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Technology, outsourcing, and the demand for heterogeneous labor: Exploring the industry dimension*

Ljubica Nedelkoska and Simon Wiederhold†

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Abstract

It has become common within the literature of skill-biased technological change to look at technologies, as well as their impact on the demand for labor as homogeneous across industries. This paper challenges this view. Using a linked employer-employee panel of Germany differentiated by industries for the period 2001-2005, we investigate substitution effects between labor of different skills (tasks) on the one hand, and technology as well as outsourcing on the other. Our findings are at odds with the idea of economy-wide homogeneity of substitution patterns. We find that in some industries IT capital substitutes for labor, while it complements it in others. However, substitution patterns are symmetric across labor types. Outsourcing often correlates negatively with the demand for labor performing explicit and problem-solving tasks. It is mainly uncorrelated or positively correlated with the demand for labor performing interactive tasks. The outsourcing-related results support the offshoring theory proposed by Blinder (2006).

JEL classification: J23, J24, O33
Keywords: demand for skills, technology, outsourcing

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1 Introduction

The economic history evidences that over the last couple of centuries there has been a number of widespread cost-saving technological innovations and organizational strategies that resulted in radical shifts in the demand for labor even at the level of economies. Automatized looms at the beginning of the nineteenth century replaced the effort of the skilled weavers in the textile industry with a punched card and few unskilled workers. Given the size and the importance of the textile industry in Great Britain at that time, the changes in the skill-mix structure caused by the introduction of the labor-saving looms had nation-wide implications. The implementation of the Fordist assembly line in the automobile industry early in the twentieth century caused an increase in the demand for routine tasks. Since this innovation encountered acceptance across various manufacturing industries it also led to an economy-wide increase in the demand for explicit tasks or tasks that can be thoroughly explained through step-by-step instructions. Turning to a more recent period, there exists growing evidence that the proliferation of personal computers caused shifts away from routine tasks toward complex, problem-solving ones (e.g. Autor, Levy, and Murnane 2003). In line with these examples, Goldin and Katz (1996, 2009) stress that within the last two centuries there existed both, technologies and organizational practices that shifted the demand toward more skilled labor (e.g. continuous processes and batch technologies in manufacturing), and those that caused aspirations for low-skilled labor (e.g. the transition from artisan shop to factory).[1]

Arguing with the above-mentioned historical events, previous technological and/or organizational changes often affected labor very differently. Also, while some of these technologies were industry-specific (labor-saving looms), others were economy-wide (assembly line or computers). The

[1] Moreover, Becker, Hornung, and Woessmann (2009) find that in the metal production sector in Prussia in thenineteenth century higher education speeded up the industrial revolution, while the opposite was the case in textile manufacturing.

recent discussion on the impact of organizational and technological change has mainly focused on capturing economy-wide patterns (e.g. Geishecker 2006; Spitz-Oener 2006; Addison et al. 2008; Baumgarten 2009; Dustmann, Ludsteck, and Schönberg 2009; Goos, Manning, and Salomons 2009). One justification for this is that consistent patterns of technological and skill changes have been found by exploring between-industry variation (e.g. Berman, Bound, and Griliches 1994; Berman, Bound, and Machin 1998; Autor, Levy, and Murnane 2003). In this article we test for the possibility that the impact of technological and organizational innovations may be industry-specific. Therefore, we adopt an empirical design that allows for technology to vary between industries while retaining the assumption that it is comparable within sectors.[2] A certain type of labor that is substitutable by technology in one industry might be unaffected by, or even complementary with, technology in some other industry if both employ qualitatively different production processes. This reasoning stems from the belief that not all technologies and organizational practices are general in the sense that they penetrate a large number of industries. Some of them may find use in only few sectors.

In the current work we will confront two possible causes of shifts in the demand for labor of different tasks: technology and outsourcing. We approximate technology by information technology (IT capital) and non-information technology (non-IT capital). However, instead of testing for economy-wide patterns, we investigate labor-technology and labor-outsourcing relations at the industry level. For that purpose we utilize a linked employer-employee panel (LIAB) of Germany, differentiated by industries for the period 2001-2005. We additionally merge the LIAB with task data from the Qualification and Career Survey. Therefore, we can distinguish between (a) abstract labor, which captures the intensity of use of complex, problem-solving skills, (b) codifiable labor, which measures the intensity of use of (manual) tasks that are of explicit or repetitive

[2]Given that industries are defined around common products and production processes such assumption is not far-fetched.

nature, and (c) interactive labor, which reflects the intensity of tasks that require direct customer support. This dataset is then used to estimate elasticities of substitution between labor and (non-)IT capital on the one hand, and labor as well as outsourcing on the other in a translog cost function framework. With the current design we are able to account for changes in the demand for tasks/skills that are due to the occupational restructuring within plants. In other words, we can only observe task/skill changes that are due to labor turnover at the level of plants, disregarding task/skill changes that arise from the within-occupational up- or downgrading of skills.

Coming to our results, several patterns are noteworthy. First, abstract and codifiable labor appear as substitutes in all industries. This means that wage increases of codifiable labor (e.g., due to union bargaining) correlate with employment boost of abstract tasks. At the same time, abstract and interactive labor always appear as complements. This does not come as a surprise because plants which increase their research capacities may also face an enhanced need for marketing and other sales capabilities. Moreover, interactive and codifiable labor are mainly substitutes. Furthermore, we do not find evidence of skill bias in the IT and non-IT capital; substitution effects across heterogeneous labor within industries are symmetric across labor types. However, at least in the case of IT there are pronounced inter-industry differences in the relationship between IT and labor demand in general; in some industries IT substitutes for labor of all tasks, while it complements labor in others. Non-IT capital is always a substitute for labor across industries. Nevertheless, the magnitudes of the substitution elasticities for both IT and non-IT capital are comparatively small and thus only explain a fairly small share of the changes in the demand for labor of different tasks. Finally, in industries where outsourcing significantly correlates with the demand for labor, the patterns resemble those described by Blinder (2006). Namely, the results suggest that in one third of the industries codifiable labor is at risk of outsourcing, while this is the case with abstract labor in one quarter of the sectors. The demand for interactive labor either correlates positively with outsourcing or is unaffected by it in all but one sectors.

The remainder of the paper is organized as follows. In section 2 we introduce the conceptual part and formulate our expectations. Section 3 describes the data and the definition of variables. Section 4 demonstrates some basic industry-level trends. Section 5 explains our methodology, while our findings are discussed in section 6. Section 7 presents the various robustness checks. Section 8 concludes.

2 Tasks, technology, and outsourcing

The skill structure of developed economies changed in a remarkable way since the second half of the twentieth century. Educational upgrading was a prevalent trend and much evidence pointed toward increases in skill-premia (e.g. Goldin and Katz 2009)[3] and increases in wage inequality (e.g. Autor, Katz, and Kearney 2008; Dustmann, Ludsteck, and Schönberg 2009). Within the last three decades numerous studies investigated the sources of change in the labor structure. The majority of these assumed the *level* of human capital as measured by educational attainment to be the most relevant dimension of human capital (e.g. Goldin and Katz 1996 and 2009; Acemoglu 1998 and 2003; Bresnahan, Brynjnolfsson, and Hitt 2002). More recent literature, starting with studies such as those by Autor, Levy, and Murnane (2003) and Blinder (2006), argued that it is rather the *type* and not the *level* of human capital that encompasses most useful information in explaining the causes of the recent trend toward skill upgrading.

Two of the dominant theories that aspire to explain the skill upgrading in the recent decades is the skill-biased technological change theory (see Katz

[3]See Lemieux (2006) for a critique and evidence against increasing skill-premia in the U.S..

and Autor 1999 for a review of earlier studies) and the opening up of trade to world markets (see Grossmann and Rossi-Hansberg 2008 for a theory of international tasks trade).

Similar to earlier research, Autor, Levy, and Murnane (2003) relate the changes in the labor structure since the 1960s to the proliferation of computers at the workplace. However, unlike much of the previous studies, they ask the critical question: what kind of tasks do computers execute that substitute or complement tasks carried out by humans? Therefore, instead of using the conventional labor group distinctions (low-skilled, medium-skilled, and high-skilled; production and non-production workers; or blue-collar and white-collar), they propose a measurement of tasks that provides an intuitive and testable explanation of the causal relationship between the introduction of new technologies and the demand for heterogeneous labor. The basic idea put forward by their work is that computers substitute for routine manual and routine cognitive tasks, while complementing nonroutine manual and nonroutine cognitive ones. This is because routine tasks embody explicit knowledge that can relatively easily be programmed, which is not the case with nonroutine tasks. Moreover, a rise, both qualitatively and quantitatively in the supply of codifiable tasks increases the marginal productivity of employees who make extensive use of nonroutine tasks (such as problem-solving and coordination) and who use routine work output as their work input (Autor, Levy, and Murnane 2003, p. 1285).

However, computers developed in different forms. The personal computers, mainly substituting for cognitive routine tasks such as calculus, proliferated in all industries, while computerized numerical control (CNC), which mainly substitutes for manual repetitive tasks, retains its presence in a limited number of manufacturing sectors. Furthermore, certain technologies such as the automatic cashier or the automated teller machine (ATM) in retail and banking substitute for repetitive tasks and result in a reduction of tasks that entail direct contact with customers (interactive tasks). There are also code-based technologies such as loyalty card systems mainly present in retail stores where there is no reason to expect a bias toward certain labor type. Hence it is quite plausible to expect that industries may exhibit pronounced idiosyncrasies in the labor-IT capital relations.

The period of IT proliferation coincided with a period of rapid increases in the international trade. According to Grossman and Rossi-Hansberg (2008), a distinct feature of modern trade is that it not only includes *goods* but also *tasks*.

> "Revolutionary advances in transportation and communications technology have weakened the link between labor specialization and geographic concentration, making it increasingly viable to separate tasks in time and space. When instructions can be delivered instantaneously, components and unfinished goods can be moved quickly and cheaply, and the output of many tasks can be conveyed electronically, firms can take advantage of factor cost disparities in different countries without sacrificing the gains from specialization." (Grossman and Rossi-Hansberg 2008, p. 1978)

While Grossman and Rossi-Hansberg (2008) leave the question of which types of tasks are outsourceable open for discussion, Blinder (2006, 2009) offers a theory of offshorability. Blinder (2006) argues that the offshorability of an occupation is neither correlated with its level of education nor with its median wage. What is important, he argues, is whether a service is delivered personally or impersonally.

Both the theory of technological change and the theory of international outsourcing provide testable hypotheses about the causes behind the recent changes in task/skill mix in developed countries. Following Autor, Levy, and Murnane (2003), the labor-IT capital relationships should be such that (a) routine (both cognitive and manual) tasks appear as technological substitutes, while (b) nonroutine manual and cognitive tasks are technological complements. Blinder predicts that most vulnerable to international outsourcing are routine (codifiable) tasks and abstract tasks that do not require personal delivery to customers. Interactive tasks, on the other hand, should show low outsourcing propensity.[4]

Having derived the main expectations that guide our empirical analysis below, we conclude the theoretical considerations by stressing that the outsourcing-labor relationship is two-dimensional. Differences in firms' outsourcing behavior across industries may either stem from the inter-industrial variation in production practices or from the stage of the outsourcing process. For example, in motor vehicles production firms are likely to outsource qualitatively different parts of the production process than those in professional business services. The former may primarily outsource product assembly, which is codifiable labor-intensive, while the latter may outsource programming and statistical analysis services, mainly affecting abstract labor. Yet over time the same industry may change the type of labor being outsourced. There is evidence that industries outsource routine tasks first and as time progresses switch over to outsource more complex firm functions as well (see e.g. Pfannenstein and Tsai 2004 for the U.S. IT industry and Maskell et al. 2007 for Danish international firms). For example, having outsourced production parts internationally from the middle of the 1990s on, the German automobile industry may have created new business opportunities which, in a more advanced stage of industry outsourcing, attract labor to foreign countries that makes intense use of abstract tasks.

[4] Goos, Manning, and Salomons (2009) provide an empirical test of the theories of Autor, Levy, and Murnane (2003) and Blinder (2009) at the economy-wide level.

3 Data and task measures

3.1 Qualification and Career Survey

The Qualification and Career Survey is administrated by the Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment (IAB). Its purpose, among others, is to track task, skill, and knowledge requirements of occupations. It is a repeated cross-section conducted on 7-years intervals, which started for a first time in 1979. The survey is a rich source of information about the types of tasks employees execute at their jobs.[5] For the purpose of this study we use the 1998/99 survey. A list of variables that we chose from this survey and their definitions can be found in appendix A, table 4. We focused on variables that we can consistently compare over time, in particular those that we can compare with past surveys. We measure task intensities at the level of occupations.[6] Unlike the wage reporting, the reporting of the employees' occupation is not one of the information categories that employers must highly accurately report, therefore, the IAB recommends an occupational aggregation of that data between the 2- and 3-digit level, which results in 120 different occupations. Out of these we drop the public administration jobs, as well as family assistants, interns and unpaid trainees. The final classification embraces 115 different occupations.

We attempt to measure three task dimensions: (1) abstract, (2) codifiable, and (3) interactive. The abstract dimension corresponds with the

[5]Previous uses of this survey are by DiNardo and Pischke (1997), Spitz-Oener (2006), Dustmann, Ludsteck, and Schönberg (2009), and Gathmann and Schönberg (2010).

