in IT capital, versatility of machinery, and a widening of the human capital base (cf. Lindbeck and Snower, 2000) trigger a reorganization of work, because they make it profitable for workers to expand their span of competence, i.e. perform a broader range of tasks. Thereby workers receive a multitasking premium, which can lead to a fanning out of the wage distribution between and within skill groups. Our analysis also indicates how the multitasking premium might contribute to explaining the polarization of work and the decoupling of the income distribution (cf. Goos and Manning, 2007).

3.1 Model Basics

We define a worker's span of competence in terms of the number of tasks performed by the worker. Generally a worker has a "primary task," which characterizes her occupation, and a number of "secondary tasks" that are usually complementary with the primary one. The worker's span of competence may then be measured by the number of secondary tasks associated with the primary one. To begin with, we consider a one-period model, although the phenomena described here occur through time. A multi-period case is discussed in the appendix.

The primary tasks $\hat{x}_i$ can be ordered according to skill along a line, from low-skilled to high-skilled tasks. Workers choose combinations of tasks clustered around their primary task. In particular, if a worker's primary task is $\hat{x}$, then the set of secondary tasks chosen is taken from the range $\left[\left(\hat{x}-\frac{s}{2}\right),\left(\hat{x}+\frac{s}{2}\right)\right]$, where s is the worker's span of competence. Our analysis provides a choice theoretic rationale for this span of competence. (In this section, we focus attention on a particular worker and thus omit subscripts identifying the primary tasks of different workers.)

The worker is endowed with T units of working time per period. She devotes a unit of time to each secondary task and the time span $(T-s)$ to the primary task. Effective labor services devoted to the primary task are $(T-s)\,\hat{x}$ and effective labor services devoted to the secondary tasks are

$$\int_{\hat{x}-\frac{s}{2}}^{\hat{x}+\frac{s}{2}} x dx = \frac{1}{2}\left(\left(\hat{x}+\frac{s}{2}\right)^2-\left(\hat{x}-\frac{s}{2}\right)^2\right) = s\hat{x}$$

3.2 Production

We assume that the productivity of a worker is the sum of (i) returns to specialization (learning by doing) and (ii) informational task complementarities.[2] Returns to specialization imply that the more time the worker devotes to a task, the more productive she becomes at that task. The informational task complementarities are modeled as an interaction term between the worker's "primary" task $\hat{x}$ and her "secondary" tasks.

Let returns to specialization in the primary task be represented by $y\,(T-s)\,\hat{x}$, where y is the productivity arising from learning-by-doing and thus depends on the time devoted to the primary task. Thus the returns from specialization (rts) are specified as the product of (i) $\hat{x}$ the productivity per unit of time at the primary task, (ii) $(T-s)$, the time devoted to the primary task and (iii) y, learning-by-doing. Setting $y=\frac{1}{2}(T-s)$ for simplicity, we obtain:

$$rts = \frac{1}{2}\,(T-s)^2\,\hat{x}.$$

We describe the informational task complementarities (itc) between the primary task and each of the secondary tasks through the following interaction effect:

$$itc = \gamma\,((T-s)\,\hat{x})\,(s\hat{x}) = \gamma\,(T-s)\,s\hat{x}^2.$$

Note that the parameter γ governs the magnitude of informational task complementarities.

The production function is the sum of the two above effects:

$$q = \frac{1}{2}\,(T-s)^2\,\hat{x} + \gamma\,(T-s)\,s\hat{x}^2.$$

3.3 The Span of Competence

The worker sets her span of competence s to maximize her wage, which we assume to be equal to her productivity. Maximizing q with respect to s, we obtain

$$s^* = \frac{T\,(\hat{x}\gamma-1)}{2\hat{x}\gamma-1},$$

where we assume that $\hat{x} > 1/\gamma$.

[2]This analysis is in the spirit of Lindbeck and Snower (2000).

Note that the optimal span of competence depends positively on the skill level at the primary task, $\hat{x}$:

$$\frac{\partial s^*}{\partial \hat{x}} = \frac{T\gamma}{(2\gamma\hat{x}-1)^2} > 0.$$

The output generated through this optimal span of competence is

$$q^* = \frac{T^2\hat{x}^3\gamma^2}{2(2\hat{x}\gamma-1)}.$$

In the absence of multitasking ($s = 0$), the output generated would be

$$q' = \frac{1}{2}T^2\hat{x}.$$

Thus the multitasking premium is

$$\begin{aligned} q^* - q' &= \frac{T^2\hat{x}^3\gamma^2}{2(2\hat{x}\gamma-1)} - \frac{1}{2}T^2\hat{x} \\ &= \frac{T^2\hat{x}(\hat{x}\gamma-1)^2}{2(2\hat{x}\gamma-1)}. \end{aligned}$$

The parameter γ, measuring informational task complementarities, is affected by improvements in ICT technologies and versatile physical capital, and through the widening of human capital. Specifically, the spread of ICT capital reduces the cost of communication and thereby enables workers to obtain more information about other jobs, share responsibilities, and engage in multitasking. The introduction of versatile machinery (programmable equipment and flexible machine tools) enables workers to respond to changing customer needs through variation in tasks. A broader human capital base enables workers to perform a wider range of tasks (Lindbeck and Snower, 2000). In our model, all these developments may be captured by an increase in the task-complementarity parameter γ.

Observe that the span of competence depends positively informational task complementarities:

$$\frac{\partial s^*}{\partial \gamma} = \frac{T\hat{x}\,(2\gamma\hat{x}-1) - 2\hat{x}T\,(\hat{x}\gamma-1)}{(2\hat{x}-\gamma)^2} = \frac{-T\hat{x}+2\hat{x}T}{(2\hat{x}-\gamma)^2} = \frac{T\hat{x}}{(2\gamma\hat{x}-1)^2} > 0.$$

3.4 Explaining the Distribution of Wage Income

We now consider the wages of workers with different occupations, where each occupation is identified by its primary task $\hat{x}_i$. Then the span of competence for a worker with occupation i is

$$s^* = \frac{T\left(\hat{x}_i\gamma_i - 1\right)}{2\gamma_i\hat{x}_i - 1}.$$

3.4.1 The Fanning Out of the Earnings Distribution

For simplicity, suppose that $\gamma_i = \gamma$ so that all occupations are identical in terms of their opportunities for informational task complementarities. Next suppose that workers fall into two skill classes, where $\hat{x}_h$ is the primary-task productivity of the high-skilled worker and $\hat{x}_l$ is that of the low-skilled worker. Then the wage differential (equal to the productivity differential) is

$$q_h - q_l = (T\gamma)^2\left(\frac{\hat{x}_h^3}{2(2\hat{x}_h\gamma - 1)} - \frac{\hat{x}_l^3}{2(2\hat{x}_l\gamma - 1)}\right).$$

In this context, an increase in informational task complementarities (driven, as noted, by the introduction of ICT and versatile physical capital, as well as a widening of human capital) has a striking effect on the wage differential. In our model, a doubling γ would more than double the productivity difference. In this way, our analysis helps account for the fanning out of the income distributions in many OECD countries between the mid-1970s and the mid-1990s.

3.4.2 The Breakup of Earnings Distribution Changes

Several papers on the polarization of work argue that the middle range of the wage distribution contains a disproportionate number of white-collar workers doing routine jobs (e.g. Goos and Manning, 2007). These jobs potentially offer relatively few opportunities for expanding the span of competence.[3] Accordingly, consider a distribution of primary-task skill classes $\hat{x}_i$ over the range $[\hat{x}^-, \hat{x}^+]$, where $\hat{x}^-$ and $\hat{x}^+$ are positive constants, $\hat{x}^- < \hat{x}^+$, and let γ_i be the

[3]Indeed, the average level of multitasking in occupations that intensively use routine tasks is indeed lower than in nonroutine-intensive occupations (2.66 vs. 2.17). We arrive at these figures by first calculating the routine and non-routine task input of each occupation using the methodology suggested by Spitz-Oener (2006). Then, occupations with a larger (non-)routine task input are designated (non-)routine task-intensive and the average multitasking is calculated.

corresponding task-complementarity parameters. The income of a worker in skill class i is

$$q_i = \frac{T^2 x_i^3 \gamma_i^2}{2(2x_i\gamma_i - 1)}$$

To capture the above characteristic of routine white-collar work, we suppose that as the task-complementarity parameter rises (for the reasons outlined above), the increase in γ_i is relatively small for workers in the middle range of the wage distribution, compared to workers in primary-task groups at the top and bottom of the wage distribution. Since $\partial q_i/\partial\gamma_i > 0$, we then find that the incomes of the routine white-collar workers will rise more slowly than the incomes at the lower and upper tails of the occupational distribution for $\hat{x}_i$. Thus the lower part of the income distribution will become more equal and the upper part of the distribution with become less equal. Thereby our analysis can help account for both the polarization of work and the decoupling of the wage distribution (see, for example, Autor et al. (2006) for the US).

