New technologies and the demand for heterogeneous labor:

Firm–level evidence for the German business–related services sector

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February 1999

Abstract: This paper investigates the impact of modern information and communication technologies on the demand for heterogeneous labor. It starts with an interrelated factor demand system. The "desired" level of employment, which is needed in such models, is derived from a generalized Leontief cost function with quasi–fixed factors. Cross–sectional data taken from an innovation survey in the service sector are used in the empirical analysis. The model is estimated by a trivariate ordered probit model. Evidence in favor of skill–biased technological change in the fast growing German business–related services sector is found. The paper suggests a new method of calculating skill– and firm–specific labor cost from information on total labor cost and the share of each skill group in total employment only. It also proposes an approach to calculate long–run elasticities in an ordered probit context.

Keywords: interrelated factor demands, Generalized Leontief cost function, heterogeneous labor demand, business–related services, labor cost decomposition, trivariate ordered probit model

JEL classification: C35, D24, J21, L84

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*Helpful comments from Bertrand Koebel, François Laisney, Georg Licht and Winfried Pohlmeier on earlier drafts of this paper are gratefully acknowledged. I am also indebted to Thorsten Doherr, Günther Ebling, Norbert Janz and Hiltrud Niggemann for setting up the data set. I thank Semka Thorvaldsen and Paul Townsend proof–reading. Christine Kaiser provided excellent research assistance.

1 Introduction

Europe's most challenging problem in current economic policy is the high unemployment rate. While a number of countries such as Denmark, The Netherlands and the United Kingdom have been successful in pushing down the unemployment level to rates of 4–6 percent, the jobless rate in Germany has steadily risen to above ten percent.[2] Workers with no formal educational training are particularly affected by unemployment in Germany. The West German unemployment rate of unskilled labor has increased from 8.1 percent in 1976 to 20 percent in 1995. In the same period, unemployment rates amongst university and technical college graduates have remained fairly stable at around three percent.[3]

What are the reasons for this decline in relative demand for unskilled labor? Since the beginning of the nineties there has been an ongoing discussion in the economic profession about the steady decline in relative demand for unskilled labor. Many developed economies have experienced this phenomena over the last few years. The decline in relative demand for unskilled labor was even steeper in Germany than in other OECD countries [OECD (1996), Papaconstaninou (1997)]. A decline in relative demand for unskilled labor is also present in the fast growing business–related services sector which is in the focus of this study.[4] The number of employees in business–related services has grown by 29.3 percent between 1982 and 1996. In comparison, total employment in manufacturing has decreased by 10.7 percent in the same time period.[5] While there is no consensus of opinions, many researchers believe that *skill–biased technical change* is the main explanation for the decline in demand for unskilled labor. Skill–biased technical change is said to exist if new technology is complementary to skilled labor and substitutive to unskilled labor.[6]

Two main criticisms apply to existing studies on skill–biased technical

[2] See Bean (1994) and Snower (1996) for surveys on European labor market problems.

[3] Source: ZEW, Mannheim Regions Monitor (MRM). The MRM is a database where information from various sources on employment, skill structure and industrial dynamics are collected by the ZEW. It is restricted to West Germany.

[4] Since there is no clear–cut and broadly accepted definition of business–related services, I follow the convention by Klodt et al. (1997) and define them by enumeration of the following sectors: transport and storage, computer and related activities, architectural and engineering activities, real estate activities, business and management consultancy, industrial cleaning, and other business–services (e.g. renting of machinery and equipment, advertising).

[5] Source: Ebling et al. (1998).

[6] Chennels and van Reenen (1998) have recently provided an extensive survey on studies dealing with explanations for the declining demand for unskilled labor.

change. First, evidence on the firm level is scarce although this is the level at which hiring and firing decisions actually arise.[7] Secondly, many studies simply differentiate between "blue collar" and "white collar" labor, although such broad categorization does not really tell us what the respective worker is actually qualified for, as put forward by Leamer (1994).

