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Abstract

This paper sheds light on how changes in the organization of work can help to understand increasing 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 helps to explain (1) rising wage inequality between groups, and (2) rising wage inequality within groups. Under certain assumptions, it also helps to explain (3) the polarization 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.

JEL-Code: J310, J240, L230.

Keywords: wage inequality, multitasking, tasks, organizational change.

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1. Introduction

Earnings inequality has risen substantially in many advanced countries during the past three decades. At the same time, significant changes in the organization of work have taken place in many OECD countries. This paper provides a theoretical and empirical analysis that helps explain important developments in wage inequality in terms of observed changes in the organization of work. The developments in wage inequality comprise rising wage inequality between skill groups, and increasing wage inequality within skill groups.[1] The changes in the organization of work comprise a multitude of organizational innovations, many of which have resulted in a broadening of workers' job task portfolios.

In our theoretical analysis, we argue that task portfolios become broader when new complementarities between different tasks arise or when workers can better exploit existing complementarities. This occurs as a result of exogenous technological change, e.g. advances in telecommunication technology or computerized versatile machines. We refer to a task portfolio of complementary tasks as the worker's span of competence. The span of competence varies along the skill distribution. Higher skilled workers have a wider span of competence than lower skilled workers because they (i) they are more able to exploit complementarities across tasks, and (ii) their jobs feature more complementarities to be exploited. As more complementarities between tasks arise due to technological change, they experience a rise in their productivity and wages relative to lower-skilled workers, which contributes to rising wage inequality. We call the resulting wage differential “multitasking premium”.

The empirical analysis shows how cross-section and time-series variations in workers' span of competence provide support for the predictions of the theoretical analysis. Using representative data of the German labour force between 1986 and 2006, we construct two simple empirical measures of the span of competence: one based on the number of tasks carried out by a worker and one based on the number of workplace tools used by a worker. Then, we first document the growing importance of multitasking at workplaces. Second, we provide evidence for a multitasking premium and show that it is rising over time. Third, we show that our measure of multitasking can explain a growing fraction of wage inequality within education groups. On the basis of this finding, we argue that multitasking represents an indicator for previously unobserved ability, namely versatility.

The paper is organized as follows. Section 2 summarizes the relevant literature and thereby provides the background for our study. Our theoretical analysis follows in section 3. Section 4 describes our data and explains the construction of the measures of multitasking. The empirical results are presented in section 5. Section 6 concludes.

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[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; Appelbaum et al., 2008). Hierarchies have become flatter, decision-making has become more decentralized (Caroli and Van Reenen, 2001), team work has become more important (OECD, 1999; Carstensen, 2001), job rotation and quality circles are more frequently used (Osterman, 2000). Many of these organizational changes have in common that workers subsequently perform broader sets of tasks. For example, flatter hierarchies may lead to more work autonomy; team work implies more involvement of employees in each other’s work processes and requires knowledge of the tasks of team members; job rotation directly implies that the worker carries out different tasks. In this article, we refer to this as an increase in the workers’ spans of competence.

A number of studies provide evidence that these organizational innovations have often gone hand in hand with technological innovations, such as improvements in information and communication technologies (ICTs) or ICT-enabled versatile machines capable of producing a greater variety of customized products. In fact, technical and organizational changes are complementary (see e.g. Caroli & Van Reenen, 2001; Brynjolfsson & Hitt, 2000; Bresnahan et al., 2002; Aghion et al., 2002; Bauer & Bender, 2004). For example, Bartel et al. (2007) report that IT-enhanced machinery required additional skills from the machine operators, namely technical and problem-solving skills. In other words, the workers’ spans of competence became broader as a result of technology adoption. Likewise, Brynjolfsson and Hitt (2000) state that “a significant component of the value of information technology is its ability to enable complementary organizational investments such as business processes and work practices” (p. 24). While a large literature carried out firm-level and aggregate analyses of organizational change and its effect on productivity, the implications of this workplace transformation for the individual in terms of tasks and wages remained largely unexplored thus far.

A detailed explanation of how various driving forces (including technological change) have affected the spans of competence of workers is provided by Lindbeck and Snower (1996; 2000). They argue that, first, the introduction of computerized information and communication systems has enabled workers to gain access to information about the work of colleagues and has enabled them to communicate more easily. As a result, employees have become more involved in each other’s tasks. Second, the introduction of flexible machine tools and programmable equipment has required workers to become more versatile in the tasks they carry out. For example, communication with customers who buy customized products that can be produced with the flexible machinery has become more important. Third, the widening of human capital, in the sense that employees acquired a variety of skills rather than a specialized skill, has enabled firms to integrate previously separated tasks within workers.

The price of ICT equipment has fallen rapidly over the past decades (e.g. Autor et al., 2003). This implies a decline in communication and coordination costs, which is usually associated with more specialization of workers (e.g. Becker & Murphy, 1992). These theories argue that coordinating specialized workers and inputs is costly, and – as costs decline – we should observe more multitasking. Yet, as documented above, we observe less specialization and more multitasking among workers. A few papers have provided a rationale for why multitasking may occur also against the background of falling coordination costs. Lindbeck and Snower (2000) explain the emergence of multitasking by the benefits of intertask learning, where the productivity in one task is increased when the workers can also draw upon knowledge and experience obtained from performing another task. Intertask learning is facilitated by ICT equipment and is likely to become more important as the price of ICT equipment falls.

Dessein and Santos (2006) argue that, by adopting improved ICTs, firms become more adaptive to a changing business environment.[2] It is then shown that, if an organization is adaptive, it can be optimal for the firm to allow its employees flexibility in the tasks they perform (i.e. task bundling) because workers can then exploit private information necessary for adaptation, and avoid costly coordination by bundling tasks. If workers would specialize instead and hence perform a predefined task, private information would either be left unused (with coordination not necessary), or—if adaptive—private information would be used, but would also require costly and imperfect communication between specialized employees. Borghans and ter Weel (2006) argue that computer technology has made workers more productive in separate tasks, which decreases the relative benefits from increased specialization, and may thus lead to multitasking.

Next to sweeping organizational changes, the wage structure has also changed significantly in many advanced countries during the past three decades. In the US, wage inequality has grown strongly during the 1980s and the earnings distribution has started to polarize more recently (Goldin & 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 & Slaughter, 2001; Goos & Manning, 2007; Dustmann et al., 2009). A major contributor to rising overall inequality is the educational wage differential (college premium), which has, for example, increased strongly since the 1980s in the US and since the 1990s in Germany (Autor et al., 2008; Dustmann et al., 2009). However, observable

[2] Similarly, versatile machines would indicate an adaptive strategy.

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 & Autor, 1999).

In the mainstream literature, the increasing college premium is explained primarily through globalization, de-industrialization, and skill-biased technological change (SBTC), with the last playing a particularly prominent role. Demand for unskilled labour has faltered, while demand for skilled labour has increased. These developments were also reflected in the wage distribution (e.g. Katz & Autor, 1999; Goldin & Katz, 2007). Yet, each of these explanations is, to some degree, a “black box” comprising various economic phenomena, including changes in spans of competence of workers. 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.

There are various problems with the conventional explanations. 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, technological change 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). We think that these problems may partly be a result of the above-mentioned black box character of the explanations.

Indeed, some contributors have suggested that technological change affects the wage structure primarily through organizational changes in the workplace (Caroli & Van Reenen, 2001; Bresnahan et al., 2002). With changes in the spans of competence of workers, we here suggest one possible avenue by which technological change affects the organization of work and thereby individual wages. 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 workers’ spans of competence evolved over time 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 & Kahn, 2005). Hence, it is still an open question what constitutes these unobserved skills that seem to drive within-group inequality. As we suggest in this paper, a worker's span of competence may capture some of this unobserved heterogeneity within skill groups.