4 Data and Construction of Variables

Our following empirical analysis is based on the German Qualification and Career Survey. The goal of the survey, conducted by the German *Bundesinstitut für Berufsbildung* (BIBB; Institute for Occupational Training), is to shed light on structural change in the labour market, and to document how it affects working conditions, work pressure, and individual mobility. For that purpose, it collects detailed data on issues, such as qualification and career profiles of the workforce, and organizational and technological conditions at the workplace. We use the four cross-sections 1985/86, 1991/92, 1999, and 2006, and can thus cover a period of 20 years.[4] This makes the dataset particularly suitable for our analysis, because the available literature suggests that major changes in the organization of work have only been observed since the late 1980s (cf. OECD, 1999). The Qualification and Career Survey has already served a large number of academic studies (e.g. DiNardo and Pischke, 1997; Pischke, 2007; Spitz-Oener, 2006). It samples from employed persons aged between 16 and 65.

The central variable in our empirical investigation is multitasking, which we use as a measure for the worker's span of competence. A unique feature of our data is is that they allow the construction of such a variable at the individual level. We provide two independent measures of multitasking, in order to assess the robustness of our results.

[4]An earlier survey wave in 1979 is available as well, but large changes in the variable definition over time make it impossible to use the earliest wave of the survey. Consequently, we start our analysis in 1985/86.

4.1 A Task-Based Measure of Multitasking

A distinctive feature of our data is that every respondent is required to indicate which tasks he performs at work. Multiple answers are possible, and indeed chosen by almost all respondents. An overview of available answer options is given in table 1. However, this overview hides two problematic inconsistencies between the different survey waves: (1) the number of available answer options changes over time, and (2) in some cases, the wording of the answers differs significantly between the survey waves. We proceed by describing how two consistent multitasking variables can nevertheless be generated.

(table 1 here)

Table C.1 in the appendix provides a detailed overview of the exact wording and occurrence of the items. We followed Spitz-Oener (2006) and Gathmann and Schoenberg (2007) in drawing up a list of 17 tasks that can potentially be identified from the data (see tables 1 and C.1). Then we use two ways to identify these tasks: (1) *directly* from the answers to the question "Which of these tasks do you perform during your work?" and (2) *indirectly* via the question "Does your job require special knowledge in any of these fields?" (printed in italics in table C.1). Note that some tasks can only be identified either via the direct way or via the indirect way, because the respective answer was not included in the relevant questionnaire. More specifically, in year I (1986) only the direct question is available. In year II (1992), the answers to the direct question are identical to the previous survey, and this time, also the indirect question is available. In year III (1999), a couple of direct answers have been dropped from the survey, but the indirect answers are often identical to the previous survey. The same holds for year IV (2006).

In 8 out of the 17 cases on our list, the answer options for the *direct* question are identical (or nearly identical) in all four survey waves. We hence use the direct question to code these tasks and mark them accordingly in the third column of table 1. In 4 out of 17 cases (*des*, *pre*, *man*, *tex*), neither the direct nor the indirect answers are comparable over time, so we drop these tasks and do not use them in the analysis. In the 5 cases left, we obtain a mix of identical *direct* answers in years I and II, together with identical *indirect* answers in years II, III, and IV. We mark these cases in the fourth column of table 1. We can hence draw upon the direct answers in years I and II, but have to use the indirect answers in years III and IV. All we need is to make sure that the direct answers in year I and II and the indirect answers in year III and IV measure the same thing, i.e. whether it can capture that the person performs the respective task.

To check this, we make use of the fact that both the direct answers and indirect answers are available in year II. We code the tasks once using the direct answers and again using the indirect answers, and then calculate the correlation between the two. Correlation coefficients are listed in the fifth column of table 1. Taking coefficients larger than 0.4 as appropriate, we find that in 4 of the 5 cases, both ways to code a task are acceptable. Accordingly, we have identified a total of 12 tasks, which are consistent and comparable across all four years of analysis.[5] The variable for multitasking is obtained by simply counting all tasks indicated by a respondent.

4.2 A Tool-Based Measure of Multitasking

Arguably, the task-based measure of multitasking described above might be contested since it could be subject to imprecision, even though we took great care to avoid this. Fortunately, our data allow the construction of an additional measure of multitasking, which we will use to check the robustness of our results. In addition to work tasks, every survey respondent was asked to indicate the tools utilized at his workplace. The tools to choose from are shown in table 2. A great advantage over the task-based measure is that the definitions of these tools hardly change between the years. Even in the few cases they do, it is easy to aggregate them consistently. Unfortunately, the question about workplace tools has been dropped in the latest wave of the survey (2006).

(table 2 here)

We consider workplace tools as a good proxy for tasks. Consider, for example, a typical woodworker. According to our data, he uses simple tools, power tools, measuring instruments, hand-controlled machines, and lift trucks. A few woodworkers in our sample also use typewriters, cash registers, files, simple writing materials, phones, and calculators. Looking at this list of workplace tools, we can infer that the average woodworker is performing tasks such as lumbering, transporting wood, transforming it into new forms. However, some of the woodworkers seem to be involved in sales or bookkeeping tasks, too. An increase in the portfolio of tasks is hence reflected in the number of tools a worker uses. Note that also Becker et al. (2009) use workplace tools as a proxy for the task content of a job.

As another example, we list the tools used by at least 20 per cent of electricians in our samples (table 3). The tasks printed in italics have newly entered the list in the respective year, i.e. they were previously performed by less than 20 per cent of the electricians. Just like in the case of the wood workers, it seems that office equipment and computers are taking on a more prominent role in an electrician's workplace, while the traditional tools remain important as

[5] Note that Spitz-Oener (2006) claims that a larger list of 17 tasks is comparable over all waves, but we consider this as highly problematic given the above-mentioned strong changes in the wording of the task description.

well. It thus appears from the tools they use, that electricians perform a broader range of tasks today than they used to.

(table 3 here)

A major problem with using tools as proxy for tasks is that certain tools can potentially be used for more than one task. While a personal computer is very versatile, i.e. it can be used for many different purposes and to perform many tasks (maybe even at the same time), a hammer or other simple tools are much less versatile, i.e. they can only be used for one specific purpose and task. In order to account for this, we subjectively rank tools according to their degree of versatility (see table 2). Tools at the top of the list can potentially be used to perform a larger number of tasks; tools at the bottom of the list can only be used to perform one or few tasks. We then aggregate the tasks into three groups: high, medium, and low versatility and attach the weights of 3, 2, and 1, respectively. The multitasking measure is the weighted sum of the number of tools.[6]

4.3 Earnings and Other Variables

Data about individual earnings are also taken from the Qualification and Career Survey. In years I–III, earnings are reported in brackets and are both bottom- and top-censored (see table 4). We impute individual earnings by taking the midpoint of each earnings bracket.[7] For the right-censored cases, we follow Pischke (2007) and assign the values stated in the column "Highest" of table 4. Due to the small size of the earnings brackets, potential measurement errors should be limited.[8] In year IV, we can abstain from imputation because respondents were asked to indicate the exact amount of their gross monthly earnings. For the regressions, we first convert monthly earnings into real hourly wages by dividing them by the reported hours worked and deflate them by the CPI in the respective year (as provided by the German Statistical Office).[9]

(table 4 here)

[6]Note that this weighting scheme has problems on its own because it is a completely arbitrary assumption that e.g. a PC is three times as versatile as a hammer and that the worker is indeed using the entire versatile potential of the PC. Nevertheless, we consider this alternative measure for multitasking as a useful device to check the empirical results derived from the task-based measure.

[7]See also DiNardo and Pischke (1997) and Pischke (2007) who use the same data for their analyses.

[8]We employ censored normal regressions in order to account for censoring in the wage data. In the appendix, we also provide the results of interval regressions to account for the bracket structure (von Fintel, 2007).

[9]Table 4 shows that the top category of earnings in 1992 is much lower than in 1986 and 1999. However, this is not a limitation for our purpose because even with the lower top category in 1992, almost the entire German wage distribution is covered. Detailed summary statistics of earnings in 1992 shows that the censoring only affects the top 2 percent of the distribution.

