Technology, outsourcing, and the demand for heterogenous skills: Exploring the industry dimension*

Preliminary, Please do not cite!

Ljubica Nedelkoska* and Simon Wiederhold*†

January 31, 2010

Abstract

Existing literature on skill-biased technical change (SBTC) and job polarization tends to neglect that the impact of technology on the labor market might differ across industries. Using a sample of German industries in the period 2001-2005, we investigate substitution effects between heterogenous tasks' quantity on the one hand and technology as well as outsourcing on the other hand. Our results are not consistent with the idea of economy-wide homogeneity of substitution patterns; in fact, we observe remarkable differences across industries. Labor using codifiable or explicit tasks is neither always substitutable by technology, nor always prone to outsourcing. Abstract labor, focusing mainly on problem solving and complex thinking, is complementary to technology in some industries, while being a technological substitute in others. Interactive (service-oriented) tasks do not always appear neutral to the introduction of technology, nor to the outsourcing strategies of plants. Our findings argue for a more nuanced way of understanding the labor demand effects of technology and outsourcing than offered by previous studies.

JEL classification: J23, J24, O33

Keywords: demand for skills, technology, outsourcing

1 Introduction

The economic history evidences that over the last couple of centuries there has been a number of widely-spread cost-saving technological innovations and

*We would like to thank Uwe Cantner, Andreas Freytag, Oliver Kirchkamp, Frank Neffke, Florian Noseleit, and Viktor Slavcev for valuable comments. We also gratefully acknowledge the assistance of Daniela Hochfellner, Peter Jacobebbinghaus, and Dana Müller at the Research Centre of the Institute for Employment Research in Nuremberg during the on-site visits and remote-access use of the data.

†*Research Training Group "Economics of Innovative Change", Carl-Zeiss-Str. 3, D-07743 Jena, Germany. E-mail: ljubica.nedelkoska@uni-jena.de; simon.wiederhold@uni-jena.de

organizational strategies that resulted in radical shifts in the demand for labor even at the level of economies.[1] These shifts often affected the labor demand in an asymmetric way, meaning that not all types of labor were influenced by the change in the same manner.[2] Goldin and Katz (1996, 2009) illustrate that within the last two centuries there existed both, technologies that shifted the demand towards more skilled labor, and technologies which caused aspirations towards low-skilled labor.[3] These technologies were often industry specific.[4]

In the search for economy-wide patterns of technology-labor relations researchers often neglect the fact that technological innovations are industry specific. A certain type of labor that is substitutable by technology in one sector might be unaffected by, or even complementary with technology in some other industry. The same can be said about organizational strategies such as outsourcing. Recognizing the lack of evidence on these issues for Germany, we adopt empirical approach that measures the relations between labor and technology, and labor and outsourcing by allowing for heterogeneity of these relations among industries.

Scholars in developed countries actively monitor the trends in the composition of labor with different skills[5], as well as the wage differentials between skill groups. The wide-spread belief of the 1980s was that the employment opportunities increase with the level of education and wages in a monotonic way (e.g. Berman, Bound, and Griliches 1994). The most prominent explanation for the monotonic relation between employment and skills has been a skill-biased technological change (SBTC) embodied in wide-spread general purpose technologies such as computers. SBTC is technological change that substitutes the skills of low-educated and complements those of highly-educated labor. However, more recent observations of the wage and employment developments in the and 1980s 1990s for several developed countries, including the US, UK, and Germany, point toward a phenomenon of job polarization (Goos and Manning 2007, Goos, Manning, and Salomons 2009). This means that the employment shares of jobs at the bottom and the top of the wage/skill distribution have been

[1]Perhaps the most well-known example is the proliferation of the Jacquard loom at the beginning of the 19th century which replaced the effort of the skilled weavers with a punched card and few unskilled workers. The revolt towards this technology from the side of the skilled artisans initiated the Luddite social movement during the Industrial Revolution in Great Britain. Given the size and the importance of the textile industry in Great Britain at the beggining of the XIXth century, the changes in the skill mix structure caused by the introduction of the Jacquard had nation-wide implications.

[2]The transition from artisan shop to factory decreased the relative demand for skilled employees, while the introduction of continuous process or batch technologies at the beginning of the XXth century in the US increased the relative demand for skilled labor (Goldin and Katz 1996, p. 253).

[3]Probably the most significant invention that increased the relative demand for routine, repetitive labor was the Fordist assembly line that was invented in the US at the beginning of the XXth century and diffused rapidly worldwide .

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

[5]I follow Goldin and Katz's (1996) definition of skills: higher level of education, ability, or job training.

rising relative to those in the middle. This is somewhat surprising, at least for some countries, because the monotonic relationship between wages/skills and employment opportunities found in the 1980s seems to have transformed into a U-shaped one in 1990s. The finding of job polarization therefore, introduces a doubt in the drivers behind the changes in the skill composition, a doubt in the way the indicated drivers affect the demand for skills, or both.

In the current work we will confront two possible causes of shifts in the demand for labor of different tasks: technology and outsourcing. However, instead of testing for economy-wide patterns, we investigate industry-specific relations between labor on one hand, and technology and outsourcing on the other hand. We find that few sectors behave according to theory and previous economy-level findings. This the case with both, outsoursing and IT.

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 variable definition. Section 4 demonstrates some basic industry-level trends. Section 5 explains our methodology. Section 6 demonstrates our findings. Section 7 concludes.

2 Skills, technology, and outsourcing

The seminal work of Autor, Levy, and Murnane (2003) (thereafter ALM) provides theory and evidence of technological change that affects the labor demand in a manner consistent with the observed job polarization. Autor, Levy, and Murnane ask the critical question: what 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, 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 heterogenous labor. The basic argument is that computers substitute for routine manual and cognitive tasks, while complementing non-routine manual and cognitive ones. Routine tasks embody explicit knowledge that can relatively easily be programmed. Once engineered, however, the machine-aided execution of such tasks increases efficiency and reduces the error rate,thereby lowering the marginal costs of production. It happens that the routine manual and cognitive tasks are found more frequently in jobs that require medium level of education, while non-routine manual and cognitive tasks are concentrated at jobs with low and high levels of education. Speaking in terms of wage distribution, routine (codifiable) tasks are rather found in the middle of the wage distribution, while non-routine (interactive and abstract) tasks intensify at the tails of the distribution.