3. A Theoretical Model of the Span of Competence

We now present a theoretical model where exogenous technological changes such as improvements in ICT capital or ICT-enabled versatile machinery, and a widening of the human capital base trigger a reorganization of work. In particular, workers set the width of their span of competence, which depends positively on the skill level (defined in terms of education). We also show that there is a multitasking premium and show how wage inequality can increase via changes in the spans of competence. Our analysis also indicates how the multitasking premium can contribute to explaining the recently observed decoupling of the income distribution (cf. Autor et al., 2006; 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 complementary with the primary one but not necessarily part of the occupation's core activity. Practical examples are easy to adduce. For example, a car mechanic's primary task is to repair car parts, while secondary tasks may include customer relations, selling car insurance, and so on. A craftman's primary task may be installing machines, while secondary tasks could involve cleaning and selling. A teacher's primary task is teaching, while secondary tasks can involve purchasing school equipment, organizing school trips, and so on. The greater the number of secondary tasks, the greater we consider a worker's span of competence to be. To begin with, we consider a one-period model, although the phenomena described here occur through time. A multi-period case is discussed in appendix B.

The primary tasks $\hat{x}_i$ can be ordered according to skill along a line, from low-skilled to high-skilled tasks. We define the primary task in efficiency units, so that $\hat{x}_i$ represents the worker's productivity per unit of time spend on the primary task. Workers choose combinations of tasks clustered symmetrically 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 $[(\hat{x}-(s/2)),(\hat{x}+(s/2))]$, where *s* is the worker's span of competence. Our analysis provides a choice theoretic rationale for this span of competence. Note that, 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 labour services devoted to the primary task are $(T-s)\hat{x}$ and effective labour services devoted to the secondary tasks are

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

3.2. Production

We assume that the productivity of a worker is the sum of (i) returns to specialization (learning by doing) and (ii) returns to complementarities, which we will refer to as informational task complementarities.[3] Returns to specialization imply that the more time the worker devotes to a task, the more productive she becomes at that task. Informational task complementarities are the result of intertask learning. If a worker is skilful in task A, this knowledge might help him to be also more skilful at task B (cf. Lindbeck & Snower, 2000). Or, in terms of our model, if a worker is skilful in his primary task $\hat{x}$, this knowledge might make him also more skilful in the secondary tasks s. We model informational task complementarities 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) the productivity per unit of time at the primary task $\hat{x}$, (ii) the time devoted to the primary task $(T - s)$ and (iii) learning-by-doing y. We assume that $y = \frac{1}{2}(T-s)$ for simplicity.[4] Then, we obtain

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

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[3] This analysis is in the spirit of Lindbeck and Snower (2000). In practice, learning by doing and the exploitation of informational task complementarities are dynamic processes. This section makes the simplifying assumption of collapsing these processes into a single time period. Appendix B provides a multi-period analysis.

[4] This assumption is arbitrary and is made for simplicity. Intuitively, it means that learning by doing improves productivity at a rate that is half the time spent on the task.

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

$$\text{itc} = \gamma\left((T-s)\hat{x}\right)\left(s\hat{x}\right) = \gamma(T-s)s\hat{x}^2 . \tag{3}$$

Note that the parameter γ governs the magnitude of informational task complementarities. The worker's production function is the sum of the two above effects:

$$q = \frac{1}{2}(T-s)^2\,\hat{x} + \gamma(T-s)s\hat{x}^2 . \tag{4}$$

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

$$s^* = \frac{T(\hat{x}\gamma - 1)}{2\hat{x}\gamma - 1}, \tag{5}$$

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

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

$$\frac{\partial s^*}{\partial \hat{x}} = \frac{T\gamma}{(2\gamma\hat{x} - 1)^2} > 0 . \tag{6}$$

The output generated through this optimal span of competence is

$$q^* = \frac{T^2\hat{x}^3\gamma^2}{2(2\hat{x}\gamma - 1)}. \tag{7}$$

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

$$q' = \frac{1}{2}T^2\hat{x} . \tag{8}$$

Thus the multitasking premium is

$$q*-q'=\frac{T^2\hat{x}^3\gamma^2}{2(2\hat{x}\gamma-1)}-\frac{1}{2}T^2\hat{x}$$
$$=\frac{T^2\hat{x}(\hat{x}\gamma-1)^2}{2(2\hat{x}\gamma-1)}. \tag{9}$$

The parameter γ governs the magnitude of informational task complementarities. It is exogenous and affected by improvements in ICT and versatile physical capital, and through the widening of human capital (see above). Observe that the span of competence depends positively informational task complementarities:

$$\frac{\partial s*}{\partial\gamma}=\frac{T\hat{x}(2\gamma\hat{x}-1)-2\hat{x}T(\hat{x}\gamma-1)}{(2\hat{x}-\gamma)^2}=\frac{-T\hat{x}+2\hat{x}T}{(2\hat{x}-\gamma)^2}=\frac{T\hat{x}}{(2\gamma\hat{x}-1)^2}>0\,. \tag{10}$$

In section 2, we discussed various empirical evidence that technology adoption indeed goes hand in hand with organizational changes affecting the spans of competence of workers, hence lending empirical support to the relationship in equation 10. Our data, which is introduced below, also allow us to approximately investigate this relationship between multitasking and its suggested driving forces empirically. In the questionnaires, respondents were asked to indicate whether the following changes occurred in their firms during the past two years: (i) adoption of new production techniques, machines, materials or computers; (ii) introduction of new and improved products or services; and (iii) restructurings or reorganizations. In appendix A, we show that such recent changes are indeed related to a higher level of multitasking of workers. Similar evidence has been reported by Appelbaum et al. (2008), Caroli and Van Reenen (2001) for the UK and France, and Carstensen (2001) for Germany.

Note, at this point, that the span of competence mirrors both worker and firm characteristics. In order for multitasking to occur, workers must have versatile skills on the one hand, and firms must be able to make use of this flexibility on the other hand. This is reflected in the above-mentioned driving forces of multitasking. A broadening of human capital has given workers greater versatility and improved ICTs and versatile capital has enabled firms to mobilize this versatility.[5]

[5] With respect to multitasking being a worker characteristic, our measure can be interpreted as measuring previously unobserved ability.

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

$$s^* = \frac{T(\hat{x}_i\gamma_i - 1)}{2\gamma_i\hat{x}_i - 1}. \qquad (11)$$

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

$$q_h - q_l = (T\gamma)^2\left(\frac{\hat{x}_h^{\ 3}}{2(2\hat{x}_h\gamma - 1)} - \frac{\hat{x}_l^{\ 3}}{2(2\hat{x}_l\gamma - 1)}\right). \qquad (12)$$

An increase in γ has a striking effect on the wage differential. In our model, a doubling of 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). 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 corresponding task-complementarity parameters. The income of a worker in skill class *i* is

$$q_i = \frac{T^2\hat{x}_i^{\ 3}\gamma_i^{\ 2}}{2(2\hat{x}_i\gamma_i - 1)}. \qquad (13)$$

Using the data introduced below, we calculate that the average level of multitasking in occupations that intensively use routine tasks is lower than in nonroutine-intensive occupations (2.66 vs. 2.17 tasks).[6] This suggests that jobs intensive in routine tasks offer relatively few opportunities for expanding the span of competence. To capture this characteristic of routine white-collar work, we suppose that as the task-complementarity parameter rises, 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 and our analysis can thereby account for a decoupling of the wage distribution.