[6]Previous work that uses the task-based approach in order to caputure relevant dimensions of the work content of jobs distinguishes three to four groups of tasks. ALM, as well as Spitz-Oener (2006) distinguish between routine cognitive, routine manual, non-routine cognitive, and non-routine manual. Goos, Manning, and Salomons (2009) differentiate abstract, routine, and service tasks. The routine dimension in this case captures both the routine cognitive and the routine manual tasks. Some of the above-mentioned studies measure these tasks at the level of individuals (Spitz-Oener 2006), others at the level of occupations (Goos, Manning, and Salomons 2009). The fact that our data come from two different sources requires that we measure the task intensities at the level of occupations.

non-routine cognitive one in ALM and the abstract one in Goos, Manning, and Salomons (2009); the interactive dimension corresponds to the service dimension in Goos, Manning, and Salomons (2009). The codifiable dimension is designed to capture two characteristics of knowledge: its repetitiveness and its explicitness. Hence it is more general than the routine measure used in previous studies.

The question that we use as a measure of explicitness of tasks reads: how often does it happen that you are being *instructed about the work-process in every detail* at your daily work? The answer is given on a likert scale: practically always, often, from time to time, seldom, practically never. As elaborated in Nedelkoska (2010), from a theoretical point of view the explicitness of a task is a better appoximation of codifiability than the repetitiveness of tasks. Therefore, in this paper we will measure codifiablility as task explicitness and we will use the measure of task repetitiveness for robustness checks.

Unlike the case of the codifiable dimension, where we have questions asking precisely the frequency of use of repetitive and explicit tasks, it is more difficult to separate interactive and abstract tasks in our data. Instead of arbitrarily defining which tasks belong to one of these categories we adopt factor analysis appoach in order to check whether subsets of variables are loading on common factors. Appendix B of this chapter contains the factor loadings and the relevant characteristics of the resulting factors.

The main result of the factor analysis is identification of two dimensions (see Table 6).Variables such as marketing and public relations, management, process improvement, research, mathematics and statistics, usage of foreign languages, and negotiation load high on the first factor. These are tasks that require complex and abstract thinking and problem-solving. Groups of occupations that score highest on this dimension are engineers, managers and entrepreneurs, technicians and scientists. We call this factor *abstract dimension*. The second factor loads on two variables: medicical knowledge and taking care of people. These are tasks that involve direct and intense contact with customers. Therefore, we refer to this factor as *interactive dimension*. The measures of abstract and the interactive skills are by construction orthogonal to each other, while the measures of explicit and routine tasks are not.

Since the occupation-specific task quantities that we use in the regression analysis are measured at one time point, a major limitation of the current empirical design is that we can only observe task changes that result from shifts in plants' occupational structure but not those changes that stem from the task up- or downgrading within same occupations over time.

3.2 Linked Employer-Employee Panel

The Linked Employer-Employee Panel (LIAB) is a dataset of up to 16,000 establishments per year matched with the employment histories of their employees for both Eastern and Western Germany in the period 1993-2008. The plant-level information comes from an annual survey of German establishments, the Establishment Panel, administrated by the Institute for Employment Research (IAB), while the individual level data comes from the German Social Security notifications. Detailed description of this dataset is given by Jacobebbinghaus (2008). For the purpose of our analysis we use a subset of this dataset. We select twelve large industries at the 2-digit industry level: chemicals; plastic and rubber; ceramics, glass, and bricks; iron and steel; metal production; vehicle manufacturing; general and special purpose machinery; electrical equipment; control, optical instruments and watches; construction; wholesale; and retail. The choice of the industries was dictated by the sample size and by the information availability on the relevant variables.[7] On the individual side, both males

[7] For example, many of the service sectors do not report sales in monetary terms and for these we cannot use the translog cost function specification where measure of output is necessary.

and females are considered. Information on the share of information technology (IT) investments in the total investments is present since 2001 (financial year 2000) in the LIAB, and, at the point of the dataset building, it was available on annual basis until 2005 (financial year 2004). The data reported at the establishment level always refers to the previous financial year. Therefore, the actual period of observation are the financial years 2000-2004. On the side of the individuals, labor data is reported each year at 30$^{\text{th}}$of June. Therefore, the labor (task) quantity and price information by construction succeeds the (non-) IT capital flow and outsourcing reportings by at least six months.

The IT investments are reported as a share of the total investments in the Establishment Panel. From the monetary value of the total investments we derive the monetary value of the annual IT investments of each establishment. Non-IT investments are accordingly the difference between total investments and IT investments. We then estimate stocks of IT and non-IT capital on the basis of investment data employing the Perpetual Inventory Method (PIM) with geometric depreciation profiles. These are the measures of IT and non-IT capital that we employ in the regression analysis. Depreciation rates differ by asset and industry.[8]Output is measured by the monetary value of sales. Outsourcing is a dummy variable. Establishments are asked to report whether they have outsourced a unit in the previous financial year. There is no information on whether outsourcing has been made to another sector or to a foreign country in the observed period.[9] We deflate the monetary values of sales, (non-) IT capital, and labor prices with industry-specific deflators provided by the German Federal Statistical Office and The German Council of Economic Experts.

For labor we have information about the number of employees by plant at each time point. For every employee, beside other information, we also

[8]The details of capital stock construction are relegated to appendix A.

[9]Starting in 2006 establishments are also asked to report whether they outsource at home or to a foreign country. The latter should not be confused with “offshoring”, meaning that jobs are moved out of the country but are not necessarily contracted out of the company.

have very reliable daily wage data.[10]This individual data comes from the employment histories of workers that are part of the German system of social security. Besides wages we also have information about the occupations of each worker. This allows us to merge the task data from the Qualification and Career Survey on occupational level with the LIAB.

The labor input can either be measured in terms of number of employees of different types (labor quantity approach) or quantity of tasks of different types (task quantity approach). Two obvious advantages of the labor quantity approach are that we have a natural labor unit-employee number of certain type, and that we can easily attach a price to each unit. This approach has a number of disadvantages, however. First, all occupations within one group are considered to be identical. Therefore, employing five engineers is treated same as employing five engineering technicians. Second, a number of occupations would have to be omitted because they score low on all three dimensions. Third, and perhaps most important is that we would not make a full usage of the information we have at hand. For example, a plant that does not employ any interactive-tasks-dominated labor will still employ some interactive tasks content that is embodied in the labor task portfolio. This information would get lost if we used the labor quantity approach. Given these drawbacks, we choose the tas -quantity approach.

For this purpose we use the two factors and the explicit tasks measure described earlier in this section and appendix B. In order to make the measures of tasks comparable among each other, we represent them in terms of their position on the occupational task distribution. In other words, they are measured in percentiles. For example, a machine engineer in our approach scores at the 98$^{\text{th}}$ percentile of the abstract tasks distribution, at the 9$^{\text{th}}$ percentile of the routine tasks distribution, and at the 2$^{\text{nd}}$ percentile of the interactive tasks distribution. The respective percentiles for a plastics' processor are 21$^{\text{st}}$, 96$^{\text{th}}$, and 8$^{\text{th}}$. Therefore, a plant employing one machine engineer and one plastics' processor will have .98+.21=1.19 units of abstract

[10]The daily wage data is right censored.Therefore, we employ wage imputation technique proposed by Gartner (2006) for the wage values that are missing due to censoring.

task quantity, .09+.96=1.15 units of routine tasks quantity, and .02+.08=.1 unit of interactive tasks quantity. The price per unit of labor is defined as follows: $P_i = \sum_{j=1}^{n}(p_i * t_{ij}/\sum_i t_{ij})$ where P is the establishment-level price of a task type, p is the individual-level wage, t represents the type of task, $j = 1, ..., n$ is the employee counter and $i = abstract, codifiable, interactive$. Think of a plant with two employees, one machine engineer and one plastics processor; the engineer earns 100 euro daily wage and the plastics' processor earns 50. The price of abstract labor for this plant will be determined as follows: 100*.98/(.98+.09+.02)+50*.21/(.21+.96+.08)=89.9+8.45=98.38 Accordingly, the prices for codifiable and interactive labor will be 46.97 and 3.24, respectively.

Although the prices of task quantities are indirectly derived, they have desirable properties. First, if occupations with high intensity of abstract tasks are also highly payed, this will be reflected in the indirect prices. Second, smaller quantities of certain tasks correlate with small total pay. Finally, by construction the task expenditures at the establishment level sum up to 100 percent of the wage bill.

3.3 The final sample

To ensure better reliability of our data, following Addison et al. (2008) we excluded from the sample those matches between the individual and the establishment data where the employment count based on the individual data was at least 20 percent larger or smaller than the reported one in the Establishment panel.[11] The final sample is an unbalanced panel with 7513

[11]Certain mismatch in these reportings should be tolerated for at least two reasons. First, the reporting periods of the establisment survey and the individual data are several months apart. Second, we only work with employment subject to social security. While for plants it may be easy to know the total number of employees, they are less precise when reporting the number of employees subject to social security. Moreover, if the misreporting would stem from the side of the individual data, there is no reason to believe that some type of selectivity takes place.

observations over a period of five years. This sample is divided among 12 industries, the smallest of which is electrical equipment manufacturing (314 observations) and the largest one is construction (1727 observations). Despite the non-negligible reduction of the industry-level subsamples due to missing values, the construction of the capital stocks and the exclusion of the mismatches, we manage to obtain samples that incude entablishments of all sizes, both in terms of employment and in terms of output. Additional descriptive statistics can be found in appendix A.

4 Changes in the demand for tasks

The main interest of this study is to see whether there are deviations from the overarching trends in skill up- and down-grading when we look at separate industries. Figure 1 presents the results of a shift-share analysis of occupation-level task changes estimated separately for 9 industries. A striking observation is that when looking at the within changes across industries for same tasks remarkable similarities occur. Namely, people in all industries report higher use of repetitive and explicit tasks, lower use of arithmetics, math and statistics and mainly higher use of educating, law and process improvement. Nevertheless, when looking at the between occupational changes we see notable discrepancies. Figure 1(a) shows a group of industries (chemicals, electronics, and machine engineering and office machinery) where occupations which make higher use of codifiable tasks has been decreasing, while occupations which use other than codifiable tasks have been increasing. In figure 1(b) we once again see a group of industries that decreased the presence of employees who report high usage of codifiable tasks, but also decreased the presence of tasks such as process improvement/trying out someting new. Finally, in figure 1(c) we see industries where even the level of employees using codifiable tasks has been increasing. Therefore, from this section we can conclude that while the within-occupational task changes are remarkably similar across industries, the between-occupational changes vary notably. As a next step we investigate whether these departing trends can be explained by differences in the technology-labor and outsourcing-labor relations across sectors.

- Figure 1 about here-

5 Theoretical model and empirical specification

The estimation of the demand for heterogeneous labor is based on a translog cost function that can be envisaged as a second-order Taylor's series approximation in logarithms to an arbitrary (twice-differentiable) cost function. While the majority of studies on labor substitutability distinguish between skilled and unskilled employees[12], and sometimes differentiates these two groups further by gender and type of employment (Freier and Steiner 2007), the focus of our study is on labor heterogeneity with respect to tasks. Thus, following the discussion in the previous section, we consider a cost function specification that incorporates task-differentiated labor as variable input. Since we are interested in the direction and the extent of substitution relations between labor of different tasks and a plant's technological base underlying production, we include capital and outsourcing in our cost function framework. We have information on the composition of plant's investment expenditures, allowing us to construct capital stocks of IT and non-IT, respectively.[13] We

[12] Examples are Berman, Bound, and Griliches (1994), Betts (1997), and Adams (1999). See Hamermesh (1993) for a detailed survey.

[13] A number of previous studies estimating substitution patterns on the labor market insert investments directly into the cost function (Van Reenen 1997; Addison et al. 2008). The implicit assumption this approach entails is that replacement investments properly reflect necessary depreciation and are therefore proportional to the unknown capital stock (Mueller 2008). However, whether or not (replacement) investments are proportional to the true capital stock cannot be verified by data (Mueller 2008). Moreover, missing values

treat (non-)IT capital stocks and outsourcing as quasi fixed, implying that producers cannot adjust freely in response to relative price changes in the short run.[14] Justifications for the quasi-fixity of the capital variables and outsourcing are the presence of institutional constraints as well as adjustment costs for these factors that are beyond the control of an individual plant.[15] Specifiying the cost function in the quasi-fixed form has the additional virtue that each variable assumed to be quasi fixed enters with its quantity rather than with its price. According to Berman, Bound, and Griliches (1994), there are no reliable price deflators available for capital, which even the more holds for IT investment and outsourcing (Aguirregabiria and Alonso-Borrego 2001). Furthermore, observed capital quantities can often be seen as closer proxies to user cost of capital than price measures (Muendler and Becker 2009).

With (non-)IT capital stocks and outsourcing being fixed at levels other than their long-run equilibrium values, the goal of the plant is to minimize the cost of variable inputs conditional on a given quantity of the quasi-fixed factors. It is thus appropriate to specify a *variable* cost function that reads in its general form:

$$VC = f(P_A, P_C, P_I, Y, K, IT, OUT), \tag{1}$$

where three variable inputs are considered, abstract labor (L_A), codifiable labor (L_C), and interactive labor (L_I), which appear in the cost function

or zero investments in one year would cause a capital stock measure of zero for that year, which obviously is implausible. In order to avoid these drawbacks we construct absolute values of capital stock.