Besides technological change, there are few other sound theories that can also explain how the demand for labor can be altered in an asymmetric way consistent with the observation of job polarization. Grossman and Rossi-Hansberg (2008) develop a theory of offshoring of tradable tasks that under certain assumptions can fit the empirical patterns. An intuitive argumentation of why outsourcing and offshoring can alter the demand for heterogenous labor is that when labor becomes mobile within and between countries, regional and industrial differences in factor prices will stimulate relocation of such factors towards the area with the lowest price. However, this is only plausible for tradable tasks. Similar to the reasoning above that concerned technology, tasks that are routine and explicit are easier to teach, train and transmit over distance. As such they will be more prone towards outsourcing than interactive tasks, which are tacit in nature or need direct contact with customers. Blinder (2007) argues that only those tasks that encompass direct contact with clients are not affected by offshoring. Many occupations that are endowed with high intensity of analytical tasks such as computer engineers or computer programmers, Blinder claims, may be more offshorable than occupations with low intensity of such tasks.[6]

Based on the theories developed by ALM (2003) as well as Blinder (2007), and taking into account previous findings for Germany (Spitz-Oener 2006), one would expect theimpact of technology and outsourcing on the demand for task-differentiated labor showsthe following general patterns: abstract labor is complementary to technology, while codifiable labor appears as a technological substitute. Interactive labor is rather complementary to technology, or at least not negatively affected by it. Moreover, both abstract and codifiable labor appear vulnerable to outsourcing, while interactive labor is less affected. Although it is intuitively plausible in light of the discussion above to expect these patters to be encountered at the level of the economy as a whole, this does not mean that each industry shows the same trends as observed on the macro level. Industries may be idiosyncratic with respect to the influence of technology and outsourcing on the labor market. Simply ignoring the industry dimension does not only hamper our understanding of real world developments, but also entails the danger of drawing wrongful policy conclusions.

We test whether and to what extent the predictions outlined above hold for twelve large German industries in the period 2001-2005. The design allows us to explore the differences in the labor-techology and labor-outsourcing relations between industries. It also offers evidence about a more recent time period than most of the literature which focuses on these relationships. In order to measure the demand for skills/tasks we adopt the task-based approach proposed by ALM and others. Therefore, instead of measuring the demand for labor of certain type (usually differentiated by the level of educational achievement), we measure the demand for heterogenous tasks. We estimate substitution elasticities between abstract, codifiable and interactive labor on one side, and technology and outsourcing on the other. The empirical design is also informative about substitution effects between different types of labor, as well the own wage elasticities.

In order to give an insight into the most recent findings concerning the

[6]Besides the theory of technological change and outsourcing/offshoring, institutional changes (Lemieux 2008) as well as labor supply (Acemoglu 2002, Goldin and Katz 2009) and product demand shifts (Manning 2004, Mazzolari and Ragusa 2007) have also been considered in the literature. These theories will stay outside the focus of the current paper.

demand for labor in the German economy, we here briefly report some more important reseach results. Dustmann, Ludsteck, and Schönberg (2009) show that episodic events such as institutional changes and labor supply shocks increased the wage inequality at the bottom of the wage distribution in the 1990s. At the top of the wage distribution, the increase in inequality is consistent with the theory of SBTC and was present already in the 1980s. Spitz-Oener finds that the largest part of the variation in the skill and educational upgrading in the period 1979-1999 can be attributed to the spread of computers. Becker, Ekholm, and Muendler (2009) find that offshoring correlates highly with the shift of demand from routine tasks and towards the demand of abstract tasks, and Baumgarten (2009) finds that international material outsourcing has a slightly negative effect on the demand for labor; which effect is more pronounced for occupations with higher intensity of routine tasks.

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 other, is to track skill 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. Previous uses of this survey are by DiNardo and Pischke (1997), Spitz-Oener (2006), Dustmann, Ludsteck, and Schönberg (2009) and Gathmann and Schönberg (forthcoming). For the purpose of this study we use the 1998/99 survey. A list of variables that we choose from this survey and their definitions can be found in the data appendix. We measure task intensities at the level of occupations. 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 among routine cognitive, routine manual, non-routine cognitive, and non-routine manual. Goos, Manning and Salomons (2009) distiniguish among 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 the individual (Spitz-Oener 2006), while other 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. Although the occupational classification available in the Occupational and Career Survey is available even at the 4-digit level (some 1117 occupations), the IABS occupational classification is only available at the 3-digit level. However, 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 try to measure three task dimensions: (1) abstract, (2) codifiable, and (3) interactive. The abstract dimension corresponds with the non-routine cognitive one in the ALM and the abstract one in Goos, Manning, and Salomons (2009); and 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. Therefore it is somewhat richer than the routine measure used in previous studies.

The questions that capture the codifiable dimension are of particular importance. The first one, explicit tasks, asks people to report, on a 5-level Likert scale, how often it happens that their work is being explained to them in all details. In our belief this question captures an important aspect of knowledge codification. Knowledge that can be explained in each detail should be more vulnerable to both, machine codification and outsourcing, because in contrast to tacit knowledge this one can be written in a manual or a computer code. The second measure of codification, repetitiveness of tasks, asks the repondents to report how frequent does it happen that a single work task is being repeated in all its details. This measure has also a 5-level Likert scale form in its original form. Therefore, instead of arbitrarily categorizing tasks into codifiable or non-codifiable, we attempt to use general measures of codification.