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 1986, 1992, 1999, and 2006, and can thus cover a period of 20 years.[7] This makes the dataset particularly suitable for our analysis, because the 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 & Pischke, 1997; Pischke, 2007; Spitz-Oener, 2006). It samples from employed persons aged between 16 and 65.

[6] 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). These task inputs per occupation are averaged over the sample period. Then, occupations with a larger (non-)routine task input are designated (non-)routine task-intensive and the average multitasking is calculated.

[7] 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.

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 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.

4.1. A Task-Based Measure of Multitasking

A distinctive feature of our data is that every respondent is asked 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, there are 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 we can nonetheless generate two consistent multitasking measures.

Table D.1 in the appendix provides a detailed overview of the exact wording and occurrence of the items. We follow 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 D.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 D.1). Note that some of the tasks can only be identified either via the direct way or via the indirect way. 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. In addition, 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) across all four survey waves. We hence use the direct question to code these tasks and mark them accordingly in column 3 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 use the *direct* answers in years I and II, together with the *indirect* answers in years II, III, and IV. We flag these cases in column 4 of table 1. 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.

Table 1 – Tasks and comparability over time

Key	Task description	(1) Direct comparable	(2) Indirect comparable	Correlation (1), (2)	Included in measure
res	Researching, analyzing, evaluating and planning	Yes	-		Yes
des	Making plans/constructions, designing, sketching	-	-		-
pro	Working out rules/prescriptions, programming	-	Yes	0.539	Yes
rul	Using and interpreting rules	-	Yes	0.402	Yes
org	Negotiating, lobbying, coordinating, organizing	Yes	-		Yes
tea	Teaching or training	Yes	-		Yes
sel	Selling, buying, advising customers, advertising	Yes	-		Yes
pre	Entertaining or presenting	-	-		-
man	Employing or managing personnel	-	-		-
cal	Calculating, bookkeeping	-	Yes	0.541	Yes
tex	Correcting texts/data	-	-		-
ope	Operating or controlling machines	Yes	-		Yes
rep	Repairing or renovating houses, apartments, machines, vehicles	Yes	-		Yes
ser	Serving or accommodating	Yes	-		Yes
ins	Manufacture, install, construct	Yes	-		Yes
sec	Secure	-	Yes	0.185	-
nur	Nurse or treat others	-	Yes	0.599	-

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.

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. The measure 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 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.[8] Unfortunately, the question about workplace tools has been dropped in the latest wave of the survey, so that this part of the analysis is restricted to the period 1986 to 1999.

Table 2 – Workplace tools and versatility classification

Degree of versatility	Tool
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 equipment 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

Workplace tools are a good proxy for tasks. To see this, consider the example of a 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 tools, we can infer that the typical woodworker is performing tasks such as lumbering, transporting wood, transforming it into new forms. However, some of the woodworkers are also involved in sales or bookkeeping tasks. A larger portfolio of tasks is hence reflected in a higher number of tools the worker uses. Note that also Becker et al. (2009) use workplace tools as a proxy for the task content of a job.

[8] Details about the aggregation can be obtained from the authors upon request.

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

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.[9]

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.[10] 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.[11] In year IV, we can abstain from imputation because respondents were asked to indicate the exact amount of their gross monthly earnings. We convert monthly earnings into real hourly wages by first dividing them by the reported hours worked and then deflating them by the CPI in the respective year (as provided by the German Statistical Office).[12]

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[9] 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.

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

[11] We employ censored normal regressions in order to account for censoring in the wage data. In appendix C.1, we also provide the results of interval regressions to account for the bracket structure (von Fintel, 2007).

[12] Table 4 shows that the top category of earnings in 1992 is much lower than in 1986 and 1999. However, this

Table 3 – Tasks carried out by Electricians, 1986-1999

Year	Tool	% 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.

The other variables which enter our regression analysis as control variables are dummies for educational attainment, years of work experience, and dummies for married, female, the interaction of the two, working part-time and residing in a city. Educational attainment refers to the highest qualification obtained by a respondent and includes 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

is not a limitation for our purpose because even with the lower top category in 1992, almost the entire German wage distribution is covered. Censoring only affects the top 2 percent of the distribution in 1992.

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.

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 precisely, no brackets			

Note: imputed earnings in top category (column "Highest") from Pischke (2007).

5. Results

We now present evidence for some of the predictions of the theoretical model discussed above.[13] Before proceeding to the results, we quickly summarize the 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 significant changes in the organization of work, which should be reflected in an increased level of multitasking of workers (cf. NUTEK, 1999; Caroli & Van Reenen, 2001). Second, we expect the level of multitasking to differ between workers with different educational level. 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

In order to obtain an idea about the importance of multitasking, we first look at the extent and development of multitasking over time in Germany. Table 5 shows summary statistics of our two measures of multitasking for all workers and by educational level. To begin with, it

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

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 1992. Both independent measures of multitasking, task-based and tool-based, paint roughly the same picture.

Table 5 – Multitasking by year and educational attainment

	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)

Note: Standard deviations are given in brackets.

Importantly, also 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. We can rule out that the increase in multitasking is resulting from a changing occupational composition of the workforce because this result also holds within occupations and when occupational employment is kept constant at its 1986 structure.

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", i.e. the difference in multitasking levels between higher- and lower-educated workers 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. Between 1986 and 1999, the multitasking gap between workers with tertiary and secondary, and between workers with secondary and primary education also increased. After 1999 is decreased slightly.

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. Furthermore, we include occupation fixed effects in order to control for the general nature of the job. After all, some occupation may, by their very nature, require more tasks to be performed by workers. In the pooled regressions, we also include year dummies. The endogenous variable is the 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.

The estimation results using our task-based measure of multitasking are shown in table 6. Model 1 is based on the pooled sample (all years) and serves as a benchmark model. It is equivalent to a standard wage regression without multitasking measures. The results are in line with usual estimates (e.g. DiNardo & Pischke, 1997).[14] 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 6 per cent higher wage.[15]

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[14] 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.

[15] 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.

Table 6 – Censored normal regression on Log gross hourly wages, task-based measure

	(1) Benchmark	(2) Pooled	(3) 1986	(4) 1992	(5) 1999	(6) 2006	(7) Interaction
Multitasking		0.0433***	0.0472***	0.0512***	0.0547***	0.0627***	0.0429***
		(16.47)	(5.25)	(8.85)	(9.92)	(7.91)	(11.74)
Multitasking^2		-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 educ.	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 educ.	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^2	-0.00039***	-0.00037***	-0.00042***	-0.00032***	-0.00034***	-0.00039***	-0.00037***
	(-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***	2.591***	2.624***	1.774***	2.622***	2.726***
	(8.89)	(8.64)	(26.60)	(41.45)	(10.30)	(8.10)	(8.61)
Year dummies	Yes	Yes	No	No	No	No	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sigma	0.386***	0.385***	0.393***	0.353***	0.367***	0.410***	0.384***
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

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Hence, the regressions reveal the existence of a multitasking premium and thereby confirm the predictions from the theoretical model. The negative coefficient for the square indicates diminishing returns to multitasking. Multicollinearity is limited since the coefficients only change very little compared to the benchmark.

Models 3–6 display the estimation results separately for each year and convey that the multitasking premium is increasing over time. To better illustrate the changing relationship between multitasking and wages, we plot multitasking-wage profiles in figure 1. The graph displays, separately for each year, a quadratic fit through the predicted log hourly wage for each level of multitasking. The multitasking-wage profile becomes steeper over time, implying a rising multitasking premium. The increasing steepness is driven by the increasing coefficient of the level of multitasking. If the increasing steepness is statistically significant can be tested using model 7. Here, 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 differences are statistically significant at a 1 per cent level.