Other variables that enter our regression analysis as control variables are dummies for the educational level, years of experience, and dummies for married, female, the interaction of the two, working part-time and residing in a city. The three educational levels indicate the highest qualification obtained by a respondent and include tertiary education (university and equivalent), secondary education (Abitur [A-levels], vocational training) and less than secondary education (schooling up to 10th grade or less). Work experience is calculated using a variable indicating the year in which respondents had their first job. The city dummy indicates whether the respondent lives in a city with more than 50,000 inhabitants. A similar set of control variables has also been used by DiNardo and Pischke (1997) who, however, investigate the wage impact of computer use.

5 Results

We now present evidence for some of the main features and predictions of the theoretical model discussed above.[10] Before proceeding to the results, we would like to quickly summarize some expected results. First, we expect the level of multitasking to rise throughout the sample period. As we mentioned above, the two decades analyzed have been characterized by a large-scale reorganization of work, which should be reflected in an increased level of multitasking of workers (cf. NUTEK, 1999; Caroli and Van Reenen, 2001). Second, we expect the level of multitasking to differ between workers with different educational level. Higher-educated individuals are more likely to expand their span of competence either because they are more able to do so or because they work in jobs where more opportunities for an expansion arise (cf. Appelbaum and Schettkat, 1990). Third, we expect to find a multitasking premium because—as shown theoretically—with a wider span of competence, employees exploit more complementarities between tasks, which raises their productivity and wages.

5.1 Facts about Multitasking

We start by presenting some preliminary empirics on the extent and development of multitasking in Germany in order to get an idea about its importance. Table 5 shows summary statistics of our two measures of multitasking for all workers and by educational level. To begin with, it becomes clear that multitasking has increased significantly over time. Even though multitasking was already slightly rising throughout the late 1980s, the biggest increase happened after

[10] Note that we do not intend to provide a structural estimation of the model.

1992. Interestingly, both independent measures of multitasking, task-based and tool-based, paint roughly the same picture. Importantly, the standard deviation of our multitasking measures is increasing over time in all groups. It is thus evident that not all workers have equally increased their spans of competence, but that the increasing average is accompanied by an increasing dispersion of multitasking *within* the groups.

(table 5 here)

Looking at multitasking by educational level, panel B reveals that—as expected—higher educated workers perform significantly more tasks on average than lower educated workers. Workers with tertiary education, i.e. with a university or technical college degree, have increased their level of multitasking from 2.2 to 6.6 tasks on average, while workers with primary education increased the level from 1.5 to 5.1 tasks only. Interestingly, the "multitasking gap" between higher- and lower-educated workers (the difference between the respective multitasking scores) has increased quite strongly throughout the late 80s and 90s, but has shrunk after 1999. Note however that the standard deviation in 2006 is relatively high for primary-educated workers compared to workers with a higher educational level, suggesting that the strong increase in multitasking for low-skilled workers in the early 2000s has only been experienced by a relatively small group of workers. [11] In general, the higher level of multitasking for higher-educated workers is notable. Either their ability to expand the number of tasks is higher, or they work in jobs where more possibilities for multitasking arise.

(table 6 here)

The data of 1999 and 2006 allow us to further investigate whether multitasking is indeed related to the introduction of ICTs, versatile machinery, or other organizational changes, as we suggested in the theoretical model. In the questionnaire, workers were asked whether there have been recent changes in production techniques, machines or computers, whether the company has developed new, improved products or services, whether there has been any organizational restructuring, and whether there have been changes in the management or the worker's superiors. Table 6 shows the average levels of multitasking (task-based measure) of workers who have and who have *not* experienced such changes. The numbers clearly convey that workers in "changing" firms perform on average almost one task more than their counterparts in

[11] On the one hand, there is anecdotal evidence in the German press that firms have begun to favour specialization of their workers again. The decreasing multitasking gap we report might be a first result of this trend. On the other hand, the high level of multitasking for the primary education group is mostly driven by office personnel, salesmen and IT experts, all of which are not typical unskilled jobs, but may yet be carried out by workers without formal secondary or tertiary education (unlike a teacher, for example). It seems that in 2006, more of these jobs were held by unskilled persons so that there might be a composition effect here. When estimating the multitasking premium, we include a robustness check with occupation fixed effects, which should deal with this.

other firms. Similar evidence has been reported by Caroli and Van Reenen (2001) for the UK and France, and Carstensen (2001) for Germany. The same picture emerges when using the tool-based measure for multitasking (not reported).

5.2 Is There a Multitasking Premium?

In the following econometric analysis, we estimate simple wage regressions, but amend them by including our multitasking measure. Besides that, the estimated wage equation is standard; it includes dummies for the educational level, years of experience, gender, marital status, the interaction of gender and marital status, dummies for part-time work and living in a city. We also include industry fixed effects (two-digit level) to account for possible industry-specific effects of organizational and technical change that might otherwise be picked up by our multitasking measure.[12] In the pooled regressions, we also include year dummies. The endogenous variable is log real gross hourly wage rate. The wage equations are estimated using a censored normal regression in order to provide for top and bottom censoring in the wage data. Our sample includes all workers and is limited to West Germany.

(table 7 here)

The estimation results using our task-based measure of multitasking are shown in table 7. Model 1 uses the pooled sample (all waves) and is equivalent to a conventional wage equation. The results are in line with usual estimates (e.g. DiNardo and Pischke, 1997).[13] In model 2, we add our task-based measure of multitasking. We also include its square term in order to account for possible diminishing returns to multitasking, which reflect the trade-off between specialization and informational task complementarities in the theoretical model. The result shows that multitasking has a positive and significant effect on hourly wages: at the mean level of multitasking, performing one additional task is associated with a 3.5 percent higher wage.[14] The regressions hence reveal the existence of a multitasking premium. The negative coefficient for the square indicates diminishing returns to multitasking. Multicollinearity is not present since the coefficients of education and experience only change very little. Our proxy for the

[12] In the appendix, we present the results of a regression also controlling for occupation. The results are confirmed.

[13] DiNardo and Pischke (1997) have used the same data and variables. However, they investigate the question whether certain tools have similar wage effects as computers. The results are not directly comparable because they include at least a variable for computer use in their regressions and approximated years of schooling instead of dummies for the educational level. Our coefficient for work experience is about 1 percent lower than their estimate.

[14] The effect is calculated at the mean level of multitasking (s) using $\partial \ln w/\partial s = \beta_1 + 2\beta_2 s$, where β_1 and β_2 are the coefficients of *multitasking* and *multitasking squared*. The mean level of multitasking of the pooled sample as it is used here is 3.638.

worker's span of competence might thus be constituting a new measure of skill that can explain wages beyond the standard measures.

Models 3–6 display the estimation results separately for each year. To illustrate the relationship between multitasking and wages, we plot multitasking-wage profiles in figure 1. The graph displays, separately for each year, the predicted log hourly wage for each level of multitasking. It is drawn for an exemplary male, married worker who has secondary education and 20.74 years of work experience (sample average), and lives in a big city. The multitasking-wage profile becomes steeper over time, implying a rising multitasking premium. The increasing steepness is driven by the the increasing coefficient of the level of multitasking. Model 7 allows us to test whether the increase in the steepness is statistically significant. There, we use the pooled sample and control for time differences in the multitasking coefficients by including an interaction *year*multitasking*. As expected, the coefficient of the interaction term is greater for later years and the difference is statistically significant.

(figure 1 here)

(table 8 here)

The coefficient of the square is rather large relative to the linear effect, resulting in the downward-sloping multitasking-wage profile for high levels of multitasking, as shown in figure 1. The empirical analysis thus suggests that there is an upper limit to how large the span of competence can be in order to remain profitable for the worker. The maximum of the multitasking-wage profiles can therefore be interpreted as the optimal level of multitasking. We calculate this limit (i.e. the point at which the downward-sloping section of the multitasking-wage profile begins) for each year in table 8. As our theoretical model predicts, the optimal span of competence was lower in earlier years when multitasking-enhancing technologies and organizational forms were not yet present or implemented. Yet, the ongoing change and implementation of the new technologies and organizational structures throughout the 20 years shifted the optimal span of competence outwards.