However, as it will be noted in section 4, the use of explicit tasks diverges from the use of repetitive tasks in the observed time period in a way that the industry-level intensity of routine tasks mainly increased and of explicit tasks mainly decreased. Thus, in the results presented in section 6 we consider the codifiable dimension as representing quantity of explicit tasks. Unlike the case of the codifiable dimension, where we have questions asking precisely the frequency of repetitive and explicit tasks use, it is more difficult to separate the interactive from the abstract tasks. Here as well, instead of arbitrarily defining which tasks belong to one of these categories we adopt explorative factor analysis appoach in order to check whether subsets of variables are loading on common factors. The data appendix explains the factor analysis (FA) approach.

The main result of the factor analysis is identification of two dimentions. 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 (table 1). 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: medicine and taking care of people. These are tasks that involve direct and intense contact with customers. We call this factor *interactive dimension*. Occupations that score highest on this factor are the nursing and medical professions, serving personnel, hairdressers and social workers. Evidently we cannot identify the routine, or codifiable dimension. This is also not necessary for the further analysis since we can as well use the original variables. The two variables that we use to indicate the level to which tasks may be codifiable: expliciteness of tasks and intensity of repetitive work load negatively on the first factor. Occupations that score highest on the explicit tasks measure are: assemblers (e.g. electrical appliance assemblers); painters and lacquerers in construction; steel metal pressers, draweres, stampers and other metal moulders; and railway engine drivers. Occupations that occupy the highest percentiles of the routine tasks measure are: painters and lacquerers in construction; spinners, fibre preparers till textile processing operatives; assemblers; and turners. The first two are by construction orthogonal to each other, where the measures of explicit and routine tasks are not.

Table 1. 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 than +/- .4 are shown

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 all 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 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 Jacobebbingshaus (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] Information on the share of IT investments in the total investments is present since 2001 in the LIAB, and, at the point of the dataset building, it was available on annual basis until 2005. Therefore, we focus on the period 2001-2005 in our analysis. The IT investments are reported as a share of the total investments. From the monetary value of the total investments we derive the monetary value of the annual IT investments of each establishment. This is our measure of technology. Non-IT capital is proxied by the annual capital investments minus the value of the IT investments. Output is measured by the monetary value of sales. Outsourcing is a dummy variable. Establishments are asked to report weather they have outsourced a unit in the last 12 months. There is no information on weather the outsourcing has been made to another sector or to a foreign country in the observed period.[8]

4 Asymmetric changes in the demand for tasks

Spitz-Oener (2006) illustrates economy-wide trends in the level of routine manual, routine cognitive, non-routine manual and non-routine cognitive tasks in the period 1979-1999 for Germany. She finds significant shifts towards higher intensity of non-routine tasks and shifts away from routine tasks. Using the latest two waves of the Qualification and Career Survey (1998/99 and 2005/06) we look at the development of the intensity of certain tasks within industries for which we later estimate cost and demand equations (section 6 and 7). For this comparison we only use those task measures that are consistently asked in both waves. Table 2 contains the results of this comparison.

[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 some measure of output is necessary.

[8] Starting in 2006 establishments are also asked to report whether they outsource at home of to a foreign country,

Table 2. Percentage change in task intensity within industries (1998/99-2005/06)

Industry	Sales, PR	Coordinate/organize	R&D	Process improvm.	Explicit tasks	Repetitive tasks
Printing and publishing	.26	.04	.14	.13	-.12	.04
Chemical industry, rubber, synthetics	.16	.10	.19	.15	-.05	.04
Iron, steel and metal producton	.08	.15	.31	.18	-.03	.02
General and special purpose tech.	.35	-.09	.08	-.18	-.26	-.10
PC and office machinery	.30	.05	-.07	.06	-.06	.13
Electrical appliances	.17	-.05	.26	.10	-.09	-.02
Measuring instruments, optics, watches	.07	-.03	.22	.10	.09	.10
Automobile production	.06	.06	.32	.17	-.08	-.01
Construction	.18	.21	.35	.16	-.09	-.01
Wholesale	.03	-.03	.20	.17	-.08	.12
Retail	.17	.07	.15	.30	.06	.13

Source: Qualification and Career Survey 1998/99 and 2005/06, own calculations.

Few observations are noteworthy. The general trend demonstrates a significant rightward shift of the tasks' distributions. This is the case with tasks such as sales and public relations, coordination and organization, R&D and process improvement. Only explicit tasks show a significant leftward shift in the distribution. Surprisingly, for most of the observed industries the intensity of repetitive tasks increased. The changes in the task intensity are not homogenous across industries. This is another justification for analysing each of these industries as a separate case. Although the use of explicit and repetitive tasks correlates highly at the individual level (r=.55 in 1998/99 and r=.33 in 2005/06), their intensities exhibit diverging trends in the observed period. Only in industries such as general- and special-purpose technology, electrical appliances, automobile production and construction the mean repetitive tasks intensity decreased.

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 overwhelming majority of studies on labor substitutability distinguishes between skilled and unskilled workers,[9] 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, and account for information technology (IT) investment and outsourcing as representing the technological base underlying production in the plant.[10] We treat the latter two input factors as quasi fixed, implying that producers cannot adjust freely in response to relative price changes in the short run. In line with previous work investigating changes in the employment strcuture in the context of a translog cost function, we also assume capital to be a quasi-fixed input.[11] Possible justifications for the quasi-fixity of capital, IT investment, and outsourcing is the presence of institutional constraints as well as adjustment costs for these factors that are beyond the control of an individual plant.[12] 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

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

[10] Recall that our data is on the plant or establishment level, respectively.

[11] See, e.g. Bartel and Lichtenberg (1987), Slaughter (1995), Adams (1999), Hollanders and ter Weel (2002), Becker et al. (2005), and Muendler and Becker (2009).

[12] 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 to sacrifice this degree of flexibility if we wanted to explicitely model the adjustment process of the quasi-fixed factors (Baltagi and Rich 2005).