The coefficient of the square is rather large relative to the linear effect. This results 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 level (i.e. the point at which the downward-sloping section of the multitasking-wage profile begins) for each year in table 7. As our theoretical model predicts, the optimal span of competence increases over time: it was lower in earlier years when multitasking-enhancing technologies and organizational forms were not yet available or implemented. Yet, the ongoing change and implementation of the new technologies and organizational structures throughout the 20-year period shifted the optimal span of competence outwards.

Figure 1 – Multitasking-wage profile, by year

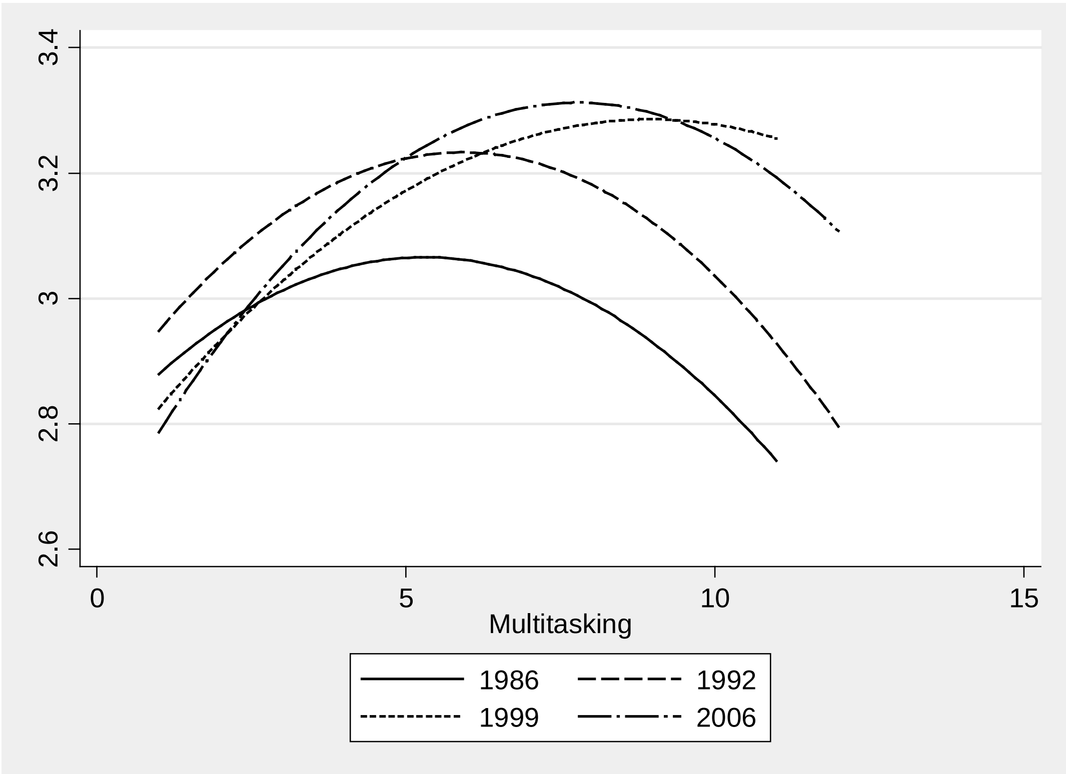

Table 7 – Optimal level of multitasking, by year

Year	Optimal level of multitasking
1986	4.701
1992	6.139
1999	8.092
2006	8.338

Note: The optimal level of multitasking is obtained by maximizing $\ln w = \beta_1 s + \beta_2 s^2$ with respect to *s*, where *s* is the span of competence and the β's are the regression coefficients for multitasking and the square of multitasking in models 3-6.

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 not 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. Accordingly, higher skilled workers benefitted relatively more from the multitasking premium than lower skilled workers. This leads to greater wage dispersion between groups and within groups.

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 the 2006 multitasking-wage profile is below the profile of earlier years. 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.

In table 8, we repeat the estimations using the tool-based measure of multitasking. The sample is larger for this exercise 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 0.6 per cent higher wage.[16] 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-

[16] The effect is calculated at the mean level of tool-based multitasking $s = 12.36$.

based measure, the yearly regressions do not confirm an increase in the multitasking premium over time. 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 (even though the difference to the 1992 coefficient is not statistically significant). Yet, the similarity of the results with the task- and tool-based measure of multitasking is striking because the two measures are truly independent from one another.

Table 8 – Censored normal regression on Log gross real hourly wages, tool-based measure

	(1)	(2)	(3)	(4)	(5)	(6)
	Benchmark	Pooled	1986	1992	1999	Interaction
Tools		0.0128^{***}	0.0121^{***}	0.0142^{***}	0.0114^{***}	0.0109^{***}
		(20.86)	(6.60)	(12.29)	(10.40)	(13.71)
Tools^2		-0.000175^{***}	-0.000225^{***}	-0.000227^{***}	-0.000125^{***}	-0.000180^{***}
		(-10.63)	(-3.71)	(-6.87)	(-5.06)	(-9.51)
Secondary educ.	0.123^{***}	0.0914^{***}	0.0632^{***}	0.131^{***}	0.0921^{***}	0.103^{***}
	(21.59)	(15.35)	(4.02)	(12.58)	(7.37)	(14.36)
Tertiary educ.	0.344^{***}	0.288^{***}	0.264^{***}	0.340^{***}	0.272^{***}	0.301^{***}
	(42.50)	(31.80)	(12.41)	(21.29)	(16.03)	(29.61)
Experience	0.0237^{***}	0.0222^{***}	0.0257^{***}	0.0201^{***}	0.0223^{***}	0.0228^{***}
	(46.45)	(41.49)	(21.59)	(20.93)	(21.53)	(38.16)
Experience^2	-0.00038^{***}	-0.00036^{***}	-0.00042^{***}	-0.00032^{***}	-0.00035^{***}	-0.00037^{***}
	(-33.28)	(-30.21)	(-15.14)	(-14.94)	(-15.68)	(-27.41)
Married	0.105^{***}	0.103^{***}	0.117^{***}	0.0812^{***}	0.108^{***}	0.104^{***}
	(25.52)	(23.10)	(11.93)	(10.15)	(13.41)	(21.10)
Female	-0.109^{***}	-0.105^{***}	-0.102^{***}	-0.130^{***}	-0.0672^{***}	-0.0996^{***}
	(-19.56)	(-17.37)	(-7.81)	(-12.06)	(-6.11)	(-14.91)
Married*Female	-0.126^{***}	-0.131^{***}	-0.132^{***}	-0.114^{***}	-0.135^{***}	-0.130^{***}
	(-19.42)	(-18.37)	(-8.27)	(-9.20)	(-10.58)	(-16.47)
Part-time	0.0176^{**}	0.0723^{***}	0.0763^{***}	0.0817^{***}	0.0494^{***}	0.0662^{***}
	(3.01)	(10.95)	(4.33)	(7.12)	(4.56)	(9.06)
Big city	0.0317^{***}	0.0344^{***}	0.0529^{***}	0.0113^{*}	0.0386^{***}	0.0337^{***}
	(10.74)	(10.93)	(7.72)	(2.01)	(6.79)	(9.72)
Year 1992*tools						0.00218^{***}
						(3.39)
Year 1999*tools						0.00226^{***}
						(3.41)
Constant	2.775^{***}	2.469^{***}	2.570^{***}	2.596^{***}	1.763^{***}	2.535^{***}
	(8.88)	(48.02)	(25.56)	(41.55)	(9.97)	(50.38)
Year dummies	Yes	Yes	No	No	No	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Occup. dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sigma	0.384^{***}	0.369^{***}	0.390^{***}	0.349^{***}	0.365^{***}	0.369^{***}
pseudo R^2	0.327	0.340	0.289	0.386	0.338	0.337
N	76382	60887	14297	17759	18044	50100

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In appendix C, we present two further robustness checks. First, remember that earnings were reported in brackets in the years 1986 to 1999. In the censored normal regressions above, we made use of midpoint imputation, assuming that brackets were sufficiently small for results to be unbiased. In appendix C.1, we additionally estimate the equations using interval regressions. The previous results are confirmed.