[14] Most of previous work investigating changes in the employment strcuture in the context of a translog cost function assumed capital to be a quasi-fixed input (Bartel and Lichtenberg 1987; Slaughter 1995; Adams 1999; Hollanders and ter Weel 2002; Becker et al. 2005; Muendler and Becker 2009).

[15] Notice that we do not specify a dynamic labor demand model (Berndt et al. 1981; Good et al. 1996; Morrison Paul and Siegel 2001), because the assumptions about adjustment cost in these models are rather crude and questionable (Hamermesh 1993; Kölling and Schank 2002). Moreover, as elaborated below, we neither impose homotheticity nor constant returns to scale on the cost function. We would have had to sacrifice this degree of flexibility if we wanted to explicitely model the adjustment process of the quasi-fixed factors (Baltagi and Rich 2005).

through their prices, P_A, P_C, and P_I, respectively; output is denoted by Y, while K, IT, and OUT represent the quantity of the quasi-fixed inputs non-IT capital, IT capital, and outsourcing.

For purposes of estimation we must employ a specific functional form for equation (2). We require it to be sufficiently flexible to allow the data to display complementarity as well as substitutability between inputs, which excludes, for example, Cobb-Douglas or constant elasticity of substitution specifications. We choose a translog variable cost function to approximate equation (1), because it places no a priori restrictions on the partial elasticities of substitution (Christensen et al. 1971 and 1973; Brown and Christensen 1981).[16] The translog variable cost function is written as:[17]

[16] A variety of functional forms allow for complex substitution patterns (see Chambers 1988 for a comprehensive overview), with translog and generalized Leontief (Diewert 1971) specifications being most prominent among these. We favor a translog over a generalized Leontief cost function since the former's dimensionality requirements are considerably leaner (Muendler and Becker 2009). In addition, the Monte Carlo analysis of Guilkey et al. (1983) finds that the translog outperforms the generalized Leontief in approximating the true data-generating process for a wide range of substitution elasticties.

[17] Since linear homogeneity in prices is imposed (see below), we can write the regressors in equation (2) as logarithms of the price ratios (Berndt and Wood, 1975). Notice further that outsourcing is a binary variable, taking only values of either zero or one, which in that case prevents us from using a logarithmic specification.

$$
\begin{aligned}
\ln VC = \quad & \alpha_0 + \alpha_A \ln \tfrac{P_A}{P_I} + \alpha_C \ln \tfrac{P_C}{P_I} + \ln P_I + \alpha_Y \ln Y \\
& + \alpha_K \ln K + \alpha_{IT} \ln IT + \alpha_{OUT} * OUT + \tfrac{1}{2}\beta_{A,A} \ln^2 \tfrac{P_A}{P_I} \\
& + \tfrac{1}{2}\beta_{C,C} \ln^2 \tfrac{P_C}{P_I} + \tfrac{1}{2}\beta_{Y,Y} \ln^2 Y + \tfrac{1}{2}\beta_{K,K} \ln^2 K \\
& + \tfrac{1}{2}\beta_{IT,IT} \ln^2 IT + \beta_{A,C} \ln \tfrac{P_A}{P_I} \ln \tfrac{P_C}{P_I} + \beta_{A,Y} \ln \tfrac{P_A}{P_I} \ln Y \\
& + \beta_{A,K} \ln \tfrac{P_A}{P_I} \ln K + \beta_{A,IT} \ln \tfrac{P_A}{P_I} \ln IT + \beta_{A,OUT} \ln \tfrac{P_A}{P_I} * OUT \\
& + \beta_{C,Y} \ln \tfrac{P_C}{P_I} \ln Y + \beta_{C,K} \ln \tfrac{P_C}{P_I} \ln K + \beta_{C,IT} \ln \tfrac{P_C}{P_I} \ln IT \\
& + \beta_{C,OUT} \ln \tfrac{P_C}{P_I} * OUT + \beta_{Y,K} \ln Y \ln K + \beta_{Y,IT} \ln Y \ln IT \\
& + \beta_{Y,OUT} \ln Y * OUT + \beta_{K,IT} \ln K \ln IT \\
& + \beta_{K,OUT} \ln K * OUT + \beta_{IT,OUT} \ln IT * OUT.
\end{aligned} \tag{2}
$$

A well-behaved (variable) cost function must be homogeneous of degree 1 in factor prices, given output, which requires that $\sum_j \alpha_j = 1$ and that $\sum_j \beta_{j,n} = \sum_n \beta_{n,j} = \sum_j \beta_{j,Y} = \sum_j \beta_{j,K} = \sum_j \beta_{j,IT} = \sum_j \beta_{j,OUT} = 0$ for all $j, n = A, C, I$. For notational convenience we avoid the indexes which point out the plant and year specificity. However, all data points are plant- and year-specific. Although the arguments of equation (1) are available at the plant level, to give our results an interpretable meaning we assume that the production technology of each plant within a (broadly defined) industry is identical. Moreover, we allow for industry-specific scale economies by not restricting the variable cost function (1) to exhibit constant returns to scale.

Cost-minimizing demand equations for variable inputs are obtained by logarithmically differentiating equation (2) with respect to variable input prices, which, when employing Shephard's Lemma, gives the share of overall labor cost attributable to each factor j:

$$\begin{aligned} S_A = \quad & \alpha_A + \beta_{A,A} \ln \tfrac{P_A}{P_I} + \beta_{A,C} \ln \tfrac{P_C}{P_I} + \beta_{A,Y} \ln Y \\ & + \beta_{A,K} \ln K + \ln \beta_{A,IT} \ln IT + \beta_{A,OUT} * OUT, \\ S_C = \quad & \alpha_C + \beta_{C,C} \ln \tfrac{P_C}{P_I} + \beta_{A,C} \ln \tfrac{P_A}{P_I} + \beta_{C,Y} \ln Y + \\ & + \beta_{C,K} \ln K + \ln \beta_{C,IT} \ln IT + \beta_{C,OUT} * OUT, \\ S_I = \quad & 1 - S_A - S_C, \end{aligned} \tag{3}$$

where $S_j \equiv P_j L_j / VC$ denotes the share of cost of labor of task type j $(j = A, C, I)$ in total labor cost $\left(VC = \sum_j P_j L_j\right)$, from which follows that $\sum_j S_j = 1$ holds.[18]

Equations (2) and (3) summarize the full range of input substitution patterns of the establishment. The coefficients capture the partial effect of the exogenous variables on the cost share of labor of skill type j. The signs of these parameters, however, do not immediately indicate the plant's substitution behavior. We therefore construct labor demand elasticties from coefficient estimates in equations (2) and (3) and mean cost shares. These elasticities quantify the response (in percentages) of labor demand for task type j to permanent changes (in percentages) in prices, output, (non-) IT capital, and outsourcing, respectively, while all other factor prices and quasi-fixed input quantities are fixed.[19] The labor demand elasticties with respect to task prices, ε_{L_j,P_n}, are obtained as:

[18]Notice that input factor demands in (3) are to be interpreted as conditional factor demands (for a given output level), in contrast with ordinary factor demands which result from the profit maximization problem. The main difference between the primal (profit maximization) and the dual (cost minimization) specification is that price effects in conditional demands capture only pure substitution effects, whereas price effects in ordinary demands also capture the effect on the optimal output level.

[19]For the dichotomous outsourcing variable, we obtain a semi-elasticity measuring the percental change in labor demand when outsourcing occurs.

$$\varepsilon_{L_j,P_n} = \frac{\delta S_j/\delta \ln P_n}{S_j} + S_n - \delta_{j,n}, \qquad (4)$$

where $j, n = A, C, I$, and $\delta_{j,n} = 1$ if $j = n$, and 0 otherwise.[20] Moreover, the labor demand elasticities with respect to output are calculated as:

$$\varepsilon_{L_j,Y} = \frac{\delta S_j/\delta \ln Y}{S_j} + \varepsilon_{VC,Y}, \qquad (5)$$

where $j = A, C, I$, and $\varepsilon_{VC,Y} = \delta \ln VC/\delta \ln Y$. Elasticties with respect to the other variables of interest follow analogously, with $\varepsilon_{L_j,OUT}$ to be interpreted as a semi-elasticity.

We characterize the structure of technology in German manufacturing and services in the period 2001-2005 by estimating labor cost and share equations given by equations (2) and (3). for broadly defined industries. Three remarks are worth making about our empirical strategy before describing it in more detail below. First, a disturbing feature of equation (3) is that prices of task-differentiated labor are directly involved in the construction of the dependent variable, inducing a correlation between the dependent variable (cost share) and the exogenous variables. Therefore, following Muendler and Becker (2009), we transform equation (3) into a system of labor demand functions, in which labor prices only appear as regressors, by multiplying both sides of each share equation in (3) with the observation-specific scalars VC/P_j $(j = A, C, I)$.[21] Second, for empirical estimation of the cost and demand functions we need to specify a stochastic framework. We append the system by an additive disturbance term, and assume that the resulting disturbance vector is independently and identically multivariate normally distributed with mean vector zero

[20] Our focus on demand elasticities deliberately contrasts with the empirical studies in the literature, which typically report Allen partial elasticities of substitution (Frondel and Schmidt 2003). According to Chambers (1988), since Allen elasticities can only be interpreted meaningfully in terms of demand elasticities, reporting the former rather than the latter just reduces transparency.

[21] Notice that the linear transformation of cost shares into labor demand equations does not affect the elasticity calculations above.

and a constant, non-singular covariance matrix. Third, since the labor cost shares in (3) always sum to 1, the sum of disturbances across the three equations is 0 at each observation. Since only $n-1$ of the share equations in (3) are linearly independent, we arbitrarily drop the interactive labor share equation in the estimation procedure. Parameter estimates of the omitted equation can be obtained by working backward from the adding-up restrictions ensuring linear homogeneity in labor prices. As discussed in Barten (1969), Berndt (1990), and Morrison Paul (1999), the estimation results are invariant to the choice of the equation to be dropped, as long as a maximum likelihood or an iterative Zellner (seemingly unrelated) estimation procedure is employed.

In light of the discussion above, we estimate a three-equation system comprised of the cost equation (2) and the transformed demand functions for abstract and codifiable labor in (3) by iteratiing Zellner's (1962) seemingly unrelated regression (SUR) over the estimated disturbance covariance matrix until the estimates converge. The system estimation takes into account that residuals across equations may be correlated due to contemporaneous labor demand choices by plants. Both cross-equation symmetry for internal consistency of the model and linear homogeneity in labor prices contingent on the underlying production theory are imposed through constraints. Since it is unlikely that the error terms in our system of equations are uncorrelated with other right-hand-side variables, controlling for fixed effects is important. Some plants may have capable managers who employ both top quality employees (mainly performing, say, abstract tasks) and information technology. Such firm-specific performance advantage may also cause demand for different tasks to expand simultaneously, which would suggest a bias of estimated labor demand elasticities toward complementarity (Aguirregabiria and Alonso-Borrego 2001; Muendler and Becker 2009). To sweep out any unobserved (and time-invariant) plant heterogeneity, we apply the within transformation to the three-equation system represented by equations (2) and (3). Standard errors for our elasticity estimates are computed by using the "delta" method.[22]

Since we are looking at the establishment level, it may be reasonable to maintain the assumption that prices for task-differentiated labor are exogenous to individual firms or plants (Berndt and Wood 1975; Berndt 1990). Following the recent discussion by Muendler and Becker (2009), regarding firms as price takers in the labor market seems to be especially justifiable in the case of Germany, because firms face bargained wage schedules resulting from industry-specific collective bargaining. Strong German labor market institutions arguably make market forces less critical in determining wage movements. In addition to that, there exists an implicit minimum wage in Germany given by the high level of means-tested welfare benefits as compared to other OECD countries (e.g. Steiner and Wrohlich 2005).[23] These institutional limits to how far the wages can fall corrobate to some extent the assumption of a fixed market wage, in particular for employees in low-paying jobs. On the other hand, it is difficult to argue that the downward inlexibility of German wages is relevant for labor whose supply is rather inelastic (e.g. university graduates). Under the assumptions that these employees are relatively mobile and know approximately the market value of their labor services, preventing them from accepting positions that pay them less, it is not too implausible to also treat high-paying labor prices as being to some extent exogenous to plants.

[22]The elasticities are calculated as combinations of first and second derivatives of equations (2) and (3), evaluated at the sample means. Thus, each elasticity depends not only on the data, but also on a combination of parameter estimates, each with its own standard error. The "delta" method allows a combined standard error to be computed for these expressions.

[23]In a few industries even statutory minimum wages prevail, for instance since 1997 in the construction industry and since 2007 in the building cleaning industry, both due to the Employee Sending Act (Arbeitnehmer-Entsendegesetz).