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. Furthermore, observed capital quantities can often be seen as closer proxies to user cost of capital than price measures (Muendler and Becker 2009).

With capital, IT investment, 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:[13]

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

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 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 capital, IT investment, and outsourcing. Since we try to measure technology directly by including IT investment in equation (1) we refrain from using a time trend that is likely to pick up a lot more than just technical change, for instance unmeasured price movements, changing demand conditions, cost shocks, etc. (Chennells and Van Reenen 1999, Baltagi and Rich 2005).

For purposes of estimation we must employ a specific functional form for equation (1). 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 CES 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, 1973, Brown and Christensen 1981).[14]The translog variable cost function is written as:[15]

[13]In fact, variable cost reduces to total labor cost in our case.

[14]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.

[15]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.

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

A well-behaved (variable) cost function must be homogenous 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 the sake of notational convenience the variables carry neither an index for the individual firm not for the period of time. However, all data on the variables are measured plant and time 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. In other words, we try to implement an effective treatment of industry heterogeneity by taking into account that input substitution patterns may vary across industries (Betts 1997). 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.

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 behaviour. 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, capital, IT investment, and outsourcing, respectively, while all other factor prices and quasi-fixed input quantities are fixed.[16] The labor demand elasticties with respect to task prices, ε_{L_j,P_n}, are obtained as:

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

where $j, n = A, C, I$, and $\delta_{j,n} = 1$ if $j = n$, and 0 otherwise.[17] Moreover, the labor demand elasticities with respect to output are calculated as:

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

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

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

[17] 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.

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, suggesting a correlation between the dependent variable (cost share) and the exogenous variables, or some kind of division bias, respectively (Berman, Bound, and Griliches 1994). Therefore, following Muendler and Becker (2009), we transform equation (3) into a system of labor demand functions, in which labor prices are regressors only, by multiplying both sides of each share equation in (3) with the observation-specific scalars VC/P_j ($j = A, C, I$).[18] Second, for estimation 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 and a constant, non-singular covariance matrix. One possible justification for such stochastic modelling is that the additive disturbances represent random errors in plants' cost-minimizing behavior.[19] 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 iterating 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 workers (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 towards com-

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

[19]In contrast, McElroy (1987) argues that the errors are in the eyes of the econometrician and not due to firms. Consequently, the entire optimization process should be embedded in a stochastic framework. We do not follow McElroy's suggestion here because it is likely to result in problems of identification of the parameters (Berndt 1990). Moreover, McElroy finds that the standard specification of the error term that we use yields very similar results as her alternative approach.

plementarity (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.[20]

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 (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 from industry-specific collective agreements between employer federations and still rather strong unions. 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).[21] These institutional limits to how far the wages can fall corrobate to some extent the assumption of a fixed market wage, in particular for workers 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 assumption that these workers know the market value of their labor services, preventing them from accepting positions that pay them less, one might still be thinking of plants as taking labor prices as fixed.

5.1 Task quantities and task prices

In order to estimate demand functions we need to decide on the criteria by which we form the labor input categories. Basically, the labor input can either be measured in terms of number of employees of different types or quantity of tasks of different types. When using the first approach we create task-intensity indexes based on which we can group each occupation into either abstract-tasks-intensive, interactive-tasks-intensive or codifiable-tasks intensive. These three categories are mutually exclusive. The second approach is to measure labor input in terms of task quantity instead of in terms of employees. The labor-quantity approach sets the limitation that each occupation is categorized as belonging to one of the following labor groups: abstract-tasks-dominated, interactive-tasks-dominated or codifiable-tasks dominated. 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,

[20]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.

[21]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).

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 task portfolio of labor that is not interactive-tasks-dominated. This information would get lost if we used the labor quantity approach. Given these drawbacks, we choose the task-quantity approach to differentiate labor by tasks.

The task-quantity approach measures labor input in terms of quantities of different tasks. For this purpose we use the two factors and the explicit tasks measure described in section 3 and the data appendix. 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 terms of percentiles. For example, a machine engineer in our approach scores at the 98th percentile of the abstract tasks distribution, at the 9th percentile of the routine tasks distribution, and at the 2nd percentile of the interactive tasks distribution. The respective percentiles for a plastics' processor are 21th, 96th and 8th. Therefore, a plant employing one machine engineer and one plastics' processor will have .98+.21=1.19 units of abstract task quantity, .09+.96=1.15 units of routine tasks quantity, and .02+.08=.1 unit of interactive tasks quantity. Now, if 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+.09+.02)*.98+50/(.21+.96+.08)*.21=89.9+13.1=103. Accordingly, the prices for codifiable and interactive labor will be 85.06 and 8.23, respectively.

Although the prices of task quantities are indirectly derived, they have one important property: if occupations using much abstract labor are also highly payed, this will be reflected in the indirect prices. Also, smaller quantities of certain tasks correlate with small total quantity prices.

6 Findings

Tables 3a to 3d present the elasticities of substitution calculated using the SUR coefficient estimates of the system of cost and demand functionsas set forth by (2) and (3) for our sample of twelve industries. The elasticities measure the percentage responses of demand for labor of different tasks to a one percent change in either the price of a variable input or the quantity of a quasi-fixed input by industry. *Elapa, Elcpc,* and *Elipi* indicate the own-price substitution elasticities of abstract, codifiable and interactive labor, while *Elapc, Elapi, Elcpi,* and their symmetric counterparts represent the set of cross-price substitution elasticities. Because of imposed symmetry of price coefficients trough constraints on the translog regression, *Elapc*, for instance, shows the effect on abstract labor of a permanent price changes of codifiable labor as well as the effect on codifiable labor of a permanent price change of abstract labor. *Elapi* and *Elcpi* have to be interpreted accordingly. The terms *ElaIT (ElcIT, EliIT), ElaOUT*

(ElcOUT, EliOUT), and *ElaCapital (ElcCapital, EliCapital)* report the reaction of abstract (codifiable, interactive) labor when the value of IT, outsourcing, or (non-IT) capital changes.[22]