Second, our empirical strategy may be criticized with regard to the orthogonality of the multitasking measure and the kinds of tasks the worker carries out. In fact, it may be the case that a high degree of multitasking may be observed mainly for workers who carry out a lot of highly rewarded tasks. A low degree of multitasking may be observed mainly for workers who carry out low-return tasks. In this case, the multitasking variable would in fact measure the returns to highly rewarded tasks and not the true effect of multitasking. Accordingly, we add also tasks to the equations. The results in appendix C.2 show that our previous estimates are robust to this inclusion.

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 two measures of skill in wage regressions: education and work experience. First, we re-estimate the wage equations 3 to 6 from table 6 without any measure of skill and report the residual standard deviation σ and the *R2* of the regression (see table 9).[17] Then we add either education, experience, or multitasking as indicators for skill, again reporting σ and *R2*.[18] This allows us to compare the additional explanatory power of the three variables and compare them to one another. The column entitled "Comparison" shows how the size of the change in σ and *R2* 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 four-fifth as important as including educational attainment into a simple wage regression, and that it is up to one-third as important as including work experience. The size of this effect is striking because, after all, we compare it with two of the major skill types that matter for wages.

This result implies that multitasking can explain a small, but growing fraction of residual wage inequality because residual wage inequality (or within-group inequality) is measured by the standard deviation of the regression residuals (σ in table 9). It is 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

[17] Actually, the figure reported is not the R^2 because the regressions are estimated using maximum likelihood. However, Stata reports an artificial pseudo-R^2, which is valid for comparing models.

[18] We consider multitasking as a proxy for versatility and thus treat it as a type of skill, which has been formerly unobserved.

suggests that the ability to perform multiple tasks constitutes at least a part of these unobservable characteristics.

Table 9 – Change in residual variance and R2 upon inclusion of skill measures

Year	Skill measure	σ	Δσ	Comparison Δσ of multitasking with other Δσ	Pseudo R^2	ΔR^2	Comparison ΔR^2 of multitasking with other ΔR^2
1986	none	0.409			0.228		
	education	0.407	-0.003	41.63%	0.237	0.009	41.30%
	experience	0.398	-0.011	9.72%	0.268	0.040	9.52%
	multitasking	0.408	-0.001		0.231	0.004	
1992	none	0.371			0.308		
	education	0.364	-0.007	28.75%	0.334	0.026	30.00%
	experience	0.363	-0.008	23.68%	0.339	0.031	25.41%
	multitasking	0.369	-0.002		0.316	0.008	
1999	none	0.385			0.265		
	education	0.381	-0.004	84.45%	0.282	0.017	86.14%
	experience	0.375	-0.010	36.14%	0.305	0.039	36.39%
	multitasking	0.382	-0.004		0.280	0.014	
2006	none	0.439			0.219		
	education	0.430	-0.008	22.06%	0.244	0.025	21.60%
	experience	0.422	-0.017	10.80%	0.266	0.047	11.42%
	multitasking	0.437	-0.002		0.225	0.005	

Note: The columns Δσ and ΔR2 show the change due to the inclusion of the respective skill measure compared to the case with no skill measure. The column entitled "Comparison" shows how the change in σ and R2 due to adding multitasking compares to the change due to adding education or work experience (in %). Example for 1986: the reduction in σ due to adding education is -0.003 (rounded). The reduction to adding multitasking is -0.001 (rounded). Calculating -0.001/-0.003 * 100 = 41.63.

6. Conclusion

This paper shows how recent changes in the organization of work can help to explain rising wage inequality in advanced industrialized economies. We offer a theoretical model, in which technological changes such as the improvements in ICT and versatile machinery, and the general widening of the human capital base trigger a reorganization of work. The technological innovations increase 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 is associated with higher productivity and hence 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.

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 dispersion 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, which implies that multitasking picks up a source of unobserved heterogeneity.

This paper is clearly just a step towards gaining a better understanding of how work organization affects wages. We explicitly do not claim to offer an alternative to skill-biased technical change as explanation for wage inequality. Rather, SBTC—along with widening of human capital—is an enabler of multitasking. In this respect, multitasking could be considered a particular avenue in which SBTC exerts its influence on wages. Whereas SBTC is often measured as a residual, our analysis helps get into the “black box” of this phenomenon. It remains for future research in this area to examine the evidence for other countries and collect better data on job tasks.

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Appendices to Chapter 2

Appendix A. Technology adoption, product innovations, organizational change and multitasking

Our data allow investigating whether technology adoption, product innovations, and organizational change are related to the level of multitasking of workers. In the questionnaires, respondents were asked to indicate whether the following changes occurred in their firms during the past two years: (i) adoption of new production techniques, machines, materials or computers; (ii) introduction of new and improved products or services; and (iii) restructurings or reorganizations. We relate this information to the number of tasks performed by the respondent. For a description of the data and the construction of variables, please refer to section 4. Information about recent changes is only available for the cross section of 1999 and 2006.

In table A.1, we present the average number of tasks carried out by workers who indicated that any of the three changes took place within the past two years, and by workers who indicated that no such change took place. We find that workers in changing environments exhibit higher levels of multitasking. In table A.2, we combine the three different types of change into one measure for recent change, which takes on the value 1 if any of the three changes occurred. We then include this dummy into a simple Poisson regression on the number of tasks carried out by the worker. As controls we include educational attainment, years of work experience, hours worked, industry dummies and occupation dummies. The results show that, conditional upon controls, a recent change is clearly associated with higher levels of multitasking.

The evidence presented holds for the task-based measure of multitasking (see section 4.1). However, the same picture emerges when using the tool-based measure for multitasking (not reported).

Table A.1 – Average number of tasks performed, by occurrence and type of change

	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/reorganizations	4.81	4.03	6.60	5.97

Table A.2 – Poisson regression on number of tasks performed, pooled sample 1999 and 2006

	Multitasking
Recent change	0.749*** (184.78)
Secondary education	0.196*** (22.44)
Tertiary education	0.247*** (23.29)
Years of experience	0.000491** (2.84)
Hours worked	0.00587*** (31.62)
Constant	0.467 (1.79)
Industry dummies	Yes
Occupation dummies	Yes
Pseudo-R^2	0.152
Observations	74010

Appendix B. 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.