6 Findings and discussion

Tables 1a to 1d and 2a to 2d present the elasticities of substitution calculated by using the coefficient estimates from the system of cost and demand functions as set forth by equations (2) and (3) for each of the twelve industries. The elasticities measure the percentage responses of demand for labor/tasks to a one percent change in either the price of a variable input or the quantity of a quasi-fixed input by industry.[24] *Elapa, Elcpc,* and *Elipi* indicate the own-price substitution elasticities of abstract, codifiable and interactive labor, while *Elapc, Elapi, Elcpi,* and their corresponding counterparts represent the set of cross-price substitution elasticities. Because of imposed symmetry of price coefficients trough constraints on the translog regression, *Elapc* and *Elcpa* (*Elapi* and *Elipa*, *Elcpi* and *Elipc*) have the same sign but are not necessarily of the same magnitude. The terms *ElaIT (ElcIT*, *EliIT), ElaOUT (ElcOUT, EliOUT),* and *ElaNonIT (ElcNonIT, EliNonIT)* report the reaction of abstract (codifiable, interactive) labor when the values of IT capital, outsourcing, or non-IT capital change.[25]

6.1 Price elasticities

Tables 1a to 1d present the price elacticities results. One common pattern is that own-price elasticities, when significant, are always negative, as

[24] In the case of outsourcing, the respective elasticities inform about the percentage change in labor demand in the presence of outsourcing.

[25] Since elasticties with respect to output are not in the focus of this study, we do not report them in the tables. Notice, however, that we find strong support in favor of increasing returns to scale across all twelve industries. This finding suggests that studies of German manufacturing and service industries should avoid using simple production functions such as constant elasticity of substitution (CES). In particular, if homotheticity or constant returns to scale are incorrectly imposed, movements along nonlinear expansion paths might be incorrectly explained as biased technical change (Betts 1997).

production theory requires.[26] A negative own-price elasticity means that labor-saving practices are stimulated within a plant if the price of labor increases. For example, in the glass, ceramics, and bricks industry, a one-percent increase in the price of abstract labor is associated with a .47 percent drop in its demand; a one-percent increase in the price of codifiable labor corresponds to a .29 percent decrease in demand; and a one-percent increase in the price of interactive labor relates to a .55 percent demand decrease. In relative terms this suggests that if prices of all three types of labor increase by one percent, interactive labor will be most negatively affected, followed by codifiable, and then by abstract labor. In general, the impact of own-price changes on labor demand is most pronounced for interactive labor; in ten out of twelve industries, the own-price elasticity of interactive labor is higher in magnitude than the respective elasticities of abstract and codifiable labor.[27] This finding is not surprising given that many of the interactive-labor intensive occupations require little or no training. As such, interactive labor can often be relatively easily acquired and replaced. Unlike many interactive tasks, codifiable tasks frequently require certain training and dexterity that cannot be immediately achieved. This should be even more the case with abstract labor. However, we observe only in six out of twelve industries that the response to own-price changes in codifiable labor is stronger than in abstract labor. These price effects may to some extent reflect the influence of still strong unions (e.g. IG Metall in iron and steel manufacturing; metal production; motor vehicles as well as IG Bau in glass, ceramics, and bricks; construction) that limit the possibilities of employers to react on price increases with saving on the respective labor. The pattern that matches most closely our expectations, $Elipi > Elcpc > Elapa$, appears in four out of twelve industries.

We now turn to the cross-price elasticities. These can have mixed signs and

[26] The only exception is interactive labor in the plastic and rubber industry. One possible reason for this result is that demand for codifiable labor exceeded its supply in our period of observation.

[27] The only exceptions are the two service industries in our sample, retail and wholesale, both of which show highest reaction of codifiable tasks demand to own-price changes.

provide an indication of factor substitutability (positive sign) and factor complementarity (negative sign) between labor of different type.
Cross-price elasticities are statistically different from zero in each industry and show remarkably similar patterns across industries. For instance, abstract and codifiable labor appear as substitutes everywhere. The magnitude of the effect of a one-percent increase in the price of abstract labor on the demand for codifiable labor (and vice versa, respectively) varies between .06 and .38 percent. Moreover, there is equally strong evidence suggesting that abstract and interactive labor complement each other. With cross-price elasticities between -.09 and -1.3 percent, the variation across industries is even stronger than in the case of abstract and codifiable labor. Our elasticity estimates for codifiable and interactive labor, except for two industries (plastics and rubber; iron and steel), point toward substitutability. The degree of between- industry variation in cross-price elasticties of codifiable and interactive labor is in the range of that of abstract and codifiable labor.

- Tables 1a to 1d around here -

6.2 IT and non-IT capital elasticities

Tables 2a to 2d presents the capital-labor elasticities and outsourcing-labor semi-elasticities calculated by using the coefficients from the system of demand and cost functions. We first draw our attention on a potential skill bias of capital. One prevalent pattern accross the twelve industries in our sample is that non-IT capital, when significant, correlates negatively with labor of any type, indicating substitutability. The range of non-IT elasticity estimates lies between -.03 and -.09, meaning that a one-percent increase in non-IT capital stock is associated with a drop in labor demand of .03 to .09 percent. Since our estimated elasticities show no considerable differences across task types, neither in magnitude nor in sign, we see no bias of non-IT capital toward labor of any particular type. The symmetry of capital-labor substitutability across tasks and industries is clearly at odds with the hypothesis that skill or education is more complementary with (non-IT) capital than unskilled or unschooled labor (Griliches 1969).

In the case of IT capital, our results are not consistent with economy-wide homogeneity of substitution patterns. Although IT capital is seldom significantly correlated with changes in the demand for task-differentiated labor - we find effects only in one third of the industries - IT substitutes for labor in some industries and complements it in others. In glass, bricks, and ceramics as well as in construction, plants that increase their IT capital stock decrease the employment of labor of *any* type. For example, a one-percent increase in IT capital in glass, bricks, and ceramics correlates with a .041 percent decrease in the demand for abstract labor, a .044 percent decrease in the demand for codifiable labor, and a .046 percent decrease in the demand for interactive labor. The magnitudes of the elasticities are apparently quite similar for the various labor types and indicate a rather low economic significance. The construction industry exhibits a comparable pattern. On the other hand, our results for chemicals and pharma as well as precision engineering, optics, and watches suggest complementarity between IT capital and labor, while again all types of labor are affected in the same way. Here again the elasticties' magnitudes are economically small; they range from .034 to .062. In fact, we do not observe a single industry where the relations between IT capital and labor behave according to the previous economy-wide results (Autor, Levy, and Murnane 2003, Spitz-Oener 2006, among others).

In line with earlier empirical studies on the determinants of occupational composition of employment, we find that the elasticities with respect to non-IT capital tend to be larger than the elasticities with repect to IT capital. In the construction industry, for instance, the elasticity of non-IT capital with respect to codifiable (interactive) labor is around three (two) times larger than the respective elasticity of IT capital. The non-IT elasticity of abstract labor in this industry is about 2.6 times as large as the IT elasticity of abstract labor. In precision engineering, optics, and watches - the only other industry in which we find significant effects for both IT and non-IT capital - the difference in the magnitudes of elasticities is less pronounced, varying between 115 percent (codifiable labor) and 170 percent (abstract labor). Moreover, elasticity estimates using data on individual firms or plants by Dunne, Haltiwanger, and Troske (1997) for the us, Aguirregabiria and Alonso-Borrego (2001) for Spain, and Addison et al. (2008) for Germany are with the same order of magnitude as the ones we obtain.[28] Hence the empirical evidence seems to suggest that even if the respective elasticities are significant, IT capital accumulation can only explain a fairly small amount of the changes in the demand for labor of different tasks or skills, respectively.

We can think of three lines of reasoning to reconcile our empirical findings with the conjecture that technology has played an important role for the demand for task-differentiated labor. The first is that the estimated elasticities are downward biased due to the presence of measurement errors in the capital stock variables. However, measurement errors cannot explain the observed symmetry in the coefficients across heterogeneous labor within same industries. Second, our design does not allow tasks to vary within occupations. We can only measure changes in the task quantities that stem from the acquisition or release of labor of certain type at the level of plants. In other words, to this end, our investigation is informative when it comes to the relations between technologies and demand for tasks that occur *due to changes in the occupational structure* at the establishment level. Therefore, we cannot claim that our results provide evidence for absence of asymmetric effects of IT capital on the overall task demand. Such effects may still be present but result in *within-occupational* task up- or downgrading. Third, following Bresnahan, Brynjolfsson, and Hitt (2002), strong effects on the skill-mix of labor at the plant level result from the

[28] We also share with the abovementioned studies that the elasticties with repect to IT capital are often insignificant. Only Addison et al. (2008) obtain mainly significant IT elasticity estimates.

combination of new technological capital and a deep reorganization of production. For example, Aguirregabiria and Alonso-Borrego (2001) find that the decision to introduce technological capital for the first time has much more explanatory power for changes in the occupational composition of labor than the continuous decision of increasing the (already existing) stock of IT capital. Unfortunately, we have no infomation on the IT investment behavior of plants before our period of observation starts. Finally, due to the short panel, we are limited in the choice of lag structure between changes in capital stock and changes in labor demand. Moreover, the timing between technological changes and shifts in labor demand may have complex dynamics which are difficult to capture with the current design.

- Tables 2a to 2d around here-

6.3 Outsourcing semi-elasticities

Outsourcing appears to be the only factor that induces asymmetric changes in the demand for labor of different tasks. The outsourcing semi-elasticties indicate trends that fit the reasoning of Blinder (2006, 2009). We expect that the presence of outsourcing is associated with declines in both abstract and codifiable labor and that it is neutral or even favorable for interactive labor. According to our results, in one third of the industries (chemicals and pharma; electrical equipment; metal production; precision engineering) the presence of outsourcing is associated with declines in the codifiable labor demand. The magnitude of the effects varies between -.43 percent in metal production to -1.31 percent in chemicals and pharma. The presence of outsourcing is also associated with declines in the demand for abstract labor in three industries (electrical equipment; motor vehicles; wholesale) with semi-elasticities of -3.82, -.67, and -.27 percent, respectively. The results also suggest that in electrical equipment abstract labor is even more adversely affected by outsourcing than codifiable labor (the presence of outsourcing is associated with a 3.82 percent decrease in abstract labor and a 2.68 percent decrease in codifiable labor). Finally, the semi-elasticities for interactive labor are significant in four out of twelve industries (chemicals and pharma; electrical equipment; plastics and rubber; wholesale). In the first three industries mentioned before, the presence of outsourcing is associated with increases in the demand for interactive labor (2.25, 14.32, and 2 percent, respectively). Only wholesale displays an unexpected pattern: here the presence outsourcing is negatively associated with the demand for interactive labor ($EliOUT$=-.73).

Since we see much inter- industry variation in the outsourcing-labor relations, the natural question arises why this is so. As argued before, we see two possible sources of variation. First, if industries employ qualitatively different production processes, the type of production being outsourced may also differ significantly. In the light of our empirical findings, chemicals and pharma, electrical equipment, metal production, as well as precision engineering may be in process of outsourcing assembly-type of production and therefore downsize labor that makes intense use of codifiable tasks. Wholesale, on the other hand, may be outsourcing some non-core service processes that involve labor that makes use of intellectual and interactive tasks. Second, industries may exhibit qualitatively similar outsourcing patterns, but some of them might have taken the lead in outsourcing earlier than others. In this line of reasoning and given our empirical results, vehicle production likely outsourced most of their assembly line processes during the 1990s (Geishecker 2002) and turned to outsourcing units with more complex tasks in the period we observe. Other manufacturing industries with production processes similar to those in motor vehicles may have started outsourcing later and are thus still primarily outsourcing assembly line-types of processes (e.g. chemicals and pharma; electrical equipment; metal production; precision engineering).

7 Sensitivity analysis

We have specified alternatives to the main model in order to check for the robustness of the results. As elaborated in section 3, we use two indicators of knowledge codification. In the above-presented results we use the expliciteness of tasks as an indicator of codification. Hence, we estimated the same system of cost and demand functions as before, but now instead of explicit tasks quantities as a measure of codifiable labor, we include repetitive tasks quantities. The results (available from the authors on request) for this second set of regressions are remarkably similar to the results of the estimation including explicit tasks for all elasticities except for the semi-elasticities with respect to outsourcing in precision engineering, optics, and watches.

Our data do not permit us to see how qualitatively different the reported IT investments are across industries. It is an assumption that the quality of capital across industries varies. At the same time, due to the fact that our task measures are occupation-specific, we assume that an occupation has the same task composition across industries. One concern that arises is whether the differences we see across industries stem from the differences in the technologies they employ, or from the differences in the task composition used by seemingly identical occupations in different industries. For example, one can rightfully ask whether the task portfolio of a manager in chemicals is significantly different from the one of a manager in retail? If the managers in chemicals have on average significantly higher intensity of abstract content than those in retail, it may be advisable to account for these differences in the analysis. After the inspection of the industry-occupation relations in our data we noticed two favourable properties of the current design. First, our industries are broadly specified such that many of the occupations become unique to certain industries. Second, the results of the analysis of variance, where the variance of each tasks we use is regressed on the occupational and industry dummies, shows that most of the task variation is explained by the occupational and to lesser extent by the industry dimension. The main results of the ANOVA are presented in table 3. For example, for R&D tasks, although the industry dummies explain a significant share of the variance of the R&D tasks' intensity, the mean sum of squares of the occupational categories is almost three times larger than the one of the industry dummies (.88 vs. .30). The total sum of squares explained by the occupational dummies is almost 48 times larger than the sum of squares explained by the industry dummies (127.87 vs. 2.68).

However, there is still a significant share of variation in many tasks that is explained by the industry dummies after controling for the occupational dimension. Therefore, it would be advisable in next versions to replace the occupational classification with a classification that further distinguishes the occupations by industries as well.