One common pattern is that own-price elasticities, when significant, are always negative, as production theory requires.[23] A negative own-price elasticity means that plants tend to reduce demand for a certain type of labor if its price increases. For example, in the plastic and rubber industry, a one percent increase in the price of abstract labor is associated with a 1.56 percent drop in its demand; a one percent increase in the price of codifiable labor corresponds to a .38 percent decrease in demand; and a one percent increase in the price of interactive labor relates to a 4.5 percent decrease in its demand. 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 abstract, and then by codifiable labor. Although the own-price elasticities are uniformly negative, there is no clear pattern we observe when comparing the relative magnitudes of these elasticitiesfor different types of labor within same industries. However, there are groups of industries that seem to follow the same trends. Similar to plastic and rubber behave glass, ceramics, and bricks, iron and steel, as well as in metal production. In chemicals, control- and optical instruments and watches, wholesale, and to some extent motor vehicles the impact of own-price changes on labor demand is most pronounced for codifiable labor, followed by interactive and abstract labor. It is also not uncommon to observe the stongest response to own-price changes in interactive labor, followed by codifiable and abstract labor (general and special purpose machinery; electrical equipment; construction). As an overarching trend we see that in more than 50 percent of the industries interactive labor has the most negative own-price elasticity. Likewise, in seven out of twelve industries, the own-price elasticity of abstract labor is lowest in magnitude. There is no industry in which the response of abstract labor to an own-price increase is stronger than for the other two labor types. However, in 33 percent of the industries abstract labor shows a more pronounced reaction on price change than codifiable labor. While it is not surprising that interactive labor often has the highest own-price elasticity in absolute value, it is more difficult to explain the cases where the own-price elasticity of abstract labor is more negative than the one of codifiable labor. Namely, interactive labor is often labor with low qualificational requirements, which makes it relatively easy to obtain and replace. Unlike many interactive tasks, codifiable tasks frequently require certain training and dexterity cannot be immediately achieved.However, this is even more the case with abstract labor.Some of these price effects may caputure effects of still strong unions (e.g. IG Metal in the metal production and ver.di in services) that limit the possibilities of employers to react on price increases with saving on the respective labor.

[22]Since elasticties with respect to output are not in the focus of this study, we suppress them here for simplicity. Notice, however, that we find strong support in favor of increasing returns to scale across all twelve industries.

[23]The only exception is codifiable labor in the retail industry. One possible reason for this result is that demand for codifiable labor exceeded its supply in our period of observation.

We now turn to the cross-price elasticities. These can have mixed signs and provide an indication of factor substitutability (positive sign) and factor complementarity (negative sign) between labor of different types. In four out of twelve industries abstract and codifiable labor appear as substitutes, while in four other industries we find both labor types to be complements. Our elasticity estimates for abstract and interactive labor, except for the retail industry, point towards substitutability. There is equally strong evidence suggesting that codifiable and interactive labor are substitutes; only in metal production both appear as complements. Hence in almost all industries we observe interactive labor to be a substitute to abstract and codifiable labor. Estimated substitution elasticities between abstract and codifiable labor indiacte marked differences across industries.

We now report our findings on the labor demand effects of, respectively, IT, outsourcing, and capital. We first draw our attention on a potential skill bias of IT investment. One striking result is that IT and abstract labor appear to be complements in most of the industries where we find significant effects. Plants that increase their investments in IT also increase the employment of abstract labor in iron and steel, general and special purpose machinery, and motor vehicles. The elasticities have magnitudes of .09, .04 and .29 percent, respectively. Thus, complementarity between IT and abstract labor seems to be strongest in the vehicle production sector; here, an increase in IT investment by one percent is associated with a .29 percent increase in the demand for abstract labor. The only industry where our results suggest substitutability between IT and abstract labor is in plastic and rubber ($ElaIT$=-.09). While our findings on abstract labor are broadly consistent with previous economy-wide studies (ALM 2003, Spitz-Oener 2006), the picture changes when we look at the pattern for codifiable labor. Only in glass, ceramics and bricks ($ElcIT$=-.18) and in iron and steel (-.04) we observe the expected substitutable relationship between IT and codifiable labor. In 33 percent of the industries, however, we find IT to be complementary to codifiable labor. This is the case in plastic and rubber, general and special purpose technology, electrical equipment, and retail with magnitudes of, respectively, .06, .063, .034, and .16. Interactive labor appears as substitutable to IT in general and special purpose machinery ($EliIT$=-.23), electrical equipment (-.60), and retail (-.11), while we observe complementarity only in glass, ceramics and bricks (.30).The skill bias of IT shows a quite similar pattern in general and special purpose machinery, electrical equipment, and retail.

Outsourcing is in general seldom significantly correlated with changes in the demand for task-differentiated labor; we find effects only in three out of twelve industriesIn the plastic and rubber industry plants that outsource show on average a decrease in abstract labor of half percent ($ElaOUT$=-.54), an increase in codifiable labor of .31 percent, and a drop in interactive labor of 2.21 percent. In general and special purpose machinery outsourcing and codifiable labor are substitutes, since plants that outsource employ on average 1.15 percent less codifiable labor. In contrast, this industry shows a complementary relationship between outsourcing and interactive labor ($EliOUT$=3.07). In electrical equipment, the instance of outsourcing is associated with a an increase in codifiable labor of .74 percent. Given the few significant findings, it is tolerably difficult to draw conclusions on the impact of outsourcing on the labor market across industries.