B.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, $\gamma((T-s)\hat{x})s\hat{x}$:

$$q_t = y_t(T-s)\hat{x} + \gamma(T-s)s\hat{x}^2, \tag{A.1}$$

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

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

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

$$q_2 = \frac{(1/2)(T-s)^2\hat{x}}{1+r} + \frac{\gamma(T-s)s\hat{x}^2}{1+r} = \frac{(T-s)\hat{x}(T+s(2\hat{x}\gamma-1))}{2(1+r)}, \tag{A.3}$$

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

$$\begin{aligned} Q &= q_1 + q_2 \\ &= (T-s)\hat{x}(1+s\hat{x}\gamma) + \frac{(T-s)\hat{x}(T+s(2\hat{x}\gamma-1))}{2(1+r)} \\ &= \frac{(T-s)\hat{x}(2+T+2r+s(2\hat{x}\gamma(2+r)-1))}{2(1+r)}. \end{aligned} \tag{A.4}$$

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

$$s^* = \frac{T(\hat{x}\gamma(2+r)-1)-r-1}{(2\hat{x}\gamma(2+r)-1)}. \tag{A.5}$$

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

$$\frac{\partial s^*}{\partial \hat{x}} = \frac{\gamma(T+2r+2)(2+r)}{(1-2\hat{x}\gamma(2+r))^2} > 0, \tag{A.6}$$

and positively on the task-complementarity parameter γ:

$$\frac{\partial s^*}{\partial \gamma} = \frac{\hat{x}(T+2r+2)(2+r)}{(1-2\hat{x}\gamma(2+r))^2} > 0. \tag{A.7}$$

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

B.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

$$q_2 = \frac{(T-s)\hat{x}\left((T-s)^\beta + \gamma s\hat{x}\right)}{1+r}. \tag{A.8}$$

The present value of output is

$$\begin{aligned} Q &= q_1 + q_2 \\ &= (T-s)\hat{x}(1+s\hat{x}\gamma) + \frac{\gamma(T-s)\hat{x}\left((T-s)^\beta + \gamma s\hat{x}\right)}{1+r} \\ &= \frac{(T-s)\hat{x}\left(1+(T-s)^\beta + r + s\hat{x}(1+\gamma+r)\right)}{1+r}. \end{aligned} \tag{A.9}$$

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 B.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 B.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 B.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 B.1 – Optimal span of competence increases in *x*

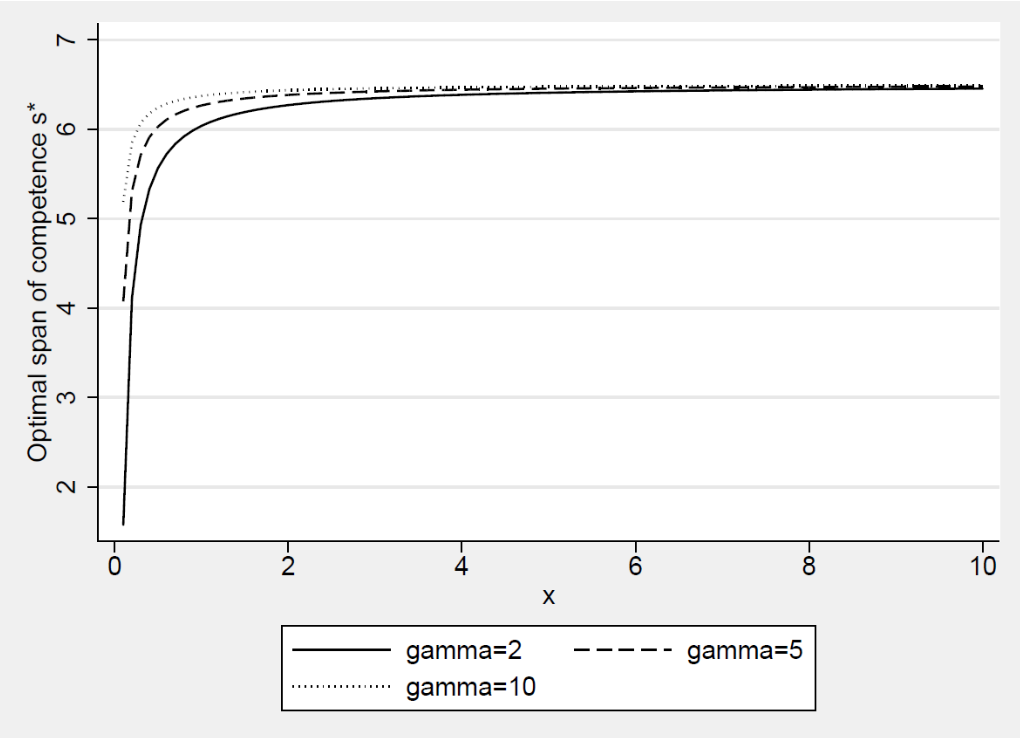


Figure B.2 – Optimal span of competence increases in *γ*

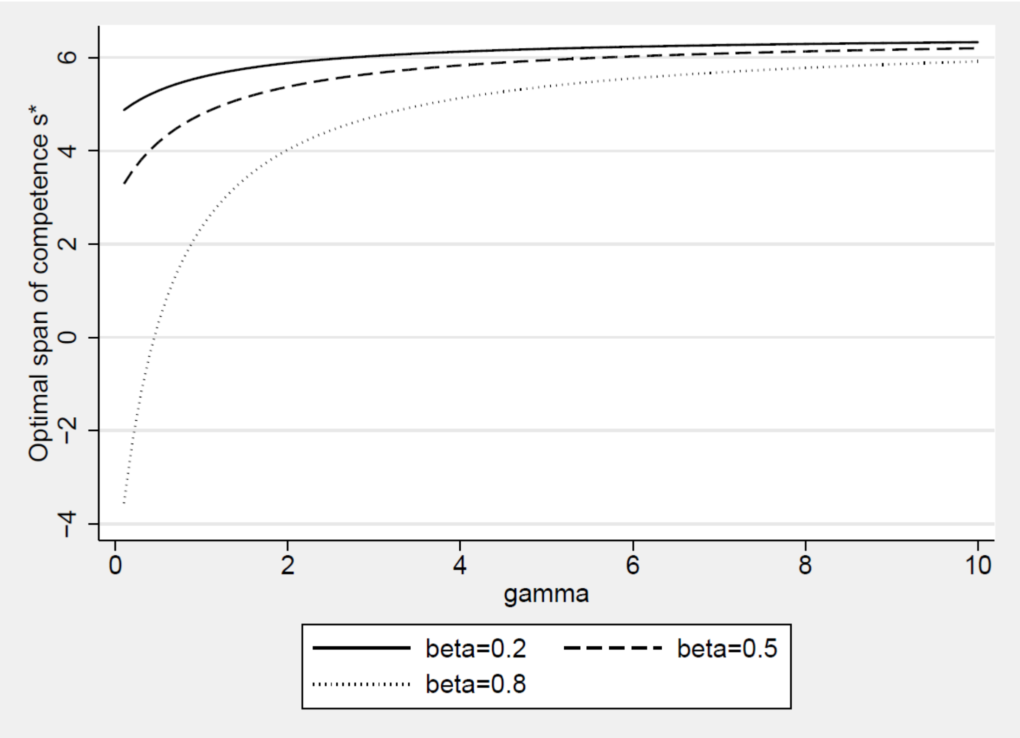
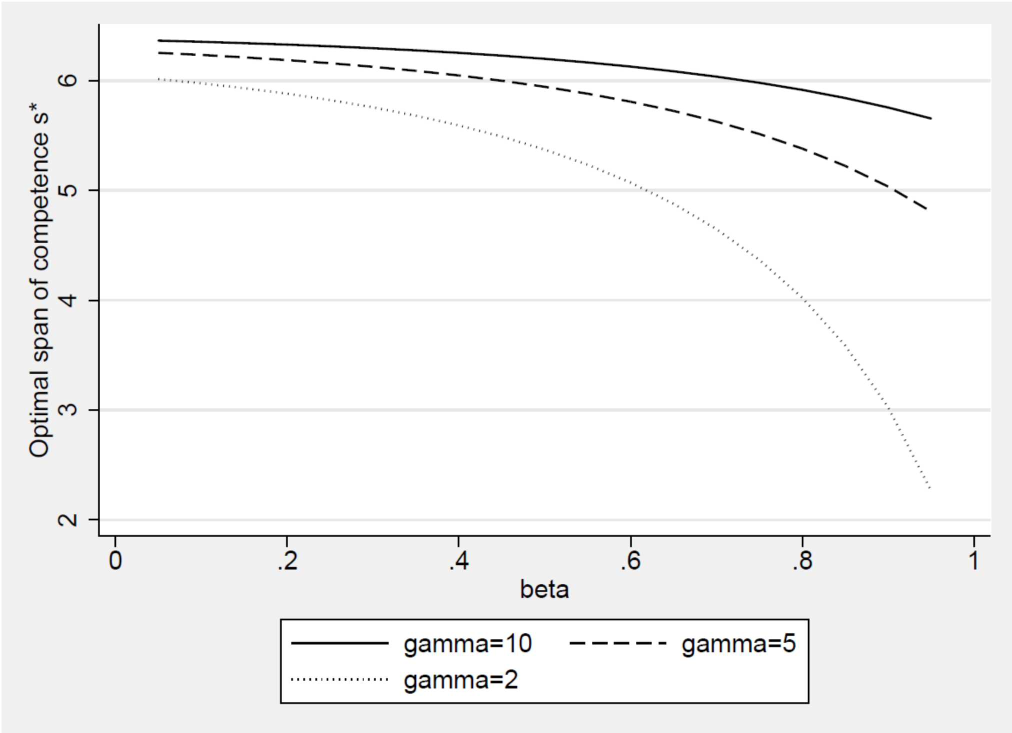