How does a multitasking premium translate into wage inequality between and within skill groups? The existence of a multitasking premium means that the ability and opportunity to expand the span of competence is rewarded. However, these abilities and opportunities are unlikely to be equally distributed across the population, so that only some workers benefit from the multitasking premium. As we showed above, higher educated workers tend to have higher levels of multitasking, and also the "multitasking gap" between higher- and lower-educated workers expanded (at least until 1999). Moreover, within educational groups, the level of multitasking was increasingly spread out. Seemingly, workers who had the ability and opportunity to widen their span of competence are found in the higher branches of the wage distribution, so that the multitasking premium leads to greater wage dispersion between groups and possibly also within groups. If opportunities to expand the span of competence arise unequally along the current wage distribution, entirely new patterns of inequality, such as the recently observed polarization, could emerge (cf. Autor et al., 2006).

Besides that, the results also show that there is a "price effect" because the multitasking premium is rising over time. Without changing their actual levels of multitasking, workers with a sufficiently high level of multitasking benefit from a higher premium, while workers with a low level of multitasking might even suffer from wage declines. The latter result evolves from figure 1 because the very left section of 2006 multitasking-wage profile is below the profile of earlier years.[15] Note, again, that the workers with higher levels of multitasking are the ones in the upper part of the wage distribution and workers with lower levels are found in the lower part, so that also the price effect (i.e. the rising premium) leads to more wage dispersion.

(table 9 here)

In table 9, we repeat the estimations using the tool-based measure of multitasking. The sample is larger for this exercise is larger because there was no need to drop observations that had potential problems with inconsistencies in the task definition. Note that the tool-based measure is no longer available in the cross section for 2006 because the questions have been dropped from the survey. The results partly confirm our findings from before. Model 2 shows that, *ceteris paribus*, using an additional tool is associated with a 1.2 percent higher wage. As before, the square of multitasking is negative, pointing to diminishing returns. Multitasking and wages are hence confirmed to be positively related. In contrast to the task-based measure, the yearly regressions show decreases in the coefficients of multitasking, even though the decline is very small (0.3 percentage points). However, the interaction model (model 6) conveys that the coefficients in 1992 and 1999 are higher than in the reference year 1986, and that the 1999 coefficient is a bit larger. A t-test for equality of the interaction coefficients for 1992 and 1999 shows that the null hypothesis of equality cannot be rejected at a 12%-level. The similarity of the results with the task- and tool-based measure of multitasking are striking because the two measures are truly independent from one another. We hence consider this as a good proof for the robustness of our results.

[15] Arguable, the result might stem from the quadratic estimated.

5.3 Explanatory Power and Within-Group Inequality

We now address the explanatory power of adding the multitasking measure to an earnings regression. For that purpose, we compare it to the importance of the other two measures of skill in wage regressions: education and work experience. First, we re-estimate the wage equations 3, 4, and 5 from table 7 without any measure of skill and report the residual standard deviation (σ) and the R^2 of the regression (see table 10).[16] Then we add either education, experience, or multitasking as indicators for skill, again reporting σ and R2. This allows us to compare the additional explanatory power of the three variables and compare them to one another. The column entitled $\frac{\text{+multitasking}}{\text{+educ./exp.}}$ shows how the size of the change in σ and R^2 due to the inclusion of multitasking compares to the change due to inclusion of education or work experience (in percent). It turns out that multitasking is up to one-third as important as including educational level into a simple wage regression, and that it is up to half as important as adding work experience. The size of this effect is striking because, after all, we compare it with two of the major explanatory factors of variation in wages. We hence consider it as clear evidence for the important role the span of competence plays in wage determination.

(table 10 here)

Another important implication of this result is that multitasking can explain a small, but growing fraction of residual wage inequality. Residual wage inequality (or within-group inequality) can be measured by the standard deviation of the regression residuals (σ in table 10), i.e. the variation in wages that cannot be explained by the variables entering the regression. Multitasking could account for a growing fraction of residual inequality until 1999, although the fraction has decreased thereafter. The rise in residual wage inequality (e.g. Dustmann et al., 2009; Lemieux, 2006) has often been attributed to increasing returns to unobservable skills. Our analysis thus suggests that the ability to perform multiple tasks constitutes at least a part of these unobservable characteristics.

6 Conclusion

This paper shows how recent changes in the organization of work help explain rising wage inequality in advanced industrialized economies. We offer a theoretical model, in which tech-

[16]Actually, the figure reported is not the R^2 because the estimations are done using maximum likelihood. However, Stata reports an artificial pseudo-R^2, which is valid for comparing models. Therefore, we report the pseudo-R^2.

nological changes such as the introduction of ICT capital and versatile machinery, and the general widening of the human capital base trigger a reorganization of work. The technological innovations let complementarities between formerly separated tasks arise so that it becomes increasingly profitable for workers to expand their span of competence and perform a multitude of tasks (multitasking) rather than just a specialized one. A wider span of competence implies a higher wage; in other words, there is a multitasking premium. Since possibilities to expand the span of competence differ between workers (e.g. the higher educated might have more such possibilities), the existence of a multitasking premium implies a rise in wage inequality between the workers with different multitasking possibilities. These differences between workers could also exist among workers with identical observed characteristics (e.g. education), so that our theory also offers an explanation for rising within-group inequality. Finally, since possibilities for multitasking are particularly rare in routine jobs in the middle of the wage distribution, our theory also helps understanding the polarization of work and incomes.

In the empirical section of our paper, we use representative data for West Germany which covers the years 1986–2006. We find support for the predictions of our theoretical analysis: (1) The level of multitasking increases on average. The standard deviation of multitasking rises within groups. (2) Higher-educated individuals have higher levels of multitasking than lower educated individuals, and the multitasking gap between higher- and lower-educated widened until 1999. (3) We find that a multitasking premium exists, and that it is rising over time. (4) We find that the level of multitasking can explain a small, but increasing fraction (until 1999) of within-group (residual) inequality.

This paper is clearly just a step towards gaining a better understanding of how work organization affects wages. It remains for future research in this area to examine the evidence for other countries and collect better data on work tasks.

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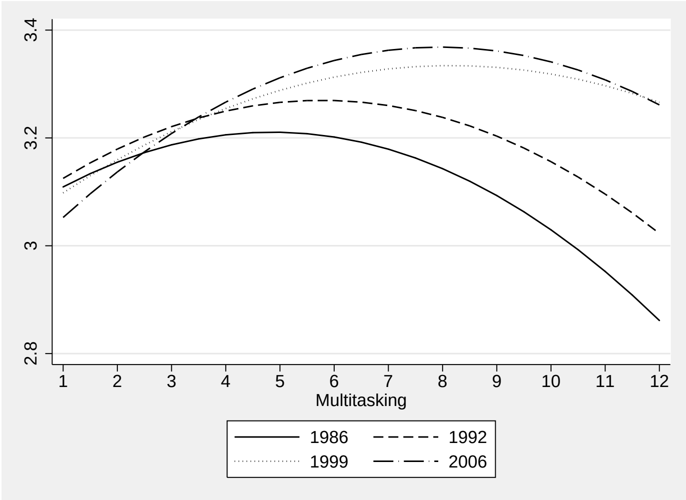

Figure 1: Multitasking-wage profile

Appendices

A Model Extensions

The model above contained two particularly extreme simplifying assumptions concerning the returns to specialization: first, the returns accrue immediately within the period of analysis and, second, that there are constant returns to specialization. We now relax these two assumptions. We first let returns to specialization accrue intertemporally, and then we consider diminishing returns to specialization.

A.1 Returns to Specialization that Accrue Intertemporally

As returns to specialization (learning-by-doing) take time to materialize, we capture this intertemporal dimension in a two-period model. As above, a worker's productivity is the sum of returns to specialization ($y(T-s)\hat{x}$) and informational task complementarities ($\gamma((T-s)\hat{x})(s\hat{x})$):

$$q_t = y_t(T-s)\hat{x} + \gamma(T-s)s\hat{x}^2$$

where $t = 1, 2$ is time. In the first period, no learning has yet taken place, so that $y = 1$:

$$q_1 = (T-s)\hat{x} + \gamma(T-s)s\hat{x}^2 = (T-s)\hat{x}(1+s\hat{x}\gamma).$$

In the second period, the returns to task specialization depend on the time $(T-s)$ spent on the primary task: $y_2 = \frac{1}{2}(T-s)$. The discounted value of output per worker in the second period is

$$q_2 = \frac{(1/2)(T-s)^2\hat{x}}{1+r} + \frac{\gamma(T-s)s\hat{x}^2}{1+r} = \frac{(T-s)\hat{x}(T+s(2\hat{x}\gamma-1))}{2(1+r)},$$

where r is the discount rate. Thus the present value of output is

$$\begin{aligned}
Q &= q_1 + q_2 \\
&= (T-s)\hat{x}(1+s\hat{x}\gamma) + \frac{(T-s)\hat{x}(T+s(2\hat{x}\gamma-1))}{2(1+r)} \\
&= \frac{(T-s)\hat{x}(2+T+2r+s(2\hat{x}\gamma(2+r)-1))}{2(1+r)}.
\end{aligned}$$

Differentiating Q with respect to s, we find the optimal span of competence s^*:

$$s^* = \frac{T(\hat{x}\gamma(2+r)-1)-r-1}{(2x\gamma(2+r)-1)}.$$

Note that s^* depends positively on the level of the primary task $\hat{x}$:

$$\frac{\partial s^*}{\partial \hat{x}} = \frac{\gamma(T+2r+2)(2+r)}{(1-2\hat{x}\gamma(2+r))^2} > 0$$

and positively on the task-complementarity parameter:

$$\frac{\partial s^*}{\partial \gamma} = \frac{\hat{x}(T+2r+2)(2+r)}{(1-2\hat{x}\gamma(2+r))^2} > 0.$$

Note the intertemporal model yields the same qualitative conclusions as the simple model of the previous section.