Table 3a. Demand elasticities

24 (Chemicals)			25 (Plastic and rubber)			26 (Glass, ceramics and bricks)		
Abstract Task Quantity								
Price elasticities								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.755** (.39)	1.56*** (.28)	3.216*** (.60)	-1.561*** (.19)	-.152 (.18)	.865* (.51)	-3.802*** (.23)	-.757*** (.26)	4.866*** (.50)
IT, outsourcing and capital elasticities								
ElaIT	*ElaOUT*	*ElaCapital*	*ElaIT*	*ElaOUT*	*ElaCapital*	*ElaIT*	*ElaOUT*	*ElaCapital*
-.026 (.03)	-.281 (.27)	-.003 (.02)	-.090** (.04)	-.535*** (.20)	.023 (.02)	0.037 (.03)	0.096 (.41)	-.001 (.02)
Codifiable Task Quantity								
Price elasticities								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-4.561*** (.68)	2.173*** (.39)	2.388*** (.85)	-.375* (.22)	-.084 (.10)	.459 (.25)	-1.865*** (.47)	-.655*** (.22)	2.520*** (.64)
IT, outsourcing and capital elasticities								
ElcIT	*ElcOUT*	*ElcCapital*	*ElcIT*	*ElcOUT*	*ElcCapital*	*ElcIT*	*ElcOUT*	*ElcCapital*
0.001 (.05)	-.062 (.30)	.095** (.04)	.060*** (.02)	.308** (.14)	-.012 (.01)	-.181*** (.04)	.772 (.92)	-.014 (.02)
Interactive Task Quantity								
Price elasticities								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-2.211 (2.25)	3.216*** (.60)	2.388*** (.85)	-4.503*** (1.22)	.865* (.51)	.459 (.25)	-11.01*** (1.36)	4.866*** (.50)	2.520*** (.64)
IT, outsourcing and capital elasticities								
EliIT	*EliOUT*	*EliCapital*	*EliIT*	*EliOUT*	*EliCapital*	*EliIT*	*EliOUT*	*EliCapital*
.230* (.12)	.557 (.90)	-.218** (.08)	-.115 (.08)	-2.207*** (.74)	.122** (.05)	.295*** (.08)	-.767 (1.65)	.068* (.04)
Observations	593			497			455	

Results from SUR regressions of cost and demand functions. Standard errors in parentheses. Demeaning on the plant level. Significant at ***1%, **5%, *10% level.

Table 3b. Demand elasticities

27 (Iron and steel)			28 (Metal production)			29 (General and special purpose machinery)		
Abstract Task Quantity								
Price elasticities								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-2.205*** (.12)	.097 (.20)	.960** (.45)	-0.819*** (.20)	-.272 (.18)	-.148 (.39)	-1.176*** (.10)	-.720*** (.10)	2.552*** (.26)
IT, outsourcing and capital elasticities								
ElaIT	*ElaOUT*	*ElaCapital*	*ElaIT*	*ElaOUT*	*ElaCapital*	*ElaIT*	*ElaOUT*	*ElaCapital*
0.088** (.04)	-.243 (.58)	.015 (.02)	.005 (.02)	-.632 (.24)	-.043** (.02)	.035** (.02)	-.649 (.15)	0.005 (.01)
Codifiable Task Quantity								
Price elasticities								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-0.035 (.25)	.060 (.12)	-.025 (.29)	-.149 (.24)	-.210 (.14)	-1.835*** (1.06)	-3.034*** (.32)	-.995*** (.14)	4.028*** (.36)
IT, outsourcing and capital elasticities								
ElcIT	*ElcOUT*	*ElcCapital*	*ElcIT*	*ElcOUT*	*ElcCapital*	*ElcIT*	*ElcOUT*	*ElcCapital*
-.040** (.02)	.116 (.31)	.020* (.01)	-.014 (.02)	-.375 (.18)	-.020* (.01)	.063* (.03)	-1.147*** (.39)	-.002 (.01)
Interactive Task Quantity								
Price elasticities								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-3.672*** (1.19)	.960** (.45)	-.025 (.29)	-2.835*** (1.06)	-.148 (.39)	-1.835*** (1.06)	-13.42*** (1.00)	2.552*** (.26)	4.028*** (.36)
IT, outsourcing and capital elasticities								
EliIT	*EliOUT*	*EliCapital*	*EliIT*	*EliOUT*	*EliCapital*	*EliIT*	*EliOUT*	*EliCapital*
-.067 (.08)	.094 (2.10)	-.026 (.04)	.026 (.07)	1.048 (.69)	.231*** (.04)	-.226** (.09)	3.071*** (.96)	.027** (.01)
Observations	529		Observations	1227		Observations	1568	

Table 3c. Demand elasticities

31 (Electrical equipment)			33 (Control- and optical instruments and watches)			34 (Motor vehicles)		
Abstract Task Quantity								
Price elasticities								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-1.312*** (.09)	-1.389*** (.19)	2.555*** (.51)	-0.0748	1.317*** (.17)	2.232*** (.39)	-.251 (.39)	.768*** (.29)	.400 (.69)
IT, outsourcing and capital elasticities								
ElaIT	*ElaOUT*	*ElaCapital*	*ElaIT*	*ElaOUT*	*ElaCapital*	*ElaIT*	*ElaOUT*	*ElaCapital*
-.003 (.02)	-.214 (.19)	.123*** (.01)	-.009 (.03)	-.510 (.24)	.026** (.01)	.291*** (.04)	-.118 (.30)	-.213*** (.04)
Codifiable Task Quantity								
Price elasticities								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-3.054 (.76)	-2.110*** (.29)	5.164*** (.83)	-4.695*** (.69)	2.458*** (.31)	2.237*** (.66)	-1.080** (.50)	.676*** (.25)	.404 (.56)
IT, outsourcing and capital elasticities								
ElcIT	*ElcOUT*	*ElcCapital*	*ElcIT*	*ElcOUT*	*ElcCapital*	*ElcIT*	*ElcOUT*	*ElcCapital*
.343*** (.05)	.737** (.37)	.104*** (.03)	-.024 (.06)	-1.50939	.045** (.02)	.001 (.04)	-.154 (.27)	.027 (.03)
Interactive Task Quantity								
Price elasticities								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-15.378*** (1.69)	2.555*** (.51)	5.164*** (.83)	-.518 (.83)	2.232*** (.39)	2.237*** (.66)	.117 (1.90)	.400 (.69)	.404 (.56)
IT, outsourcing and capital elasticities								
EliIT	*EliOUT*	*EliCapital*	*EliIT*	*EliOUT*	*EliCapital*	*EliIT*	*EliOUT*	*EliCapital*
-.598*** (.11)	-1.13412	-.389*** (.07)	.022 (.06)	1.758 (1.11)	-.060** (.02)	-0.562 (.12)	.092 (.75)	.402*** (.09)
Observations	534		Observations	586		Observations	494	