Figure B.3 – Optimal span of competence increases in *β*



Appendix C. Robustness checks

C.1. Interval regressions

Table C.1 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.

Table C.1 – Interval regressions on Log gross real hourly wages; task-based measure

	(1)	(2)	(3)	(4)	(5)	(6)
	Benchmark	Pooled	1986	1992	1999	Interaction
Tasks		0.0449***	0.0472***	0.0506***	0.0533***	0.0429***
		(14.23)	(5.29)	(9.29)	(10.18)	(11.25)
Tasks squared		-0.00298***	-0.00501***	-0.00423***	-0.00325***	-0.00375***
		(-8.15)	(-3.35)	(-5.65)	(-6.04)	(-8.78)
Secondary education	0.125***	0.112***	0.0742***	0.143***	0.0913***	0.111***
	(18.72)	(16.75)	(4.80)	(14.69)	(8.21)	(16.63)
Tertiary education	0.326***	0.307***	0.278***	0.337***	0.276***	0.306***
	(34.34)	(32.29)	(13.42)	(22.93)	(17.84)	(32.22)
Experience	0.0224***	0.0220***	0.0256***	0.0192***	0.0209***	0.0220***
	(38.58)	(38.10)	(21.71)	(20.61)	(21.44)	(38.13)
Experience squared	-0.00036***	-0.00035***	-0.00042***	-0.00031***	-0.00032	-0.00036***
	(-28.24)	(-27.62)	(-15.27)	(-14.93)	.	(-27.65)
Married	0.108***	0.105***	0.119***	0.0805***	0.107***	0.105***
	(22.40)	(21.85)	(12.18)	(10.59)	(13.82)	(21.88)
Female	-0.110***	-0.103***	-0.103***	-0.131***	-0.0724***	-0.103***
	(-17.06)	(-16.09)	(-8.02)	(-12.74)	(-6.97)	(-16.05)
Married*Female	-0.129***	-0.126***	-0.133***	-0.107***	-0.131***	-0.126***
	(-16.95)	(-16.67)	(-8.41)	(-9.01)	(-10.86)	(-16.72)
Part-time	0.0652***	0.0733***	0.0765***	0.0836***	0.0695***	0.0738***
	(9.36)	(10.55)	(4.51)	(7.63)	(6.86)	(10.62)
Big city	0.0340***	0.0353***	0.0556***	0.00901	0.0428***	0.0355***
	(10.10)	(10.56)	(8.17)	(1.69)	(7.91)	(10.61)
Year 1992*tasks						0.00616
						(1.76)
Year 1999*tasks						0.0117**
						(3.28)
Constant	2.602***	2.551***	2.586***	2.631***	1.836***	2.560***
	(54.09)	(53.76)	(27.27)	(44.13)	(11.77)	(53.81)
Year dummies	Yes	Yes	No	No	No	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Occupation dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sigma	0.358	0.356	0.389	0.329	0.345	0.356
N	51131	51131	14469	18304	18358	51131

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2. Regressions including task measures

Our empirical strategy may be criticized with regard to the orthogonality of the multitasking measure and the kinds of tasks the worker carries out. In fact, it may be the case that a high degree of multitasking may be observed mainly for workers who carry out a lot of highly rewarded tasks. A low degree of multitasking may be observed mainly for workers who carry out low-return tasks. In this case, the multitasking variable would in fact measure the returns to highly rewarded tasks and not the true effect of multitasking. Accordingly, we additionally include task measures into the equations.

For the construction of task measures, we follow Antonczyk et al. (2009) who use the same data as we do in this study. First, we allocate tasks to the five task categories nonroutine interactive, nonroutine analytic, routine cognitive, routine manual, and nonroutine manual. Our allocation is shown in table C.2. Then, for each task category, they calculate the following index:

$$TS_{i\,jt} = \frac{\text{number of tasks in category } j \text{ performed by } i \text{ at time } t}{\text{total number of tasks performed by } i \text{ at time } t} \cdot 100\,.$$

This index can be interpreted as a proxy for the time share each worker spends on the respective task category. Included in our regressions, this measure should pick up different returns to high-skilled and low-skilled tasks.

In table C.3, we show the results of different regressions with *year*multitasking* interaction terms: (i) the regression with multitasking and occupation dummies, but without the task measures (as in table 6 above); (ii) the regression with multitasking and the task measures, but without the occupation dummies, and (iii) the regression with multitasking, task measures and occupation dummies. Since the task measures add up to 100, we exclude nonroutine manual tasks to avoid multicollinearity.

A comparison of the results conveys that coefficients hardly change. The difference between the *multitasking*year* interaction terms remains statistically significant. Our findings are, hence, robust to the inclusion of task measures.

Table C.2 – Allocation of tasks to task categories

Task category	Tasks included
Nonroutine interactive	Researching, analyzing, evaluating and planning; Working out rules/prescriptions, programming; Using and interpreting rules
Nonroutine analytic	Teaching or training; Selling, buying, advising customers, advertising; Negotiating, lobbying, coordinating, organizing
Routine cognitive	Calculating, bookkeeping
Routine manual	Operating or controlling machines; Manufacture, install, construct
Nonroutine manual	Repairing or renovating houses, apartments, machines, vehicles; Serving or accommodating; Nurse or treat others