- Table 3 around here-

8 Conclusions

The recent scientific discourse on the impact of technology and outsourcing on the labor market suggests the idea that the demand for different skills is not uniformly affected by technological and organizational change. Following authors such as Autor, Levy, and Murnane (2003), Spitz-Oener (2006), Goos and Manning (2007), as well as Blinder (2009), one can hypothesize that repetitive or routine tasks should be easily substitutable by technology and at the same time internationally outsourceable. Moreover, labor of any kind that does not involve direct contact with customers should possess certain proneness to be outsourced to another sector, region, or country. This also holds for labor that mainly performs problem-solving tasks. Nevertheless, problem-solving and complex thinking skills (i.e., abstract tasks) should be complementary to technology. It is furthermore argued that tasks involving customer-interaction (i.e., interactive tasks) can neither be outsourced nor substituted by technology. Previous research on the empirical plausibility of these hypotheses has largely focused on economy-wide patterns. It has often been mute on potential inter- industry differences in the nature of the technology-outsourcing-labor nexus. Variation among industries in the capital-labor (outsourcing-labor) relations stem from differences in the types of production processes employed (outsourced). In the case of outsourcing, they also stem from the cross-sectoral differences in the outsourcing stage. The main purpose of this article is to test for inter-industry idiosyncrasies in the capital-labor and outsourcing-labor relations.

Using a sample of twelve German industries in the period 2001-2005, we explore the relations between the demand for heterogeneous labor on the one hand and capital and outsourcing on the other hand. Our results are only to a certain degree consistent with the predictions outlined above. First, perhaps most at odds with previous studies are our results for technology as captured by IT capital. In the industries where we observe significant effects, IT elasticities are either positive for all types of labor (chemicals and pharma; precision engineering, optics, and watches) or negative througout (glass, bricks, ceramics; construction). Moreover, the magnitude of the elasticities of demand for task-differentiated labor with respect to IT capital is fairly small. Nevertheless, we do not claim that our results provide evidence for the absence of effects of technology on labor demand. Such effects may still be present but result mainly in within occupational task up- or downgrading, something we cannot observe with the current empirical design. This is one evident shortcoming of the current approach.

Second, our results provide some evidence against the capital–skill complementarity conjecture advanced originally by Griliches (1969). One of the most salient patterns across the twelve industries in our sample is that non-IT capital is associated with declines in the employment of labor of any type, indicating a substitutive relationship. The magnitude of the substitution effects is economically small, although higher than that of IT capital.

Third, our findings for outsourcing closely match the predictions posited by Blinder (2009). In half of the industries we find an indication of an adverse effect of outsourcing either on codifiable or on abstract labor, or on both. At the same time, outsourcing is either neutral or favorable to the demand for interactive labor in all but one industry.

Fourth, when it comes to the substitution patterns between labor of different types, we capture the following: abstract and codifiable labor appear as substitutes in all industries, abstract and interactive labor appear as complements everywhere, while interactive and codifiable labor show a substitutive relationship in ten industries and complementarity in two.

We conclude that in our exploration of skill bias in the capital-labor and outsourcing-labor relationships among industries the only notable variation we see is in outsourcing. The results support the reasoning about international outsourcing put forward by Blinder (2006, 2009).

References

[1] Acemoglu, Daron. 1998 "Why do new Technologies Complement Skills? Directed Technical Change and Wage Inequality," *Quarterly Journal of Economics*, Vol. No. pp. 1055-1089.

[2] Acemoglu, Daron. 2002 "Technical Change, Inequality, and the Labor Market," *Journal of Economic Literature*, Vol. 40, No. 1, pp. 7-72.

[3] Acemoglu, Daron. 2003 "Patterns of Skill Premia," *Review of Economic Studies,* Vol 70, No. 2, pp. 199-230.

[4] Adams, James D. 1999 “The Structure of Firm R&D, the Factor Intensity of Production, and Skill Bias,” Review of Economics and Statistics, Vol. 81, No. 3, pp. 499-510.

[5] Addison, John, Bellmann, Lutz, Schank Thorsten and Teixeira, Paulino. 2008 “The Demand for Labor: An Analysis Using Matched Employer-Employee Data from the German LIAB. Will the High Skilled Worker Own Wage Elasticity Please Stand Up?,” *Journal of Labor Research*, No. 29, pp. 114-137.

[6] Aguirregabiria, Víctor, Alonso-Borrego, César. 2001 “Occupational structure, technological innovation, and reorganization of production,” *Labour Economics*, Vol. 8, No. 1, pp 43-73.

[7] Autor, David H., Levy, Frank and Murnane, Richard J. 2003 “The Skill Content of Recent Technological Change: An Empirical Exploration,” *Quarterly Journal of Economics*, Vol. 118, No. 4, pp. 1279-1333.

[8] Autor, David, Katz, Lawrence and Kearney, Mellisa. 2008 “Trends in U.S. Wage Inequality: Revisiting the Revisionists,” *The Review of Economics and Statistics*, Vol. 90, No. 2, pp.300-323.

[9] Baltagi, Badi H., Rich, Daniel P. 2005 “Skill-biased technical change in US manufacturing: a general index approach,” *Journal of Econometrics*, Vol. 126, pp. 549–570

[10] Bartel, Ann P., Lichtenberg, Frank R. 1987 “The Comparative Advantage of Educated Workers in Implementing New Technology,” *Review of Economics and Statistics*, Vol. 69, No. 1, pp. 1-11

[11] Barten, A. P. 1969 “Maximum Likelihood Estimation of a Complete System of Demand Equations,” *European Economic Review*, Vol. 1, Nr. 1, pp. 7-73.

[12] Baumgarten, Daniel. 2009 "International Outsourcing, the Nature of Tasks, and Occupational Stability – Empirical Evidence for Germany," Ruhr Economic Papers 0108.

[13] Becker, Sascha O., Ekholm, Karolina, Muendler, Marc-Andreas. 2009 “Offshoring and the Onshore Composition of Occupations, Tasks and Skills,” CEPR Discussion Papers 7391.

[14] Becker, Sascha O., Ekholm, Karolina, Jäckle, Robert, Muendler, Marc-Andreas. 2005 "Location Choice and Employment Decisions: A Comparison of German and Swedish Multinationals," *Review of World Economics*, Vol. 141, Nr. 4, pp. 693-731.

[15] Becker, Sascha O., Hornung, Erik, Woessmann, Ludger. 2009 "Catch Me If You Can: Education and Catch-up in the Industrial Revolution," *Stirling Economics Discussion Paper*, No. 2009-19.

[16] Berman, Eli, Bound, John and Machin, Stephan. 1998 "Implications of Skill-Biased Technological Change: International Evidence," *Quarterly Journal of Economics*, Vol. 113, No. 4, pp. 1245-1279.

[17] Berman, Eli, Bound, John and Griliches, Zvi. 1994 "Changes in the Demand for Skilled Labor within U.S. Manufacturing Industries: Evidence from the Annual Survey of Manufacturing," *Quarterly Journal of Economics*, Vol. 109, No. 1, pp. 367-397.

[18] Berndt, Ernst R. 1990 "The practice of econometrics :classic & contemporary," Addison Wesley Publishing.

[19] Berndt, Ernst R., Wood, David O. 1975 "Technology, Prices, and the Derived Demand for Energy," *Review of Economics and Statistics*, Vol. 57, No. 3, pp. 259-268.

[20] Berndt, Ernst R., Morrison, Catherine J., Watkins, G. Campbell. 1981 "Dynamic Models of Energy Demand: An Assessment and Comparison," in Berndt, Ernst R., Field, Barry C. (eds), *Measuring and Modelling Natural Resource Substitution*. Cambridge, M.I.T. Press.

[21] Betts, Julian R. 1997 "The Skill Bias of Technological Change in Canadian Manufacturing Industries," *Review of Economics and Statistics*, Vol. 79, No. 1, pp. 146-150.

[22] Blinder, Alan S. 2006 "Offshoring: the next industrial revolution?" *Foreign Affairs*, Vol. 85, No. 2, pp. 112-128.

[23] Blinder, Alan S. 2009 "How Many U.S. Jobs might be Offshorable?" *World Economics*, Vol. 10, No. 2, pp.41 78.

[24] Bollen, Kenneth A. 1989 "Structural Equations with Latent Variables", New York: Wiley

[25] Bresnahan, Timothy F., Brynjolfsson, Erik, Hitt, Lorin M. 2002 "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *Quarterly Journal of Economics*, Vol. 117, No. 1, pp. 339-376.

[26] Brown, Randall S., Christensen, Laurits R. 1981 "Estimates of Elasticities of Substitution in a Model of Partial Static Equilibrium: An Application to U.S. Agriculture, 1947-1974," in Berndt, Ernst R., Field, Barry C. (eds.), Modeling and measuring natural resource substitution, Cambridge, MIT Press, pp. 209-222.

[27] Chambers, Robert G. 1988 "Applied Production Analysis," Cambridge, Cambridge University Press.

[28] Chennells, Lucy, Van Reenen, John. 1999 "Has technology hurt less skilled workers," *The Institute for Financial Studies Working Paper*, No. W99/27.

[29] Christensen, Laurits R., Jorgenson, Dale W., Lau, Lawrence, J. 1971 "Conjugate Duality and the Transcendental Logarithmic Production Function," *Econometrica*, Vol. 39, No. 4, pp. 255-256.

[30] Christensen, Laurits R., Jorgenson, Dale W., Lau, Lawrence, J. 1973 "Transcendental Logarithmic Production Frontiers," *Review of Economics and Statistics*, Vol. 55, No. 1, pp. 28-45.

[31] Diewert W. E. 1971 "An Application of the Shepard Duality Theorem: A Generalized Leontief Production Function," *Journal of Political Economy*, Vol. 79, No. 3, pp. 481-507.

[32] DiNardo, John E., Pischke, Jorn-Steffen. 1997 "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?" *Quarterly Journal of Economics*, Vol. 112, No. 1, pp. 291-303.

[33] Dunne, Timothy, Haltiwanger, John, Troske, Kenneth R. 1997 "Technology and jobs: secular changes and cyclical dynamics," *Carnegie-Rochester Conference Series on Public Policy*, Vol. 46, pp. 107-178.

[34] Dustmann, Christian, Ludsteck, Johannes and Schönberg, Uta. 2009 "Revisiting the German Wage Structure," *Quarterly Journal of Economics*, Vol. 124, No. 2, pp. 843-881.

[35] Fraumeni, Barbara. 1997 “The Measurement of Depreciation in the US National Income and Product Accounts,” *Survey of Current Business*, July 1997.

[36] Freier, Ronny, Steiner, Viktor. 2007 “‘Marginal Employment’ and the Demand for Heterogenous Labour: Empirical Evidence from a Multi-Factor Labour Demand Model for Germany,” *DIW Berlin Discussion Papers*, No. 662.

[37] Frondel, Manuel, Schmidt, Christoph M. 2003 “Rejecting capital–skill complementarity at all costs,” *Economics Letters*, Vol. 80, pp. 15-21.

[38] Gathmann, Christina, Schönberg, Uta. 2010 "How General is Human Capital? A Task-Based Approach", *Journal of Labor Economics*, Vol. 28, No. 1, pp. 1-50.

[39] Geishecker, Ingo 2002 “Outsourcing and the Demand for Low-skilled labor in German Manufacturing: New Evidence,” *DIW Discussion Paper*, No. 313.

[40] Geishecker, Ingo (2006) “Does Outsourcing to Central and Eastern Europe Really Threaten Manual Workers’ Jobs in Germany?” *The World Economy*, Vol. 29, No. 5, pp. 559-583.

[41] Goldin, Caludia and Katz, Lawrence F. 1996 “Technology, Human Capital, and the Wage Structure,” *American Economic Review*, Vol. 86, No. 2, pp. 252-257.

[42] Goldin, Claudia and Katz, Lawrence F. 1998 “The Origins of Technology-Skills Complementarity,” *Quarterly Journal of Economics*, Vol 113, No. 3, pp. 693-732.

[43] Goldin, Claudia and Katz, Lawrence F. 2009 “The Race between Education and Technology”, Harvard University Press, Harvard.

[44] Good, David H., Nadiri, M. Ishaq, Sickles, Robin C. 1996 “Index Number and Factor Demand Approaches to the Estimation of Productivity,” *NBER Working Paper*, No. W5790.

[45] Goos, Maarten and Manning, Alan. 2007 “Lousy and Lovely Jobs: The Rising Polarization of Work in Britain,” *Review of Economics and Statistics*, Vol. 89, No. 1, pp. 118-133.

[46] Goos, Maarten, Manning, Alan and Salomons, Anna. 2009 “Job Polarization in Europe,” *American Economic Review Papers and Proceedings*, Vol. 99, No. 2, pp. 58-63.

[47] Griliches, Zvi. 1969 “Capital-Skill Complementarity,” *Review of Economics and Statistics*, Vol. 51, No. 4, pp. 465-468.

[48] Grossman, Gene M. and Rossi-Hansberg, Esteban. 2008 “Trading Tasks: A Simple Theory of Offshoring,” *American Economic Review*, Vol. 98, No. 5, pp. 1978-1997.

[49] Guilkey, David K., Lovell, C. A. Knox, Sickles, Robin C. 1983 “A Comparison of the Performance of Three Flexible Functional Forms,” *International Economic Review*, Vol. 24, No. 3, pp. 591-616.