Table 3d Demand elasticities

45 (Construction)			51 (Wholesale)			52 (Retail)		
Abstract Task Quantity								
Price elasticities								
Elapa	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*	*Elapa*	*Elapc*	*Elapi*
-.547*** (.11)	.202** (.10)	.890*** (.20)	-.033 (.10)	.007 (.10)	.200 (.17)	-.489*** (.18)	-765*** (.18)	-1.000** (.39)
IT, outsourcing and capital elasticities								
ElaIT	*ElaOUT*	*ElaCapital*	*ElaIT*	*ElaOUT*	*ElaCapital*	*ElaIT*	*ElaOUT*	*ElaCapital*
.005 (.02)	-.019 (.31)	.003 (.01)	.002 (.01)	.037 (.10)	.012** (.01)	.016 (.02)	.602* (.32)	.005 (.01)
Codifiable Task Quantity								
Price elasticities								
Elcpc	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*	*Elcpc*	*Elcpa*	*Elcpi*
-1.264*** (.14)	.182** (.09)	1.082*** (.14)	-1.635*** (.29)	.015 (.21)	1.619*** (.36)	1.547** (.66)	-1.396*** (.33)	-.151 (.65)
IT, outsourcing and capital elasticities								
ElcIT	*ElcOUT*	*ElcCapital*	*ElcIT*	*ElcOUT*	*ElcCapital*	*ElcIT*	*ElcOUT*	*ElcCapital*
-.015 (.02)	.007 (.19)	-.004 (.01)	-0.00165	.514 (.33)	.027* (.01)	.163*** (.05)	-1.150 (.73)	.065*** (.01)
Interactive Task Quantity								
Price elasticities								
Elipi	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*	*Elipi*	*Elipa*	*Elipc*
-3.473*** (.59)	.890*** (.20)	1.082*** (.14)	-1.241*** (.39)	.200 (.17)	1.619*** (.36)	-1.079*** (.38)	-1.000** (.39)	-.151 (.65)
IT, outsourcing and capital elasticities								
EliIT	*EliOUT*	*EliCapital*	*EliIT*	*EliOUT*	*EliCapital*	*EliIT*	*EliOUT*	*EliCapital*
.104* (.05)	-.323 (.63)	-.002 (.02)	.070** (.03)	-0.14326	-.021 (.01)	-.110*** (.03)	-.400 (.34)	-.017* (.01)
Observations	2246		Observations	1395		Observations	1432	

7 Conclusions

The recent scientific discourse on the impact of technology and outsourcing on the labor market suggests the idea that labor of different skills is not uniformly affected by technological and organizational change. Following authors such as Autor, Levy, and Murane (2003), Spitz-Oener (2006), Goos and Manning (2007), as well as Blinder (2007), one can predict that repetitive and routine tasks (i.e., codifiable labor) should be easily substitutable by technology. Moreover, codifiable labor is supposed to possess a high proneness to be outsourced to another sector, region or country. In the same line of reasoning, labor that makes intense use of problem-solving and complex thinking skills (i.e., abstract labor) should be complementary to technology, and not be easily outsourcable. It is furthermore argued that labor with high intensity of customer-interaction (i.e., interactive labor) can neither be outsourced, nor substituted by technology. Although this view is intuitively plausible, previous research has largely focused on economy-wide patterns. It has been astonishingly mute on potential inter-industry differences in the nature of the technology-outsourcing-labor nexus.

Using a sample of twelve German industries in the period 2001-2005, we explore the relations between the demand for heterogenous labor on one hand and IT capital and outsourcing on the other hand. Our results are only to a certain degree consistent with the predictions outlined above. In fact, we find a remarkable heterogeneity across industries. ; With respect to technology, for instance, the glass, ceramics, and bricks as well as the iron and steel industry are in line with economy-wide predictions. On the other hand, in plastic and rubber, general and special purpose machinery, electrical equipment, and retail we observe that IT and codifiable labor are complements, while IT and interactive labor often appear as substitutes. For outsourcing we also find a number of cases that imply exceptions from the suggested economy-wide pattern, for instance in the plastic and rubber industry.

Moreover, analyzing own-price and cross-price elasticties sheds some light on the substitution possibilities between labor of different types across industries. Some patterns emerge clearly here: in more than 50 percent of the industries the response of interactive labor on an own-price increase is most pronounced. In seven out of twelve industries, the own-price elasticity of abstract labor is lowest in magnitude. There is no industry in which the response of abstract labor to an own-price increase is stronger than for the other two labor types. There is also clear evidence that interactive labor is substitutable with both abstract and codifiable labor. However, we do not observe unambigious cross-industry evidence that abstract and codifiable labor are substitutes, as previous studies suggest. In general, our findings, although very preliminary, quest for more profound understanding of the technologies and outsourcing practices that different industries employ. The search for economy-wide patterns may disguise relevant idiosyncracies in the labor demand needs of industries. Since the neglect of the industry dimension might lead to wrong and potentially dangerous policy recommendations, future research should put more emphasis on explaining why the labor market in distinct industries responds so differently to technological and organizational change.

Appendix

Factor Analysis

The basic idea behind the use of FA is that the multiple tasks that enter our empirical design can actually be reduced to few dimensions that give us almost the same information as the full set of variables. The resulting factors from FA are orthogonal by construction which is a very favourable feature in multiple regression. The FA can also be confirmatory to the belief that there exist abstract, interactive and codifiable dimensions.