Table C.3 – Comparison of regressions including and excluding task measures

	(2) Without task measures	(3) With tasks, no occupations	(4) With tasks and occupations
Secondary education	0.122*** (18.49)	0.140*** (22.22)	0.106*** (16.09)
Tertiary education	0.338*** (38.25)	0.436*** (54.17)	0.311*** (35.19)
Experience	0.0239*** (42.91)	0.0235*** (41.93)	0.0236*** (42.58)
Experience squared	-0.000374*** (-29.99)	-0.000370*** (-29.36)	-0.000368*** (-29.70)
Married	0.103*** (23.33)	0.106*** (23.64)	0.0994*** (22.75)
Female	-0.0981*** (-16.48)	-0.0965*** (-16.58)	-0.101*** (-16.98)
Married*Female	-0.119*** (-17.30)	-0.120*** (-17.14)	-0.116*** (-16.90)
Part-time	0.0191** (3.07)	0.0147* (2.37)	0.0221*** (3.57)
Big city	0.0329*** (10.36)	0.0378*** (11.76)	0.0326*** (10.32)
Tasks	0.0429*** (11.74)	0.0352*** (9.43)	0.0310*** (8.48)
Tasks squared	-0.00403*** (-11.17)	-0.00373*** (-10.11)	-0.00310*** (-8.60)
Year 1992*tasks	0.00948** (2.65)	0.0107** (2.92)	0.00932** (2.62)
Year 1999*tasks	0.0137*** (3.88)	0.0214*** (5.92)	0.0145*** (4.12)
Year 2006*tasks	0.0251*** (5.91)	0.0349*** (8.00)	0.0262*** (6.19)
NA		0.286*** (37.37)	0.182*** (21.84)
NI		0.252*** (34.44)	0.187*** (24.06)
RC		0.257*** (24.13)	0.153*** (13.20)
RM		0.0575*** (8.09)	0.0428*** (5.84)
Constant	2.726*** (8.61)	2.365*** (121.76)	2.604*** (8.37)
Year dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
Occupation dummies	Yes	No	Yes
Sigma	0.384***	0.391***	0.382***
pseudo R^2	0.330	0.305	0.338
N	66538	66735	66538

Note: t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D. Original task definitions

Table D.1 – Original task and expertise definitions, 1986-2006

Key	1986	1992	1999	2006
res	Analysieren; forschen, erproben, prüfen, messen	Analysieren; forschen, erproben, prüfen, messen, planen	Entwickeln, forschen	Entwickeln, forschen, konstruieren
			Informationen sammeln/auswerten, recherchieren	Informationen sammeln, recherchieren, dokumentieren
des	Planen, konstruieren, entwerfen/gestalten, zeichnen	Konstruieren, entwerfen, zeichnen, künstlerisch gestalten		
		Kenntnisse Konstruktionszeichnen, technisches Zeichnen	*Kenntnisse Gestaltung, Design, Visualisierung, Medien, Layout*	*Kenntnisse Layout, Gestaltung, Visualisierung*
pro	EDV-Tätigkeiten, programmieren	EDV-Tätigkeiten, programmieren		Software entwickeln, programmieren, Systemanalyse
		Kenntnisse Programmieren, Datenverarbeitung (EDV-Software)	*Kenntnisse Entwicklung von Computersoftware, Programmieren, Systemanalyse*	
rul	Gesetze/Vorschriften anwenden, auslegen; beurkunden	Gesetze/Vorschriften anwenden, auslegen; beurkunden		
		Kenntnisse Arbeitsrecht (Betriebsverfassungsgesetz, Tarifrecht, Kündigungsschutz u.ä.)	*Kenntnisse Arbeitsrecht (Betriebsverfassungsgesetz, Tarifrecht, Kündigungsschutz u.ä.)*	*Kenntnisse Rechtskenntnisse*
		Kenntnisse Sonstige Rechtskenntnisse	*Kenntnisse Andere Rechtskenntnisse*	
org	Disponieren, koordinieren, organisieren; führen/leiten (Management, Controlling)	Entscheiden, koordinieren, organisieren, disponieren	Organisieren, planen (über die unmittelbare Vorbereitung der eigenen Arbeit hinaus)	Organisieren, planen, vorbereiten von Arbeitsprozessen
		Kenntnisse Betriebsführung/Management, Organisation, Personalwesen		
tea	Erziehen/lehren/ausbilden; beratend helfen	Erziehen, lehren, ausbilden, beratend helfen	Ausbilden, lehren, unterrichten	Ausbilden, lehren, unterrichten, erziehen
		Kenntnisse Erziehung, Pädagogik, Psychologie		
sel	Kaufen/verkaufen, kassieren; vermitteln, Kunden beraten, verhandeln, werben	Kaufen, verkaufen, kassieren, vermitteln, Kunden beraten, werben	Andere Beraten, informieren	Beraten, informieren
			Einkaufen, beschaffen, verkaufen	Einkaufen, beschaffen, verkaufen
			Werben, Öffentlichkeitsarbeit/PR, Marketing, Akquirieren	Werben, Marketing, Öffentlichkeitsarbeit, PR
		Kenntnisse Einkauf, Beschaffung	*Kenntnisse Vertrieb, Marketing, Werbung, PR/Öffentlichkeitsarbeit*	
		Kenntnisse Vertrieb/Verkauf, Marketing, Werbung		
pre	Publizieren, unterhalten, vortragen	Publizieren, unterhalten, vortragen, gestalten		-
			Kenntnisse Vortragstechnik, freie Rede, Verhandlungsführung	
man	Mitarbeiter anleiten/anweisen, einstellen	Personal einstellen, Mitarbeiter anleiten, kontrollieren, beurteilen		
			Kenntnisse Management, Personalführung, Organisation, Planung	*Kenntnisse Projektmanagement*

(continued on next page)

Table D.1 continued

cal	Kalkulieren/berechnen, buchen	Kalkulieren, berechnen, buchen		
		Kenntnisse Buchhaltung, Rechnungswesen	*Kenntnisse Finanzierung, Kreditwesen, Steuern*	*Kaufmännische, betriebswirtschaftl. Kenntnisse*
		Kenntnisse Geld-/Kredit-/Steuerwesen; Finanzierung	*Kenntnisse Rationalisierungstechniken, Arbeitsstudien, Kostenwesen/Controlling*	
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	Überwachen, steuern von Maschinen, Anlagen, technischen Prozessen	Überwachen, steuern von Maschinen, Anlagen, techn. Prozessen
		Kenntnisse Computertechnik (EDV-Hardware)		
rep	Reparieren, warten, instandsetzen	Maschinen/Anlagen reparieren, warten, instandsetzen	Reparieren, instandsetzen	Reparieren, instandsetzen
ser	Bewirten, beherbergen	Bewirten, servieren, beherbergen	Versorgen, bedienen, betreuen von Menschen	Bewirten, beherbergen, Speisen bereiten
	Bügeln, reinigen/Abfall beseitigen, entsorgen	Putzen, bügeln, reinigen		Reinigen, Abfall beseitigen, recyceln
		Abfall beseitigen, entsorgen		
ins	Stoffe erzeugen, ausformen; verarbeiten/bearbeiten; kochen	Stoffe erzeugen, ausformen, verarbeiten, bearbeiten, Speisen bereiten	Herstellen, produzieren von Waren und Gütern	Herstellen, produzieren von Waren und Gütern
	Bauen/ausbauen, installieren, montieren	Gebäude/Anlagen/Gerte bauen, ausbauen, installieren, montieren		
sec	Sichern (Arbeitssicherheit-, Werkschutz-, Verkehrsregelung), bewachen	Sichern, bewachen (Gebäude, Verkehr, Arbeitsschutz)		Sichern, beschützen, bewachen, überwachen, Verkehr regeln
		Kenntnisse Unfallverhütung, Sicherheits- und Umweltvorschriften	*Kenntnisse Arbeitsschutz, Unfallverhütung, Sicherheits- und Umweltvorschriften*	
nur	Pflegen/versorgen, medizinisch/kosmetisch behandeln	Pflegen, versorgen, medizinisch/kosmetisch behandeln, frisieren		Pflegen, betreuen, heilen
		Kenntnisse Medizinische Kenntnisse	*Kenntnisse Medizinische Kenntnisse*	*Kenntnisse med. pflegerischer Bereich*

Note: Expertise items are printed in italics.

Source: Qualification and Career Survey 1986-2006.