[50] Hamermesh, Daniel S. 1993 “Labor Demand,” Princeton University Press, Princeton.

[51] Hollanders, Hugo, ter Weel, Bas. 2002 “Technology, knowledge spillovers and changes in employment structure: evidence from six OECD countries,” *Labour Economics*, Vol. 9, pp. 579–599.

[52] Hulten, Charles R., Wykoff, Frank C. 1981 “The estimation of economic depreciation using vintage asset prices: An application of the Box-Cox power transformation,” *Journal of Econometrics*, Vol. 15, No. 3, pp. 367-396.

[53] Jacobebbinghaus, Peter. 2008 “LIAB-Datenhandbuch,” *FDZ Datenreport*, No. 3/2008.

[54] Katz, Lawrence F., Autor, David H. 1999 "Changes in the wage structure and earnings inequality," in Ashenfelter, Orley, Card, David (eds.), Handbook of Labor Economics, Elsevier, pp. 1463-1555.

[55] Kölling, Arnd, Schank, Thorsten. 2002 “Skill-biased technological change, international trade and the wage structure,” Paper presented at the 10th International Conference on Panel Data, Berlin, July 5-6, 2002.

[56] Lemieux, Thomas. 2008 “The Changing Nature of Wage Inequality,” *Journal of Population Economics*, Vol. 21, No. 1, pp. 21-48.

[57] Levy, Frank and Murnane, Richard J. 1992 “U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations,” *Journal of Economics Literature*, Vol. 30, No. 3, pp. 1333-1381.

[58] Manning, Alan. 2004 “We Can Work it Out: The Impact of Technological Change on the Demand for Low-Skill Workers,” *Scottish Journal of Political Economy*, Vol. 51, No. 5, pp. 581-608.

[59] Mazzolari, Francesca and Ragusa, Giuseppe. 2007. “Spillovers from High-Skill Consumption to Low-Skill Labor Markets,” *IZA Discussion Paper*, No. 3048.

[60] McElroy, Marjorie B. 1987 “Additive General Error Models for Production, Cost, and Derived Demand or Share Systems,” *Journal of Political Economy*, Vol. 95, No. 4, pp. 737-757.

[61] Morrison Paul, Catherine J. 1999 ”Cost Structure and the Measurement of Economic Performance,” Springer, Berlin.

[62] Morrison Paul, Catherine J., Siegel, Donald S. 2001 “The Impacts of Technology, Trade and Outsourcing on Employment and Labor Composition,” *Scandinavian Journal of Economics*, Vol. 103, No. 2, pp. 241-264.

[63] Mueller, Steffen. 2008 “Capital Stock Approximation Using Firm Level Panel Data,” *Jahrbücher für Nationalökonomie und Statistik*, Vol. 228. No. 4.

[64] Muendler, Marc-Andreas, Becker, Sascha O. 2009 “Margins of Multinational Labor Substitution,” *NBER Working Paper*, No. 14776.

[65] O’Mahony, Mary, Timmer, Marcel. 2009 “Output, Input and Productivity Measures at the Industry Level: the EU KLEMS Database,” *Economic Journal*, Vol. 119, No. 538, pp. F374-F403.

[66] Nedelkoska, Ljubica. 2010 “Occupations at risk: The task content and job stability,” mimeo.

[67] Pfannenstein, Laura L. and Tsai, Ray J. 2004 “Offshore Outsourcing: Current and Future Effects on Americal IT Industry,” *Information Systems Management*, Fall, pp. 72-80.

[68] Slaughter, Matthew J. 1995 “Multinational Corporations, Outsourcing, and American Wage Divergence,” *NBER Working Paper*, No. 5253.

[69] Spitz-Oener, Alexandra. 2006 “Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure,” *Journal of Labor Economics*, Vol. 24, No. 2, pp. 235-270.

[70] Steiner, Viktor, Wrohlich, Katharina. 2005 "Work Incentives and Labor Supply Effects of the 'Mini-Jobs Reform' in Germany," *Empirica*, Vol. 32, pp. 91-116.

[71] Timmer, Marcel, van Moergastel, Ton, Stuivenwold, Edwin, Ypma, Gerard, O'Mahony, Mary, Kangasniemi, Mari. 2007 "EU KLEMS Growth and Productivity Accounts," http://www.euklems.net/

[72] Van Reenen, John. 1997 "Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms," *Journal of Labor Economics*, Vol. 15, No. 2, pp. 255-284.

[73] Zellner, Arnold. 1962 "An Efficient Method for Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias," *Journal of the American Statistical Association*, Vol. 57, No. 298, pp. 348-36.

Appendix A

-Table 4 around here -

- Tables 5a to 5d around here -

Measurement of capital stocks

We use investment expenditure data reported in the Linked Employer-Employee Panel (LIAB) to approximate stocks of IT and non-IT capital. Working with measures of capital stock rather than with capital flows has the virtue one does not need to rely on the assumption of proportionality of (replacement) investments and capital stock, which is difficult to test empirically. Moreover, in our approach so far missing values and zero investments lead to implausibly high variations in the (by assumption) proportional capital data series, probably causing measurement errors and an attenuation bias (Mueller 2008). Constructing capital stocks will alleviate these problems. The most commonly employed approach in capital stock measurement is the Perpetual Inventory Method (PIM). This method bases on constant exponential decay of capital goods (geometric deterioration), implying that capital services never actually reach zero and every unit of investment is perpetually part of the capital stock[29]. With a given constant rate of depreciation $\delta_i$that is constant over time, but different for each asset type i, the PIM essentially assumes that $K_{i,t} = K_{i,t-1}(1-\delta_i) + I_{i,t}$, where $K_{i,t}$ is the capital stock (for a particular asset type i) at the end of period t, and $I_{i,t}$ denotes the investments in asset type i in period t. For the practical implementation of PIM we divide capital inputs into two asset types, namely IT and non-IT capital. We derive depreciation rates by industry from the EU KLEMS database as described in O'Mahony and Timmer (2009)[30]. There are several advantages of U.S.ing the depreciation rates provided by EU KLEMS (Timmer et al. 2007). First, the rates are based on empirical research, rather than ad-hoc assumptions based on e.g. tax laws. Second, the EU KLEMS depreciation rates are available by industry and have much more

[29]Hulten and Wykoff (1981) tested several standard assumptions regarding depreciation rates and found that constant exponential depreciation performed reasonably well in describing exhibited data patterns.

[30]In fact, depreciation rates used in the EU KLEMS database are obtained from the U.S. Bureau of Economic Analysis (BEA). See Fraumeni (1997) for details.

asset detail than the investment series published by the German Statistical Office. Specifically, it turned out that the components of IT in EU KLEMS closely match the definition of IT employed in the LIAB data. Third and finally, since in particular IT assets are subject to rapid technological change and improvements in quality, hedonic price measurement is adopted in the calculation of EU KLEMS depreciation rates to adjust for quality. Altogether, EU KLEMS provides depreciation rates for eight different asset types. Three of these (computing equipment, communications equipment, software) comprise our IT capital variable, while the remaining five (transport equipment, other machinery and equipment, total non-residential investment, residential structures, other assets) enter our non-IT capital variable. We construct industry-specific depreciation rates for the stocks of IT and non-IT capital by calculating a weighted average of EU KLEMS depreciation rates, where we employ the intensity to which each asset type is used in an industry in the period 2000-2004 as our weight.

Because PIM always needs the capital stock of the previous year, the fundamental problem is to find an appropriate value for the initial capital stock. Since there is no widely-accepted solution how to overcome this problem, we follow the approach recently proposed by Mueller (2008) for analyses that rely on within-firm information. We compute the starting value of the capital stock as the arithmetic mean of investments over the first three years we observe a plant in our sample.

Appendix B

Factor analysis

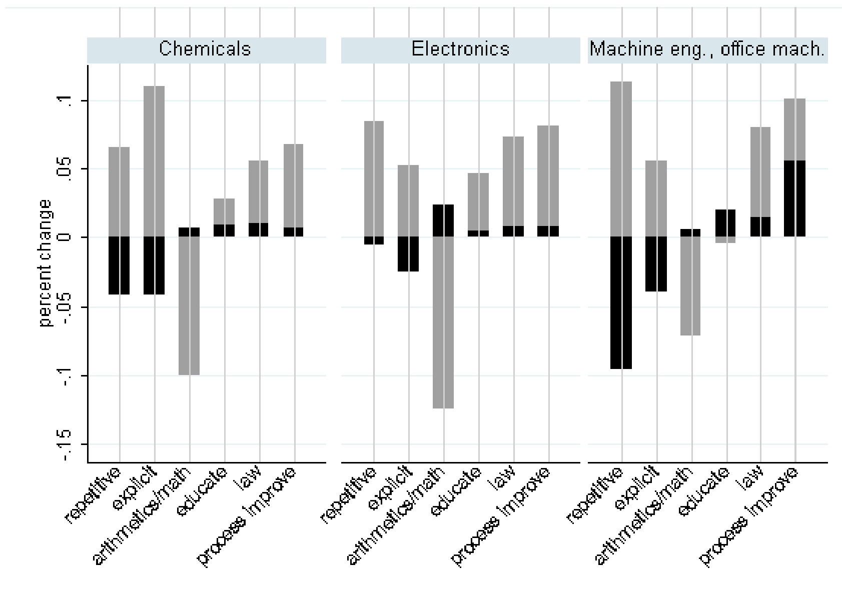
The 12 variables resulted in two factors that had eigenvalues above one. The eigenvalues measure the variance in all variables that is accounted by a factor. As a rule of thumb factors with eigenvalues of at least one are considered to explain non-trivial amount of the total variance in the data. In the 1998/1999 wave these two factors have eigenvalues of 6.55 and 1.59 and together explain 87% of the total variance. Based on the factor loadings on different variables and the occupational rankings on each of these factors we interpret the first one as abstract dimension and the second one as interactive dimension.

- Table 6 around here -

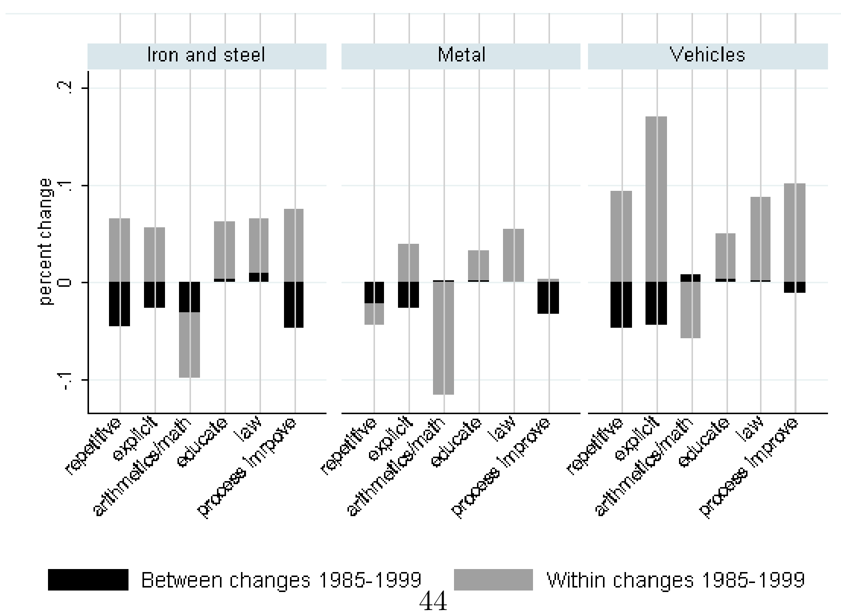
Figures and tables

Figure 1: Between- and within-occupational task changes by industries (1985-1999)

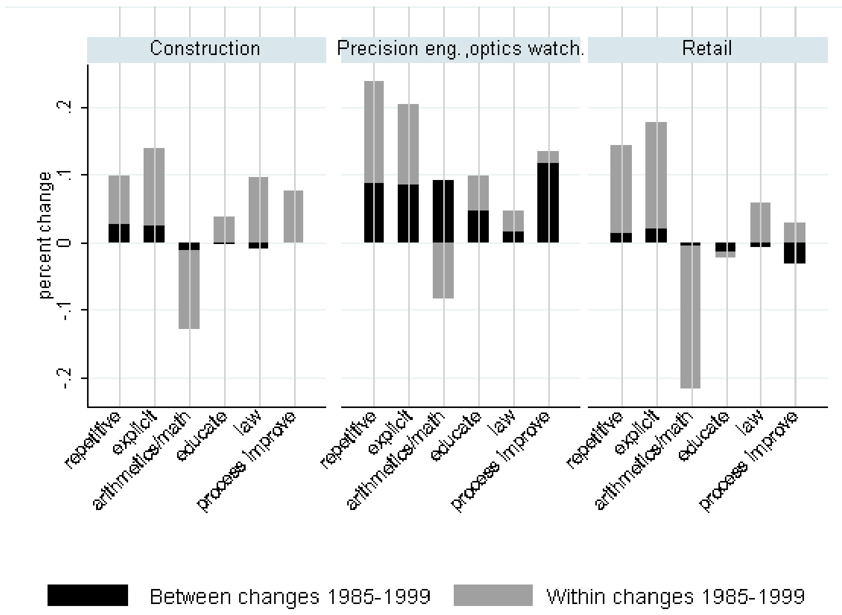
(a)



(b)



(c)



Source: Qualification and Career Survey 1985, 1991/1992 and 1998/1999

Note: Changes in arithmetics/math/statistics are estimated for the period 1992-1999. The iindustrial classifications in the 1979 and 2005/2006 waves differ from those

of the 1985, 1991/1992 and 1998/1999.