Formally, FA assumes that L characteristic tasks of occupations can be represented by K task dimensions, where $K < L$ without much loss of information. The identification of these underlying dimensions (factors) can be represented with the following set of linear models:

(1) $C_{ij} = \lambda_{i1}\theta_{ij} + \lambda_{i2}\theta_{2j} + ... + \lambda_{ik}\theta_{kj} + \varepsilon_{ij}$

where $i = 1, ..., l$ and $C_{ij}$is the intensity of task i for occupation j. $\theta_{kj}$is the amount of the underlying task k present in occupation j, $\lambda_{ik}$is the factor loading of task j on task dimension k and $\varepsilon_{ij}$is an independently distributed error term which may differ in each equation. In this set of models only C_{ij} are known to us. As evident from the formulation, FA posits that C_{ij} are a linear combination of k unobserved factors indicated with the letter θ in the above equations. The intercepts of the equations are by construction equal to zero[24].

The above set of models can be represented in a matrix form:

(2) $\mathbf{c_j} = \mathbf{\Lambda}\boldsymbol{\theta}_\mathbf{j} + \boldsymbol{\varepsilon}_\mathbf{j}$,

where $\mathbf{c_j}$ is l by 1 vector of observed variables, $\mathbf{\Lambda}$ is an l by k matrix of factor loadings, $\boldsymbol{\theta_j}$is a k by 1 vector of underlying factors, and $\boldsymbol{\varepsilon_j}$is a l by 1 vector of measurement errors. We can stack equation (2) over occupations and drop the index $\boldsymbol{j}$ which yields:

(3) $\boldsymbol{C} = \mathbf{\Theta\Lambda'} + \boldsymbol{E}$,

where now $\boldsymbol{C}$ is a n by l matrix of observed variable values, $\mathbf{\Theta}$is an n by k matrix of scores of the underlying factors, $\mathbf{\Lambda'}$is the transpose of an l by k matrix of factor loadings and $\boldsymbol{E}$ is an n by l matrix of measurement errors.

The only input that enters the factor analysis is the matrix $\boldsymbol{C}$. In fact, all the information necessary for the estimation of $\mathbf{\Theta}$and$\mathbf{\Lambda}$is the covariance matrix of the observable variables. In order to identify these matrices we necessitate certain assumptions:

(4a) $E(\boldsymbol{E'}\mathbf{\Theta}) = E(\mathbf{\Theta'}\boldsymbol{E}) = 0$

(4b) $E(\boldsymbol{E'E}) = \mathbf{\Delta}_{\boldsymbol{e}}$

(4c) $E(\mathbf{\Theta'\Theta}) = \mathbf{\Phi}$

(4d) $E(\boldsymbol{C'C}) = \mathbf{\Sigma}$,

[24]On one hand the intercepts are of no interest for the FA purpose, on the other it is not possible to estimate both the factor loading and the intercept simultaneously (e.g. Bollen 1989).

where $\mathbf{\Phi}$ is a k by k variance-covariance matrix of the underlying factors, $\mathbf{\Sigma}$ represents the l by l variance-covariance matrix of the data and $\mathbf{\Delta_e}$is an l by l variance-covariance matrix of the errors. Under these assumptions we can rewrite (3) as:

(5) $\mathbf{\Sigma} = \mathbf{\Lambda \Phi \Lambda'} + \mathbf{\Delta_e}$

This means that the variances and the covariances among the observed variables can be decomposed into a component attributable to the underlying factors and a component attributable to the variaces and covariances of the measurement errors. Because the number of unique elements in (5) $l(l+1)/2$ is still larger than the number of elements that need to be estimated $lk+k(k+1)/2+l(l+1)/2$, two further constraints need to be made in order to make (5) identifiable. One constraint is that $\mathbf{\Phi}$ is identity matrix (which results in factors that are orthogonal among each other and with variance 1). The second one is that $\mathbf{\Delta_e}$must to be diagonal.

Using the notation from equation (5), $\mathbf{\Sigma}$ is the variance-covariance matrix of the variables listed in table 1 in section 3.

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.

References

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

[2] 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.

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

[4] 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

[5] 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

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

[7] Baumgarten ?

[8] Becker, Sascha O., Ekholm, Karolina, Muendler, Marc-Andreas. 2009 “Offshoring and the Onshore Composition of Occupations, Tasks and Skills,” ?

[9] 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.

[10] 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.

[11] 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.

[12] Berndt, Ernst R. 1990 “The practice of econometrics :classic & contemporary,” Addison Wesley Publishing.

[13] 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.

[14] 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.

[15] 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.

[16] Blinder, Alan S. 2007 “How Many U.S. Jobs might be Offshorable,” *CEPS Working Paper*, No. 142.

[17] 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, Ermst R., Field, Barry C. (eds.), Modeling and measuring natural resource substitution, Cambridge, MIT Press.

[18] Chambers, Robert G. 1988 “Applied Production Analysis,” Cambridge, Cambridge University Press.

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

[20] 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.

[21] 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.

[22] 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.

[23] 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.

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

[25] 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.

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

[27] Gathmann, Christina, Schönberg, Uta. 2010 ?

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

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

[30] Goldin, Claudia and Katz, Lawrence F. 2009 ?

[31] 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.

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

[33] 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.

[34] 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.

[35] 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.

[36] Hamermesh, Daniel S. 1993 "Labor Demand," Princeton University Press, Princeton.

[37] 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

[38] Jacobebbinghaus, Peter. 2008 "LIAB-Datenhandbuch," *FDZ Datenreport*, No. 3/2008.

[39] 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.

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

[41] 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.

[42] 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.

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

[44] 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.

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

[46] 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.

[47] Muendler, Marc-Andreas, Becker, Sascha O. 2009 "Margins of Multninational Labor Substitution," *NBER Working Paper*, No. 14776.

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

[49] 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.

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

[51] 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. 348-368.