A.2 Non-linear returns to specialization

We now introduce diminishing returns to specialization. Specifically, in the second period, we set $y_2 = (T-s)^\beta$, where $0 < \beta < 1$. Thus output per worker in the second period is

$$q_2 = \frac{(T-s)\hat{x}((T-s)^\beta + \gamma s\hat{x})}{1+r}.$$

The present value of output is

$$\begin{aligned} Q &= q_1 + q_2 \\ &= (T-s)\hat{x}(1+s\hat{x}\gamma) + \frac{\gamma(T-s)\hat{x}((T-s)^\beta + \gamma s\hat{x})}{1+r} \\ &= \frac{(T-s)\hat{x}(1+(T-s)^\beta + r + s\hat{x}(1+\gamma+r))}{1+r}. \end{aligned}$$

Again, deriving this present value production function with respect to s gives the first order condition for the optimal span of competence s^*. We are unable to solve the FOC for s^* analytically, so we evaluate the function numerically. We set $T = 13$ and $r = 0.1$ in all simulations. The simulations show that, indeed, $\partial s^*/\partial \hat{x} > 0$. Figure A.1 plots the behaviour of the optimal span of competence, where we set $beta = 0.2$ and $\gamma = 2, 5, 10$. Also the simulation for $\partial s^*/\partial \gamma$ confirms that the optimal span of competence increases with the level of γ (see figure A.2). Here, we set $x = 0.75$ and $\beta = 0.2, 0.5, 0.8$. Finally, we solve for the optimal span of competence for varying values of the returns to specialization β (see figure A.3). Again, we set $x = 0.75$ and $\gamma = 2, 5, 10$. As expected, the higher are returns to specialization, the smaller is the optimal span of competence.

(figure A.1 here)

(figure A.2 here)

(figure A.3 here)

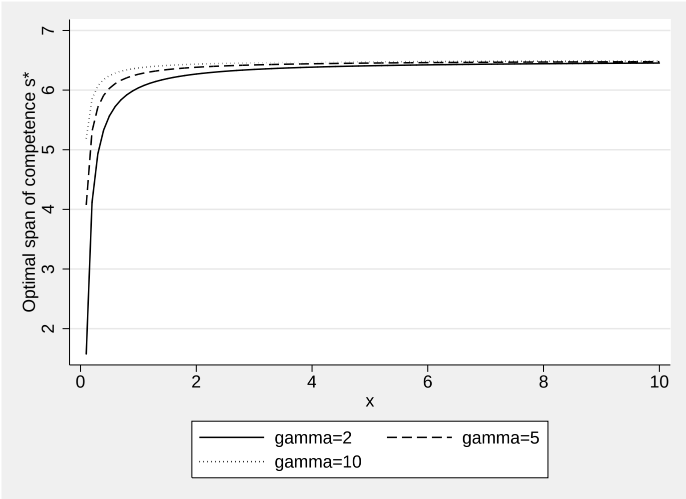

Figure A.1: Optimal span of competence increases in x

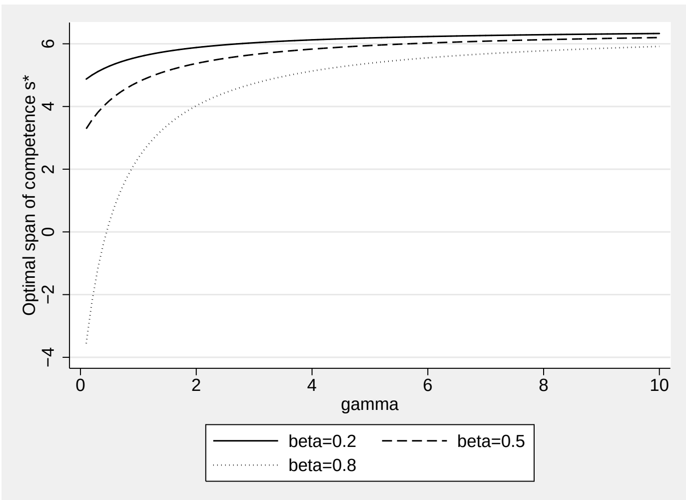

Figure A.2: Optimal span of competence increases in γ

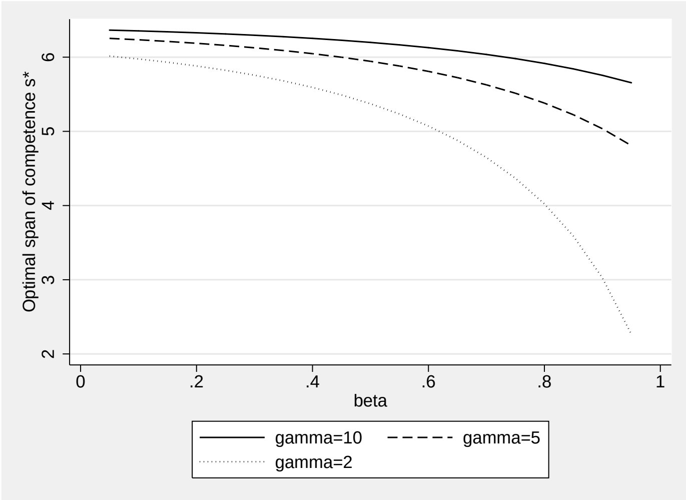

Figure A.3: Optimal span of competence decreases in β

B Robustness Checks

B.1 Regressions Controlling for Occupation

As a robustness check for our estimation results, we included occupation fixed effects into the earnings regression. The results are shown in table B.1. All results continue to hold after inclusion of occupation fixed effects.

B.2 Interval Regression

Table B.2 shows the regression results of an interval regression. This method deals with bracketed income data and with top- and bottom-censoring as in our data. Note that we left 2006 out of the estimations here because income is no longer bracketed in the survey. The coefficient estimates are only slightly lower than the results from the censored normal regressions, so that our results are confirmed by this alternative regression technique.

C Original Task Definitions

(table C.1 here)

Table 1: Tasks and comparability over all waves

Variable	Description	(1) *Direct* comparable	(2) *Indirect* comparable	correlation (1),(2)	Included in measure
res	Researching, analyzing, evaluating and planning	x			x
des	making plans/constructions, designing, sketching				
pro	working out rules/prescriptions, programming		x	0.539	x
rul	using and interpreting rules		x	0.402	x
org	negotiating, lobbying, coordinating, organizing	x			x
tea	teaching or training	x			x
sel	selling, buying, advising customers, advertising	x			x
pre	entertaining or presenting				
man	employing or managing personnel				
cal	calculating, bookkeeping		x	0.541	x
tex	correcting texts/data				
ope	operating or controlling machines	x			x
rep	repairing or renovating houses, apartments, machines, vehicles	x			x
ser	Serving or accommodating	x			x
ins	Manufacture, install, construct	x			x
sec	Secure		x	0.185	
nur	Nurse or treat others		x	0.599	x

Note: Qualification and Career Survey 1986-2006; variable names from Spitz-Oener (2006) and Gathmann and Schoenberg (2007). The column *correlation* shows the correlation between the coding of the task using (1) the direct and (2) the indirect way. *Source:* Qualification and Career Survey 1986-2006.