Table 1a: Price elasticities

Glass, ceramics, and bricks			Chemicals and pharma			Construction		
Abstract tasks								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.472***	.220***	-.315***	-.270***	.162***	-.268***	-.331***	.251***	-.462***
(.01)	(.01)	(.01)	(.01)	(.00)	(.01)	(.00)	(.00)	(.00)
Codifiable tasks								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-.289***	.174***	.115***	-.393***	.219***	.174***	-.274***	.200***	0.074***
(.01)	(.00)	(.01)	(.01)	(.00)	(.01)	(.00)	(.00)	(.00)
Interactive tasks								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-.545***	-.433***	.199***	-.557***	-.631***	.303***	-.371***	-.986***	.199***
(.02)	(.01)	(.02)	(.02)	(.02)	(.01)	(.02)	(.01)	(.01)

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses

Table 1b: Price elasticities

Electrical equipment			Iron and steel manufacturing			Machine engineer./office mach.		
Abstract tasks								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.345***	.206***	-.146***	-.481***	.240***	-.711***	-.300***	.241***	-.175***
(.01)	(.00)	(.01)	(.01)	(.00)	(.01)	(.00)	(.00)	(.00)
Codifiable tasks								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-.450***	.285***	.165***	-.097***	.136***	-.039***	-.500***	.297***	.203***
(.01)	(.01)	(.01)	(.01)	(.00)	(.01)	(.00)	(.00)	(.00)
Interactive tasks								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-.604***	-.342***	.279***	-.285***	-1.173***	-.113***	-.568***	-.442***	.418***
(.03)	(.02)	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.01)

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses

Table 1c: Price elasticities

Metal production			Precision engin, optics, watches			Plastics and rubber		
Abstract tasks								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.361***	.088***	-.646***	-.305***	.119***	-.093***	-.546***	.376***	-.840***
(.01)	(.01)	(.01)	(.01)	(.00)	(.01)	(.01)	(.01)	(.02)
Codifiable tasks								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-.142***	.064***	.078***	-.513***	.196***	.317***	-.009	.202***	-.192***
(.01)	(.00)	(.01)	(.01)	(.00)	(.01)	(.01)	(.00)	(.01)
Interactive tasks								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-.645***	-1.094***	.182***	-.533***	-.132***	.271***	.294***	-1.313***	-.560***
(.02)	(.02)	(.02)	(.01)	(.01)	(.00)	(.01)	(.01)	(.01)

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses

Table 1d: Price elasticities

Motor vehicles			Retail			Wholesale		
Abstract tasks								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.452***	.240***	-.326***	-.307***	.078***	-.109***	-.169***	.173***	-.103***
(.01)	(.00)	(.01)	(.01)	(.00)	(.01)	(.01)	(.00)	(.01)
Codifiable tasks								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-.275***	.203***	.072***	-.418***	.139***	.279***	-.679***	.364***	.315***
(.01)	(.00)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Interactive tasks								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-.555***	-.608***	.159***	-.347***	-.099***	.140***	-.234***	-.165***	.241***
(.02)	(.02)	(.02)	(.01)	(.01)	(.00)	(.01)	(.01)	(.01)

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses

Table 2a: Technology and outsourcing elasticities

Glass, ceramics, and bricks			Chemicals and pharma			Construction		
Abstract tasks								
ElaIT	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*
-.041*	-.911	-.020	.035*	.118	-.050	-.032**	-.152	-.082***
(.03)	(.70)	(.03)	(.02)	(.31)	(.03)	(.02)	(.48)	(.02)
Explicit tasks								
ElcIT	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*
-.044**	-.320	-.020	.034*	-1.313***	-.046	-.027*	-.052	-.090***
(.03)	(.55)	(.03)	(.02)	(.40)	(.03)	(.02)	(.18)	(.02)
Interactive tasks								
EliIT	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*
-.046**	2.661	.007	.045**	2.247*	-.059*	-.038**	-.273	-.070***
(.03)	(2.07)	(.03)	(.02)	(1.20)	(.03)	(.02)	(.97)	(.02)
R^2cost		.33			.31			.33
R^2demand abstract		.90			.92			.90
R^2demand codifiable		.94			.90			.91
Observations		349			382			1727

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses. For outsourcing semi-elasticities are reported

Table 2b: Technology and outsourcing elasticities

Electrical equipment			Iron and steel manuf			Machine engineer./office mach.		
Abstract tasks								
ElaIT	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*
-.005	-3.824***	.036	-.022	-.177	-.046	.025*	-.096	.012
(.03)	(1.44)	(.03)	(.03)	(.12)	(.04)	(.01)	(.13)	(.02)
Explicit tasks								
ElcIT	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*
-.010	-2.677**	.025	-.012	-.065	-.069*	.017	-.387	.011
(.03)	(1.08)	(.03)	(.03)	(.45)	(.04)	(.01)	(.25)	(.02)
Interactive tasks								
EliIT	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*
.006	14.316***	.035	-.012	-.501	-.044	.007	-.201	.015
(.03)	(4.88)	(.03)	(.03)	(1.23)	(.04)	(.01)	(.61)	(.02)
R^2cost		.14			.23			.32
R^2demand abstract		.29			.88			.21
R^2demand codifiable		.64			.97			.68
Observations		314			394			940

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses. For outsourcing semi-elasticities are reported

Table 2c: Technology and outsourcing elasticities

Metal production			Precision engin., optics, watches			Plastics and rubber		
Abstract tasks								
ElaIT	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*
-.005	-.142	-.021	.042*	-1.214	-.075***	.0003	-.582	-.078***
(.02)	(.38)	(.02)	(.02)	(.35)	(.03)	(.03)	(.90)	(.03)
Explicit tasks								
ElcIT	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*
-.005	-.427*	-.033*	.062***	-.581*	-.071***	-.006	.368	-.075***
(.02)	(.23)	(.02)	(.02)	(.33)	(.03)	(.03)	(.49)	(.03)
Interactive tasks								
EliIT	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*
.015	-.129	-.052***	.046**	.312	-.070**	.003	1.979**	-.052*
(.02)	(.76)	(.02)	(.02)	(1.03)	(.03)	(.03)	(.92)	(.03)
R^2cost		.31			.34			.38
R^2demand abstract		.92			.86			.71
R^2demand codifiable		.96			.84			.95
Observations		844			333			384

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses. For outsourcing semi-elasticities are reported

Table 2d: Technology and outsourcing elasticities

Motor vehicles			Retail			Wholesale		
Abstract tasks								
ElaIT	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*	*ElaIT*	*ElaOut*	*ElaNonIT*
-.001	-.665**	-.012	.020	1.03	-.046***	.017	-.272**	-.076***
(.03)	(.32)	(.04)	(.02)	(1.11)	(.02)	(.02)	(.13)	(.02)
Explicit tasks								
ElcIT	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*	*ElcIT*	*ElcOut*	*ElcNonIT*
.010	-.453	-.024	.019	.849	-.043**	.013	.321	-.078***
(.03)	(.46)	(.04)	(.02)	(.70)	(.02)	(.02)	(.29)	(.02)
Interactive tasks								
EliIT	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*	*EliIT*	*EliOut*	*EliNonIT*
-.004	1.217	-.003	.022	-1.313	-.047***	.009	-.726**	-.077***
(.03)	(1.01)	(.04)	(.13)	(1.00)	(.02)	(.02)	(.32)	(.03)
R^2cost		.40			.29			.37
R^2demand abstract		.58			.98			.84
R^2demand codifiable		.83			.97			.37
Observations		377			812			657

Results from demeaned SUR of cost and demand functions. Delta standard errors in parentheses. For outsourcing semi-elasticities are reported

Table 3: Explaning task variation: occupational vs. industrial dimension

Source	Patial SS	df	MS	F	Prob<F	Partial SS	df	MS	F	Prob<F
Coordinate, organize						*Sales, PR*				
Model	116.23	154	.75	9.24	.00	1.32	154	.07	4.85	.00
Occupation	111.25	145	.77	9.39	.00	9.24	145	.06	4.61	.00
Industry	2.05	9	.23	2.79	.00	.17	9	.02	1.39	.19
$AdjR^2$	.73					.56				
R&D						*Management*				
Model	136.52	154	.89	13.96	.00	12.84	154	.08	5.67	.00
Occupation	127.87	145	.88	13.89	.00	12.37	145	.09	5.8	.00
Industry	2.68	9	.3	4.69	.00	.13	9	.01	.95	.48
$AdjR^2$	.81					.61				
Negotiate						*Medical knowledge*				
Model	113.57	154	.74	13.36	.00	4.78	154	.03	3.4	.00
Occupation	107.05	145	.74	13.37	.00	3.73	145	.03	2.82	.00
Industry	.61	9	.07	1.23	.27	.37	9	.04	4.57	.00
$AdjR^2$	.8					.44				
Taking care of people						*Explicit knowledge*				
Model	64.1	154	.42	4.52	.00	206	154	1.34	3.78	.00
Occupation	39.5	145	.27	2.96	.00	188.06	145	1.3	3.67	.00
Industry	3.92	9	.44	4.73	.00	3.94	9	.44	1.24	.27
$AdjR^2$	.53					.47				
Mathemantics, statistics						*Repetitive knowledge*				
Model	16.36	154	.11	2.23	.00	202.25	154	1.31	5.15	.00
Occupation	15.64	145	.11	2.26	.00	194.42	145	1.34	5.26	.00
Industry	.4	9	.04	.93	.50	2.09	9	.23	.91	.51
$AdjR^2$	.29					.57				
Foreign languages										
Model	1.41	154	.07	2.82	.00					
Occupation	9.02	145	.06	2.59	.00					
Industry	.83	9	.09	3.84	.00					
$AdjR^2$	.37									

Source: Qualification and Career Survey 1998/99, ANOVA estimations.

*There are 9 instead of 12 industries because the industry classifications in the LIAB and the BIBB differ.

Table 4: Definition of the variables used in the factor analysis

Variable	Original question (wave 1998/1999)	Scale
	Strictly comparable questions	
Explicitness of tasks	Wie häufig kommt es bei Ihrer täglichen Arbeit vor, dass Ihnen die Arbeitsdurchführung bis in alle Einzelheiten vorgeschrieben ist?	1-5
Repetitiveness of tasks	Wie häufig kommt es bei Ihrer täglichen Arbeit vor, dass ein und derselbe Arbeitsgang sich bis in alle einzelheiten wiederholt?	1-5
Process improvement	Wie häufig kommt es bei Ihrer Arbeit vor, dass Sie bisherige Verfahren verbessern oder etwas neues auszuprobieren?	1-5
Arithmetic/math/statistics	Brauchen Sie bei Ihrer derzeitige Tätigkeit besondere Kentnisse, also nicht nur Grundkentnisse in der Gebiet: Rechnen, Mathematik, Statistik?	dummy
Use of law	Brauchen Sie bei Ihrer derzeitige Tätigkeit besondere Kentnisse, also nicht nur Grundkentnisse in der Gebiet: Arbeitsrecht, Betriebsverfassungsgesetz, Tarifrecht, Kündigungsschutz oder andere Rechtskentnisse?	dummy
Educate, teach	Wie haüfig kommt bei Ihrer Arbeit vor: Ausbilden, Lehren, Unterrichten?	1-3
	Comparable questions	
Research	Wie haüfig kommt bei Ihrer Arbeit vor: Entwickeln, Forschen?	1-3
Negotiate, consult	Wie haüfig kommt bei Ihrer Arbeit vor: Verhandlunge führen?	1-3
Taking care of people	Wie haüfig kommt bei Ihrer Arbeit vor: Versorgen, Bedienen, Betreuen von Menschen?	1-3
Medical knowledge	Brauchen Sie bei Ihrer derzeitige Tätigkeit besondere Medizinische Kentnisse, also nicht nur Grundkentnisse?	dummy
Organize/coordinate	Wie haüfig kommt bei Ihrer Arbeit vor: Organizieren, Planen?	1-3
Markeing/sales	Wie haüfig kommt bei Ihrer Arbeit vor: Werben, PR, Marketing, Akquirieren?	1-3

Management	Brauchen Sie bei Ihrer derzeitige Tätigkeit besondere Kentnisse, also nicht nur Grundkentnisse in der Gebiet: Management, Personalführung, Organisation, Planung?	dummy