Table 2: Workplace tools and classification

Degree of versatility	Task
high versatility	PC
	Computer network (external)
	Computer, terminal
	Computer network (internal)
	Presentation tools (radio tv overh.)
	Phone
	File, database
	CNC/NC-machine
medium versatility	Simple writing material
	Computer-controlled medical equ.
	Motor vehicle
	Measuring instruments
	Precision and optical instruments
	Calculator
	Books, teaching material
	Cash register
	Simple means of transport
	Text processor
	Accounting machine, spreadsheets
	Process plant
	Production plant
	Simple tools
	Medical instruments
	Hand-controlled machine
	Powered tools
low versatility	Other tools
	Conveying machinery
	(Semi-) Automatic machine
	Lift trucks
	Crane, lifting gear
	Plants for power generation
	Rail, ship, plane
	Voice recorder
	Typewriter
	Fax machine
	Graphical and specialist software

Source: Qualification and Career Survey 1986-1999

Table 3: Tasks done by an Electrician 1986–1999

Year	Description	% of workers
1986	Simple tools	85.3
	Measuring instruments	60.8
	Powered tools	52.5
	Motor vehicle	41.8
	Other tools	33.4
	Simple writing material	28.4
	Phone	24.6
1992	Simple tools	80.4
	Measuring instruments	65.0
	Powered tools	57.9
	Simple writing material	56.7
	Phone	49.1
	Other tools	41.2
	Motor vehicle	40.7
	Calculator	40.0
	File, database	27.5
	Fax machine	23.4
	Books, teaching material	20.5
1999	Simple tools	82.9
	Simple writing material	77.8
	Measuring instruments	77.7
	Phone	72.2
	Powered tools	60.0
	Other tools	58.5
	Motor vehicle	45.2
	Calculator	44.1
	Medical instruments	38.6
	PC	37.2
	Hand-controlled machine	34.4
	Computer-controlled medical equ.	29.3
	Fax machine	28.4
	Text processor	27.3
	Graphical and specialist software	23.0
	Computer network (internal)	21.5
	Computer, terminal	21.2

Note: The table lists all tasks, which are performed by more than 20 per cent of the Electricians in the sample. Tasks printed in italics are new in the list.

Table 4: Earnings in the Qualification and Career Survey, in DM

Year	Lower bound	Upper bound	Bracket size	Highest
1986	400	15,000	200 up to 1,000; 250 up to 3,000; 500 up to 6,000; 2,000 up to 10,000; 5,000 up to 15,000	16,500
1992	600	8,000	500 up to 6,000; 1,000 up to 8,000	10,500
1999	600	15,000	500 up to 6,000; 1,000 up to 10,000; 5,000 up to 15,000	17,500
2006	earnings reported directly, no brackets			

Source: Qualification and Career Survey 1986-2006; imputed earnings in top category (column *highest*) from Pischke (2007).

Table 5: Multitasking by year and group

	I. Task-based measure				II. Tool-based measure		
	1986	1992	1999	2006	1986	1992	1999
A. Overall							
	1.965	2.227	4.229	6.266	10.052	12.762	15.149
	(1.227)	(1.531)	(2.035)	(2.219)	(6.401)	(8.140)	(8.826)
B. Educational level							
primary	1.549	1.533	2.999	5.173	5.682	6.590	9.405
	(0.919)	(0.927)	(1.789)	(2.409)	(4.573)	(5.661)	(7.121)
secondary	1.968	2.243	4.247	6.255	10.266	13.076	15.252
	(1.230)	(1.531)	(2.026)	(2.266)	(6.272)	(7.980)	(8.560)
tertiary	2.246	2.709	5.099	6.643	13.362	16.840	19.548
	(1.319)	(1.709)	(1.759)	(1.904)	(6.252)	(7.660)	(8.515)

Source: Qualification and Career Survey 1986-2006. Standard deviations are given in brackets.

Table 6: Level of multitasking of workers reporting recent changes

	1999		2006	
Type of change	Yes	No	Yes	No
Production techniques, machines, computers	4.81	3.77	6.54	5.60
New improved products/services	4.88	3.92	6.76	5.84
Restructuring/reorganisations	4.81	4.03	6.60	5.97
Relocation of tasks, work areas	4.87	4.21	–	–
Change in management or superiors	4.79	4.11	6.54	5.99

Source: Qualification and Career Survey 1986-2006. Question on the relocation of tasks and work areas is not available in 2006. All differences are statistically significant.

Table 7: Censored normal regression on Log gross real hourly wages; task-based measure

	(1) Std.	(2) All	(3) 1986	(4) 1992	(5) 1999	(6) 2006	(7) Interaction
Multitasking		0.0630***	0.0664***	0.0734***	0.0752***	0.104***	0.0611***
		(23.52)	(7.17)	(12.29)	(13.41)	(12.97)	(16.29)
Multitasking squared		-0.00378***	-0.00684***	-0.00636***	-0.00461***	-0.00654***	-0.00602***
		(-14.39)	(-4.40)	(-7.69)	(-7.94)	(-10.81)	(-16.21)
Secondary education	0.218***	0.189***	0.146***	0.212***	0.143***	0.220***	0.188***
	(34.95)	(30.13)	(9.79)	(22.47)	(12.67)	(11.78)	(29.90)
Tertiary education	0.571***	0.530***	0.488***	0.577***	0.450***	0.543***	0.528***
	(73.98)	(67.63)	(25.89)	(43.43)	(31.28)	(27.05)	(67.40)
Experience	0.0245***	0.0240***	0.0262***	0.0213***	0.0217***	0.0269***	0.0241***
	(42.77)	(42.15)	(21.24)	(21.33)	(20.47)	(19.74)	(42.23)
Experience squared	-0.000393***	-0.000379***	-0.000437***	-0.000352***	-0.000333***	-0.000385***	-0.000379***
	(-30.44)	(-29.54)	(-15.08)	(-15.66)	(-14.69)	(-12.40)	(-29.56)
Married	0.117***	0.111***	0.127***	0.0940***	0.120***	0.109***	0.112***
	(25.51)	(24.46)	(12.72)	(11.39)	(14.31)	(11.09)	(24.60)
Female	-0.0783***	-0.0708***	-0.0940***	-0.110***	-0.0483***	-0.0452***	-0.0705***
	(-13.29)	(-12.08)	(-7.39)	(-10.50)	(-4.50)	(-3.63)	(-12.04)
Married*Female	-0.130***	-0.125***	-0.136***	-0.121***	-0.137***	-0.113***	-0.126***
	(-18.15)	(-17.59)	(-8.27)	(-9.50)	(-10.54)	(-7.65)	(-17.75)
Part-time	-0.00875	0.00643	0.0579**	0.0583***	0.0421***	-0.0740***	0.00912
	(-1.39)	(1.02)	(3.28)	(5.03)	(3.87)	(-6.15)	(1.45)
Big city	0.0398***	0.0411***	0.0650***	0.0148*	0.0525***	0.0381***	0.0414***
	(12.03)	(12.56)	(9.21)	(2.55)	(8.96)	(4.98)	(12.64)
Year 1992*tasks							0.0134***
							(3.61)
Year 1999*tasks							0.0223***
							(6.08)
Year 2006*tasks							0.0362***
							(8.16)
Constant	2.432***	2.371***	2.411***	2.491***	2.447***	2.244***	2.388***
	(129.64)	(126.57)	(64.94)	(71.68)	(74.33)	(41.23)	(123.74)
Year dummies	Yes	Yes					Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sigma	0.402***	0.399***	0.408***	0.369***	0.380***	0.427***	0.399***
	(188.68)	(186.17)	(85.54)	(112.91)	(89.56)	(93.38)	(186.36)
pseudo R^2	0.268	0.280	0.233	0.314	0.284	0.251	0.281
N	66735	66735	14520	18304	18441	15470	66735

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Optimal level of multitasking

Year	Level
1986	4.854
1992	5.770
1999	8.156
2006	7.951

Note: The optimal level of multitasking is obtained by maximizing the equation $\ln w = \beta_1 s + \beta_2 s^2$, where s is the level of multitasking (the span of competence), and the β's are the regressions coefficients of models 3–6 (see table 7).