Source: Qualification and Career Survey, wave 1998/1999

Table 5a: Descriptive statistics

Construction					
	mean	median	min	max	obs
Employment Interactive	15.82	4.51	0.12	738.18	1727
Employment codifiable	29.18	9.19	0.21	1,116.05	1727
Employment repetitive	22.75	6.57	0.08	1,103.42	1727
Employment abstract	24.38	7.11	0.02	995.45	1727
Plant-level wage bill (abstract)	419.81	71.08	1.06	20,306.93	1727
Plant-level wage bill (codifiable)	403.6	105.99	1.43	12,816.63	1727
Plant-level wage bill (interactive)	138.51	36.17	1.17	6,488.72	1727
Average daily wage (codifiable)	7.35	7.09	1.43	20.79	1727
Average daily wage (abstract)	5.8	4.98	1.05	37.5	1727
Average daily wage (interactive)	2.51	2.38	1.17	6.43	1727
Variable costs	961.92	229.21	4.94	34,790.64	1727
Deflated sales in euro	6,949,110	1,223,750	12,727	431,000,000	1727
Non-IT capital stock	756,148	85,110	4	74,100,000	1727
IT capital stock	42,805	4,873	2	3,037,984	1727
Outsourced units	0.01	0	0	1	1727
Retail					
Employment Interactive	65.03	12.7	0.18	1,443.43	812
Employment codifiable	30.11	6.52	0.02	597.69	812
Employment repetitive	43.75	7.98	0.04	919.39	812
Employment abstract	46.82	11.38	0.51	1,041.48	812
Plant-level wage bill (abstract)	404.75	86.49	1.65	8,686.11	812
Plant-level wage bill (codifiable)	227.3	49.95	1.07	4,599.84	812
Plant-level wage bill (interactive)	528.33	85.99	1.55	12,890.73	812
Average daily wage (codifiable)	2.66	2.29	1.07	12.98	812
Average daily wage (abstract)	5	4.26	1.58	40.67	812
Average daily wage (interactive labor)	5.16	5.29	1.55	9.75	812
Variable costs	1,160.38	241.86	5.33	26,176.68	812
Deflated sales in euro	15,300,000	3,017,037	17,216	273,000,000	812

Non-IT capital stock	1,294,074	79,132	4	74,900,000	812
IT capital stock	69,071	9,916	2	2,379,464	812
Outsourced units	0.02	0	0	1	812
Wholesale					
Employment Interactive	53	16	0.31	714	657
Employment codifiable	35	10	0.07	424	657
Employment repetitive	41	12	0.17	464	657
Employment abstract	58	17	0.45	1,178	657
Plant-level wage bill (abstract)	1,026	194	2.62	31096.17	657
Plant-level wage bill (codifiable)	334	91	1.13	4,771	657
Plant-level wage bill (interactive)	471	139	2.09	6,841	657
Average daily wage (codifiable)	3.61	3.02	1.13	13.35	657
Average daily wage (abstract)	9.07	6.76	1.35	107.35	657
Average daily wage (interactive)	4.69	4.74	2.09	8.79	657
Variable costs	1,831.20	472.99	6.29	39,168.26	657
Deflated sales in euro	80,200,000	9,723,200	56,640	5,300,000,000	657
Non-IT capital stock	1,924,389	250,238.50	4	182,000,000	657
IT capital stock	338,983	29,577	2	14,800,000	657
Outsourced units	0.02	0	0	1	657

Table 5b: Descriptive statistics

Metal Production					
	mean	median	min	max	obs
Employment Interactive	65.22	19.78	0.27	1,256.22	844
Employment codifiable	96.98	33.89	0.34	1,346.64	844
Employment repetitive	88.4	27.03	0.26	1,342.44	844
Employment abstract	66.66	18.1	0.04	1,304.19	844
Plant-level wage bill (abstract)	1,387.07	287.82	1.13	27,488.75	844
Plant-level wage bill (codifiable)	1,574.55	448.77	2.05	27,961.38	844
Plant-level wage bill (interactive)	591.76	166.65	2.12	11,515.48	844
Average daily wage (codifiable)	8.37	7.29	2.05	29.83	844
Average daily wage (abstract)	6.16	5.42	1.13	23.04	844
Average daily wage (interactive)	3.3	3.25	1.58	6.48	844
Variable costs	3,553	1,034	7.25	57503.43	844
Deflated sales in euro	23,300,000	5,176,750	55,800	473,000,000	844
Non-IT capital stock	3,612,680	458,443	4	129,000,000	844
IT capital stock	266,569	29,147	2	15,700,000	844

Outsourced units	0.02	0	0	1	844
General- and special purpose machinery					
Employment Interactive	124.52	27.75	0.3	2107.9	940
Employment codifiable	171.6	42.1	0.28	2654.63	940
Employment repetitive	157.54	37.14	0.26	2513.1	940
Employment abstract	139.18	35.2	0.02	3020.93	940
Plant-level wage bill (abstract)	4034.95	690.27	1.07	124741.8	940
Plant-level wage bill (codifiable)	2705.15	598.34	2.87	42851.11	940
Plant-level wage bill (interactive)	1189.1	238.88	2.21	22650.37	940
Average daily wage (codifiable)	7.34	6.4	1.57	22.22	940
Average daily wage (abstract)	10.26	8.59	1.07	55.4	940
Average daily wage (interactive)	3.41	3.41	1.41	7.78	940
Variable costs	7929.191	1649.214	10.75628	190243.3	940
Deflated sales in euro	61,600,000	7,832,000	97,500	1,020,000,000	940
Non-IT capital stock	5,683,119	1,014,585	4	84,700,000	940
IT capital stock	467,389	86,727	2	15,600,000	940
Outsourced units	0.02	0	0	1	940
Control-, optical instruments, and watches					
Employment Interactive	53.98	12.21	0.4	557.22	333
Employment codifiable	69.43	8.33	0.44	686.09	333
Employment repetitive	64.28	7.83	0.38	669.37	333
Employment abstract	76.09	12.04	0.36	1020.98	333
Plant-level wage bill (abstract)	2549.89	86.84	2.18	59998.65	333
Plant-level wage bill (codifiable)	975.69	53.62	1.94	13010.6	333
Plant-level wage bill (interactive)	488.58	85.22	2.38	5368.61	333
Average daily wage (codifiable)	4.27	2.9	1.54	12.78	333
Average daily wage (abstract)	8.45	4.81	1.95	46.55	333
Average daily wage (interactive)	4.14	4.1	1.8	6.4	333
Variable costs	4014.15	235.83	7.54	69673.49	333
Deflated sales in euro	29,200,000	1,026,000	39,560	940,000,000	333
Non-IT capital stock	4,221,914	85,949	4	137,000,000	333
IT capital stock	452,513	11,749	2	22,300,000	333
Outsourced units	0.02	0	0	1	333

Table 5c: Descriptive statistics

Motor vehicle manufacturing					
	mean	median	min	max	obs
Employment Interactive	380.95	36.88	0.21	8061.11	377
Employment codifiable	592.66	51.24	0.31	10173.14	377
Employment repetitive	541.33	42.01	0.2	9374.28	377
Employment abstract	373.76	33.69	0.31	9209.84	377
Plant-level wage bill (abstract)	13106.3	478.43	1.98	418190	377
Plant-level wage bill (codifiable)	11818.1	706.3	1.61	197324.8	377
Plant-level wage bill (interactive)	3812.71	316.75	1.3	81735.96	377
Average daily wage (codifiable)	9.04	7.07	1.61	23.4	377
Average daily wage (abstract)	7.38	6.09	1.35	31.49	377
Average daily wage (interactive)	3.41	3.34	1.3	6.03	377
Variable costs	28737.1	1562.72	5.39	646867.5	377
Deflated sales in euro	241,000,000	10,800,000	58,560	9,780,000,000	377
Non-IT capital stock	36,600,000	1,100,035	4	1,590,000,000	377
IT capital stock	1,452,781	69,455	2	50,000,000	377
Outsourced units	0.04	0	0	1	377
Chemicals and pharma					
Employment Interactive	187.73	50.4	0.08	2790.07	382
Employment codifiable	226.91	63.64	0.17	2348.53	382
Employment repetitive	217.58	62.19	0.03	2392.09	382
Employment abstract	223.33	51.9	0.17	4522.25	382
Plant-level wage bill (abstract)	5357.99	1171.78	1.53	139218.9	382
Plant-level wage bill (codifiable)	2820.9	764.73	2.58	29127.45	382
Plant-level wage bill (interactive)	1669.24	407.37	2.35	27311.94	382
Average daily wage (codifiable)	6.55	6.83	1.38	13.3	382
Average daily wage (abstract)	9.6	8.99	1.53	48.09	382
Average daily wage (interactive)	3.71	3.73	1.18	5.44	382
Variable costs	9848.13	2350.43	11.51	193829.3	382
Deflated sales in euro	116,000,000	21,400,000	24,044	2,740,000,000	382
Non-IT capital stock	22,200,000	2,995,810	4	395,000,000	382
IT capital stock	996,466	124,272	2	36,300,000	382
Outsourced units	0.04	0	0	1	382
Plastics and rubber					
Employment Interactive	54.63	23.57	0.33	1188.74	384
Employment codifiable	103.19	52.5	0.68	1513.45	384
Employment repetitive	100.56	46.81	0.66	1627.52	384
Employment abstract	53.04	25.71	0.23	600.26	384

Plant-level wage bill (abstract)	1010.36	362.56	4.12	18745.05	384
Plant-level wage bill (codifiable)	1972.88	665.75	2.78	26073.51	384
Plant-level wage bill (interactive)	531.82	213.15	3.51	12054.63	384
Average daily wage (codifiable)	10.52	9.31	1.39	25.41	384
Average daily wage (abstract)	5.48	4.99	0.99	19.37	384
Average daily wage (interactive)	3.16	2.89	1.29	8.27	384
Variable costs	3515.06	1412.36	10.42	52633.7	384
Deflated sales in euro	25,900,000	7,486,200	37,050	460,000,000	384
Non-IT capital stock	4,620,146	1,093,687	4	126,000,000	384
IT capital stock	176,956	39,848	2	3,281,417	384
Outsourced units	0.04	0	0	1	384

Table 5d: Descriptive statistics

Glass, bricks, and ceramics	mean	median	min	max	obs
Employment Interactive	56.31	23.01	0.58	383.64	349
Employment codifiable	77.84	29.12	0.34	666.34	349
Employment repetitive	76.08	27.31	0.36	585.64	349
Employment abstract	48.64	18.78	0.34	423.92	349
Plant-level wage bill (abstract)	750.51	250.88	2.53	6044.29	349
Plant-level wage bill (codifiable)	952.89	298.88	2.02	7886.96	349
Plant-level wage bill (interactive)	474.15	179.57	3.33	3259.98	349
Average daily wage (codifiable)	6.83	6.49	1.9	18.9	349
Average daily wage (abstract)	5.65	4.85	1.24	26.09	349
Average daily wage (interactive)	3.76	3.73	1.49	6.65	349
Variable costs	2177.54	775.49	10.05	16130.42	349
Deflated sales in euro	17,200,000	6,857,038	40,508	142,000,000	349
Non-IT capital stock	2,556,022	697,106	4	24,200,000	349
IT capital stock	158,579	20,724	2	1,836,399	349
Outsourced units	0.02	0	0	1	349
Iron and steel					
Employment Interactive	168.02	37.17	0.28	2379.22	394
Employment codifiable	246.58	67.22	0.34	3329.61	394
Employment repetitive	228.44	62.54	0.36	3052.98	394
Employment abstract	157.5	34.36	0.13	2307.28	394
Plant-level wage bill (abstract)	3177.75	563.22	2.37	44736.92	394
Plant-level wage bill (codifiable)	4300.08	1292.6	2.06	48199.85	394
Plant-level wage bill (interactive)	1607.87	343.72	2.87	22213.24	394
Average daily wage (codifiable)	11.01	10	2.06	26.23	394

Average daily wage (abstract)	6.01	5.51	1.18	16.67	394
Average daily wage (interactive)	3.38	3.28	1.44	5.26	394
Variable costs	9085.7	2336.06	10.36	115068.3	394
Deflated sales in euro	90,400,000	11,300,000	97,186	2,270,000,000	394
Non-IT capital stock	15,800,000	1,634,427	4	271,000,000	394
IT capital stock	911,353	86,943	2	40,200,000	394
Outsourced units	0.02	0	0	1	394
Electrical equipment					
Employment Interactive	107.14	34.09	0.23	858.45	314
Employment codifiable	141.61	47.07	0.28	1541.67	314
Employment repetitive	132.98	45.95	0.17	1445.02	314
Employment abstract	94.72	44.5	0.67	672.32	314
Plant-level wage bill (abstract)	2476.13	755.21	4.93	21343.48	314
Plant-level wage bill (codifiable)	1974.82	615.7	2.35	34016.91	314
Plant-level wage bill (interactive)	923.42	270.03	2.1	8137.16	314
Average daily wage (codifiable)	6.39	5.53	1.34	16.15	314
Average daily wage (abstract)	9.98	7.62	1.28	62.18	314
Average daily wage (interactive)	3.57	3.66	1.82	5.41	314
Variable costs	5374.37	1904.16	10.98	58205.28	314
Deflated sales in euro	53,600,000	15,300,000	100,000	570,000,000	314
Non-IT capital stock	9,030,690	1,571,511	4	99,200,000	314
IT capital stock	613,103	57,066	2	19,600,000	314
Outsourced units	0.02	0	0	1	314

Table 6: Factor loadings

Variable	Abstract	Interactive
Marketing, Public Relations	0.70	
Coordinate, organize	0.95	
Research, information analysis	0.93	
Negotiate	0.95	
Process improvement	0.77	
Management	0.82	
Foreign language	0.66	
Calculate, math, statistics		-0.51
Explicit tasks	-0.86	
Repeatable tasks	-0.83	
Medical knowledge		0.81
Taking care of people		0.74

Only loadings with absolute value higher/lower than +/- .4 are shown. Source: Qualification and Career Surver 1998/99, principal factor analysis