Table 9: Censored normal regression on Log gross real hourly wages; tool-based measure

	(1) All	(2) All	(3) 1986	(4) 1992	(5) 1999	(6) Interaction
Tools		0.0191***	0.0217***	0.0198***	0.0187***	0.0188***
		(32.38)	(16.38)	(19.08)	(17.98)	(29.07)
Tools squared		-0.000274***	-0.000404***	-0.000319***	-0.000234***	-0.000294***
		(-16.67)	(-8.03)	(-10.14)	(-9.45)	(-16.20)
Secondary education	0.203***	0.129***	0.0930***	0.154***	0.123***	0.128***
	(37.59)	(22.64)	(9.13)	(17.77)	(11.17)	(22.48)
Tertiary education	0.562***	0.453***	0.416***	0.504***	0.414***	0.452***
	(79.89)	(56.43)	(28.24)	(39.38)	(28.77)	(56.32)
Experience	0.0239***	0.0225***	0.0238***	0.0208***	0.0225***	0.0225***
	(45.76)	(41.30)	(25.05)	(23.00)	(22.04)	(41.33)
Experience squared	-0.000389***	-0.000365***	-0.000401***	-0.000340***	-0.000346***	-0.000365***
	(-33.14)	(-30.12)	(-18.18)	(-16.87)	(-15.90)	(-30.14)
Married	0.116***	0.111***	0.121***	0.0878***	0.116***	0.111***
	(27.24)	(24.06)	(15.31)	(11.45)	(14.19)	(24.10)
Female	-0.0786***	-0.0848***	-0.105***	-0.108***	-0.0433***	-0.0846***
	(-14.38)	(-14.51)	(-10.56)	(-11.12)	(-4.13)	(-14.48)
Married*Female	-0.135***	-0.136***	-0.146***	-0.121***	-0.139***	-0.136***
	(-20.21)	(-18.79)	(-11.50)	(-10.10)	(-10.88)	(-18.84)
Part-time	0.000977	0.0667***	0.0872***	0.0806***	0.0378***	0.0670***
	(0.16)	(10.03)	(6.73)	(7.25)	(3.58)	(10.09)
Big city	0.0395***	0.0403***	0.0597***	0.0110*	0.0445***	0.0403***
	(12.91)	(12.51)	(10.69)	(2.04)	(7.77)	(12.49)
Year 1992*tools						0.000915
						(1.64)
Year 1999*tools						0.00164**
						(2.76)
Constant	2.432***	2.390***	2.412***	2.500***	2.456***	2.396***
	(146.50)	(140.35)	(86.19)	(88.46)	(77.73)	(138.33)
Year dummies	Yes	Yes				Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sigma	0.399***	0.380***	0.396***	0.358***	0.378***	0.380***
	(202.06)	(173.98)	(103.34)	(116.90)	(90.06)	(173.97)
pseudo R^2	0.272	0.299	0.255	0.332	0.293	0.299
N	76617	61059	22014	20082	18963	61059

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Change in residual variance and Pseudo-R2

		σ	$\Delta\ \sigma$	$\frac{\text{+multitasking}}{\text{+educ./exp.}}$	Pseudo R2	Δ R2	$\frac{\text{+multitasking}}{\text{+educ./exp.}}$
1986	no skill measure	0.436			0.138		
	+ education	0.422	-0.014	10.90%	0.183	0.045	11.70%
	+ experience	0.409	-0.013	11.54%	0.227	0.044	12.07%
	+ multitasking	0.408	-0.002		0.233	0.005	
1992	no skill measure	0.407			0.174		
	+ education	0.382	-0.025	12.03%	0.266	0.092	13.18%
	+ experience	0.372	-0.010	30.30%	0.302	0.036	33.70%
	+ multitasking	0.369	-0.003		0.314	0.012	
1999	no skill measure	0.415			0.158		
	+ education	0.397	-0.018	31.98%	0.222	0.064	34.12%
	+ experience	0.386	-0.011	50.91%	0.263	0.041	52.93%
	+ multitasking	0.380	-0.006		0.284	0.022	
2006	no skill measure	0.471			0.127		
	+ education	0.449	-0.022	18.75%	0.190	0.064	20.63%
	+ experience	0.431	-0.018	23.86%	0.238	0.048	27.23%
	+ multitasking	0.427	-0.004		0.251	0.013	

Note: The column "$\frac{\text{+multitasking}}{\text{+educ./exp.}}$" shows how the change of σ and R2 due to adding multitasking compares to the change due to inclusion of education or work experience (in percent). Example for 1986: the reduction in σ due to adding education is -0.014, the reduction due to adding multitasking is -0.002. Calculating $-0.002/-0.014 = 0.109$ (= 10.90%)

Table B.1: Censored normal regression on Log gross real hourly wages with occupation dummies; task-based measure

	(1) Std.	(2) All	(3) 1986	(4) 1992	(5) 1999	(6) 2006	(7) Interaction
Tasks		0.0433***	0.0472***	0.0512***	0.0547***	0.0627***	0.0429***
		(16.47)	(5.25)	(8.85)	(9.92)	(7.91)	(11.74)
Tasks squared		-0.00244***	-0.00502***	-0.00417***	-0.00338***	-0.00376***	-0.00403***
		(-9.48)	(-3.33)	(-5.22)	(-5.97)	(-6.26)	(-11.17)
Secondary education	0.135***	0.122***	0.0736***	0.144***	0.0939***	0.169***	0.122***
	(20.52)	(18.47)	(4.73)	(14.19)	(7.90)	(9.27)	(18.49)
Tertiary education	0.356***	0.338***	0.279***	0.356***	0.283***	0.401***	0.338***
	(40.26)	(38.27)	(13.30)	(22.63)	(17.26)	(19.42)	(38.25)
Experience	0.0243***	0.0239***	0.0257***	0.0199***	0.0218***	0.0270***	0.0239***
	(43.45)	(42.88)	(21.59)	(20.37)	(21.04)	(20.39)	(42.91)
Experience squared	-0.000385***	-0.000374***	-0.000424***	-0.000322***	-0.000340***	-0.000386***	-0.000374***
	(-30.75)	(-29.99)	(-15.19)	(-14.66)	(-15.48)	(-12.88)	(-29.99)
Married	0.106***	0.102***	0.119***	0.0850***	0.109***	0.100***	0.103***
	(23.90)	(23.23)	(12.13)	(10.65)	(13.56)	(10.60)	(23.33)
Female	-0.106***	-0.0986***	-0.104***	-0.137***	-0.0726***	-0.0798***	-0.0981***
	(-17.82)	(-16.57)	(-8.03)	(-12.75)	(-6.65)	(-6.39)	(-16.48)
Married*Female	-0.122***	-0.119***	-0.133***	-0.114***	-0.131***	-0.105***	-0.119***
	(-17.53)	(-17.19)	(-8.33)	(-9.20)	(-10.37)	(-7.34)	(-17.30)
Part-time	0.00748	0.0174**	0.0704***	0.0712***	0.0481***	-0.0644***	0.0191**
	(1.20)	(2.80)	(4.06)	(6.30)	(4.48)	(-5.44)	(3.07)
Big city	0.0314***	0.0327***	0.0557***	0.00908	0.0437***	0.0273***	0.0329***
	(9.84)	(10.29)	(8.09)	(1.61)	(7.68)	(3.69)	(10.36)
Year 1992*tasks							0.00948**
							(2.65)
Year 1999*tasks							0.0137***
							(3.88)
Year 2006*tasks							0.0251***
							(5.91)
Constant	2.758***	2.715***	2.330***	2.369***	2.382***	2.622***	2.726***
	(8.89)	(8.64)	(16.21)	(25.80)	(9.60)	(8.10)	(8.61)
Year dummies	Yes	Yes					Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sigma	0.386***	0.385***	0.393***	0.353***	0.367***	0.410***	0.384***
	(181.56)	(180.18)	(81.90)	(110.68)	(86.30)	(91.65)	(180.28)
pseudo R^2	0.323	0.329	0.285	0.378	0.336	0.303	0.330
N	66538	66538	14469	18304	18358	15407	66538

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.2: Interval regression on Log gross real hourly wages; task-based measure

	(1) Std.	(2) All	(3) 1986	(4) 1992	(5) 1999	(6) Interaction
Tasks		0.0606***	0.0663***	0.0713***	0.0732***	0.0577***
		(18.65)	(7.21)	(12.65)	(13.74)	(14.75)
Tasks squared		-0.00398***	-0.00683***	-0.00629***	-0.00444***	-0.00522***
		(-10.47)	(-4.42)	(-8.08)	(-8.02)	(-11.80)
Secondary education	0.204***	0.177***	0.146***	0.210***	0.139***	0.175***
	(32.58)	(28.17)	(9.89)	(23.04)	(13.17)	(27.87)
Tertiary education	0.548***	0.506***	0.487***	0.548***	0.440***	0.504***
	(67.22)	(61.11)	(26.09)	(44.12)	(32.50)	(60.90)
Experience	0.0228***	0.0224***	0.0261***	0.0205***	0.0207***	0.0224***
	(38.31)	(37.74)	(21.35)	(21.52)	(20.81)	(37.80)
Experience squared	-0.000375***	-0.000362***	-0.000435***	-0.000341***	-0.000313***	-0.000363***
	(-28.18)	(-27.43)	(-15.15)	(-15.90)	(-14.77)	(-27.48)
Married	0.120***	0.114***	0.127***	0.0889***	0.118***	0.115***
	(23.97)	(23.08)	(12.78)	(11.28)	(14.64)	(23.13)
Female	-0.0854***	-0.0791***	-0.0927***	-0.106***	-0.0481***	-0.0790***
	(-13.47)	(-12.57)	(-7.35)	(-10.54)	(-4.72)	(-12.55)
Married*Female	-0.137***	-0.132***	-0.136***	-0.114***	-0.137***	-0.133***
	(-17.49)	(-17.02)	(-8.37)	(-9.29)	(-11.10)	(-17.10)
Part-time	0.0521***	0.0643***	0.0645***	0.0713***	0.0643***	0.0651***
	(7.38)	(9.16)	(3.75)	(6.34)	(6.27)	(9.27)
Big city	0.0426***	0.0438***	0.0648***	0.0145**	0.0513***	0.0441***
	(12.22)	(12.70)	(9.29)	(2.63)	(9.21)	(12.76)
Year 1992*tasks						0.00912*
						(2.51)
Year 1999*tasks						0.0186***
						(4.99)
Constant	2.469***	2.411***	2.412***	2.503***	2.468***	2.424***
	(127.94)	(124.34)	(65.23)	(76.64)	(77.85)	(122.44)
Year dummies	Yes	Yes			Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sigma	-0.987***	-0.995***	-0.908***	-1.067***	-1.027***	-0.995***
	(-165.19)	(-163.67)	(-80.90)	(-122.17)	(-95.00)	(-163.76)
pseudo R^2						
N	51265	51265	14520	18304	18441	51265

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.1: Original task definitions (as appearing in the German-only questionnaire)

	1986	1992	1999	2006
Res	Analysieren; forschen, erproben, prfen, messen	Analysieren; forschen, erproben, prfen, messen, planen	Entwickeln, forschen Informationen sammeln/auswerten, recherchieren	Entwickeln, forschen, konstruieren Informationen sammeln, recherchieren, dokumentieren
Des	Planen, konstruieren, entwerfen/gestalten, zeichnen	Konstruieren, entwerfen, zeichnen, knstlerisch gestalten *Kenntnisse Konstruktionszeichnen, technisches Zeichnen*	*Kenntnisse Gestaltung, Design, Visualisierung, Medien, Layout*	*Kenntnisse Layout, Gestaltung, Visualisierung*
Pro	EDV-Ttigkeiten, programmieren	EDV-Ttigkeiten, programmieren *Kenntnisse Programmieren, Datenverarbeitung (EDV-Software)*	*Kenntnisse Entwicklung von Computersoftware, Programmieren, Systemanalyse*	Software entwickeln, programmieren, Systemanalyse
Rul	Gesetze/Vorschriften anwenden, auslegen; beurkunden	Gesetze/Vorschriften anwenden, auslegen; beurkunden *Kenntnisse Arbeitsrecht (Betriebsverfassungsgesetz, Tarifrecht, Kndigungsschutz u..)* *Kenntnisse Sonstige Rechtskenntnisse*	*Kenntnisse Arbeitsrecht (Betriebsverfassungsgesetz, Tarifrecht, Kndigungsschutz u..)* *Andere Rechtskenntnisse*	*Rechtskenntnisse*
Org	Disponieren, koordinieren, organisieren; fhren/leiten (Management, Controlling)	Entscheiden, koordinieren, organisieren, disponieren *Kenntnisse Betriebsfhrung/Management, Organisation, Personalwesen*	Organisieren, planen (ber die unmittelbare Vorbereitung der eigenen Arbeit hinaus)	Organisieren, planen, vorbereiten von Arbeitsprozessen
Tea	Erziehen/lehren/ausbilden; beratend helfen	Erziehen, lehren, ausbilden, beratend helfen *Kenntnisse Erziehung, Pdagogik, Psychologie*	Ausbilden, lehren, unterrichten	Ausbilden, lehren, unterrichten, erziehen
Sel	Kaufen/verkaufen, kassieren; vermitteln, Kunden beraten, verhandeln, werben	Kaufen, verkaufen, kassieren, vermitteln, Kunden beraten, werben *Kenntnisse Einkauf, Beschaffung* *Kenntnisse Vertrieb/Verkauf, Marketing, Werbung*	Andere Beraten, informieren Einkaufen, beschaffen, verkaufen Werben, ffentlichkeitsarbeit/PR, Marketing, Akquirieren *Kenntnisse Vertrieb, Marketing, Werbung, PR/ffentlichkeitsarbeit*	Beraten, informieren Einkaufen, beschaffen, verkaufen Werben, Marketing, ffentlichkeitsarbeit, PR
Pre	Publizieren, unterhalten, vortragen	Publizieren, unterhalten, vortragen, gestalten	*Kenntnisse Vortragstechnik, freie Rede, Verhandlungsfhrung*	
Man	Mitarbeiten anleiten/anweisen, einstellen	Personal einstellen, Mitarbeiter anleiten, kontrollieren, beurteilen	*Kenntnisse Management, Personalfhrung, Organisation, Planung*	*Kenntnisse Projektmanagement*
Cal	Kalkulieren/berechnen, buchen	Kalkulieren, berechnen, buchen *Kenntnisse Buchhaltung, Rechnungswesen* *Kenntnisse Geld-/Kredit-/Steuerwesen; Finanzierung*	*Kenntnisse Finanzierung, Kreditwesen, Steuern* *Kenntnisse Rationalisierungstechniken, Arbeitsstudien, Kostenwesen/Controlling*	*Kaufmnnische, betriebswirtschaftl. Kenntnisse*
Tex	Schreibarbeiten/Schriftverkehr, Formulararbeiten	Schreibarbeiten/Schriftverkehr, Formulararbeiten *Kenntnisse Schreibmaschine schreiben*	*Kenntnisse Deutsch, Rechtschreibung, schriftlicher Ausdruck*	*Kenntnisse Deutsch, Rechtschreibung, schriftlicher Ausdruck*
Ope	Maschinen, Automaten, Anlagen bedienen, steuern, beschicken	Maschinen/Anlagen bedienen, steuern, beschicken *Kenntnisse Computertechnik (EDV-Hardware)*	berwachen, steuern von Maschinen, Anlagen, technischen Prozessen	berwachen, steuern von Maschinen, Anlagen, techn. Prozessen
Rep	Reparieren, warten, instandsetzen	Maschinen/Anlagen reparieren, warten, instandsetzen	Reparieren, instandsetzen	Reparieren, instandsetzen
Ser	Bewirten, beherbergen Bgeln, reinigen/Abfall beseitigen, entsorgen	Bewirten, servieren, beherbergen Putzen, bgeln, reinigen Abfall beseitigen, entsorgen	Versorgen, bedienen, betreuen von Menschen	Bewirten, beherbergen, Speisen bereiten Reinigen, Abfall beseitigen, recyceln
Ins	Stoffe erzeugen, ausformen; verarbeiten/bearbeiten; kochen Bauen/ausbauen, installieren, montieren	Stoffe erzeugen, ausformen, verarbeiten, bearbeiten, Speisen bereiten Gebude/Anlagen/Gerte bauen, ausbauen, installieren, montieren	Herstellen, produzieren von Waren und Gtern	Herstellen, produzieren von Waren und Gtern
Sec	Sichern (Arbeitssicherheit-, Werkschutz-, Verkehrsregelung), bewachen	Sichern, bewachen (Gebude, Verkehr, Arbeitsschutz) *Kenntnisse Unfallverhtung, Sicherheits- und Umweltvorschriften*	*Kenntnisse Arbeitsschutz, Unfallverhtung, Sicherheits- und Umweltvorschriften*	Sichern, beschtzen, bewachen, berwachen, Verkehr regeln
Nur	Pflegen/versorgen, medizinisch/kosmetisch behandeln	Pflegen, bersorgen, medizinisch/kosmetisch behandeln, frisieren *Kenntnisse Medizinische Kenntnisse*	*Kenntnisse Medizinische Kenntnisse*	Pflegen, betreuen, heilen *Kenntnisse med., pflegerischer Bereich*