The data set mainly used in this paper, the Mannheim Innovation Survey in the Service Sector (MIP–S), makes it possible to overcome both of these criticisms. It is a micro–level data set and allows us to explicitly distinguish between three different skill levels: university and technical college graduates (*highly skilled*), workers who have completed vocational training, and/or possibly additional technical training (*medium skilled*), and workers with no formal educational background (*unskilled*).

The focus of this paper is on the impact that new technology has on the demand for heterogeneous labor. It seeks to reveal if skill–biased technical change is also present in the business–related services sector.[8]

In this study I use investment in new information and communication technologies as proxy variable for technical progress. This appears to be useful since new technologies are often named as a typical example for technical progress.[9] Other variables for proxying technical progress such as R&D expenditures are not as important for services as for manufacturing industries (Licht et al., 1997). Other studies have often used more or less crude proxy variables for new technology. Besides R&D expenditures, other candidates have been PC–intensity, plant age, innovative activity, capital stock or a simple time trend.[10]

Most studies on the declining demand for heterogeneous labor are concerned with manufacturing industries. Some studies additionally investi-

[7]Exceptions are Betts (1997) for Canada, Breshnahan et al. (1998) and Doms et al. (1997) for the U.S., Brouwer et al. (1993) for The Netherlands, Duguet and Greenan (1998) for France, Entorf and Pohlmeier (1991) for Germany, Machin and van Reenen (1996) for Great Britain.

[8]Other main explanations for the declining relative demand for unskilled labor are the decreasing demand for goods where a large amount of unskilled labor is needed (between–industry shifts), a relative increase in the supply of high skilled labor and Stolper–Samuelson effects from increased exposures from trade with developing countries.

[9]There is a newer discussion of the impact of information technology on workplace organization. See, e.g., Breshnahan et al. (1998) and Brynjolfsson and Hitt (1998).

[10]R&D expenditures are used in Klotz and Pohlmeier (1997) and Machin and van Reenen (1998). Autor et al. (1998) proxy technical progress by PC–intensity, Bartel and Lichtenberg (1987) utilize plant age. Brouwer et al. (1993), Duguet and Greenan (1998) and Entorf and Pohlmeier (1991) consider innovative activity. Capital stock is applied by Berman et al. (1994). Time trends are taken into account by Betts (1997) and Falk and Koebel (1997). Dewan and Min (1997) also use IT–investment as a measure of technical progress.

gate a very broadly defined service sector, often simply defined as "non–manufacturing".[11] Such a broad definition of services is clearly cumbersome given the heterogeneity of this sector.

Both the dynamic nature of technical progress and the dynamic development of the service sector call for a dynamic labor demand framework. Straightforwardly, the theoretical part of this paper starts with a dynamic interrelated factor demand system for three different types of labor. The "desired" level of employment, which is an ingredient of such factor demand systems, is derived from a Generalized Leontief cost function with quasi–fixed factors introduced by Morrison (1988 and 1990). IT–capital is treated as a quasi–fixed factor.
This system could be directly estimated by a seemingly unrelated regression approach if there was not the drawback that the MIP–S does not provide metric information on firms' actual changes in their demand for heterogeneous labor. Instead, firms are asked to indicate the direction of change in labor demand on a three–point scale. Therefore, the system of equations derived in the theoretical part of this paper is estimated by use of a trivariate ordered probit model [Lee (1985)].
To my knowledge, the present paper is the first approach to estimate a factor demand model with categorial data as dependent variables.
A drawback of the MIP–S is that it contains information on total labor cost and on the share of the three skill groups in total employment. In this paper I suggest a new method for calculating skill–specific and firm–specific labor cost.

2 Theoretical framework

2.1 The model

In order to yield a structural framework for the empirical investigation, I start from the interrelated factor demand system introduced by Nadiri and Rosen (1969 and 1973). If, e.g., three factors of heterogeneous labor

[11] Autor et al. (1998), Dewan and Min (1997), Greenan et al. (1998).

(L_{1t}, L_{2t}, L_{3t}) are used in the production, this model is given by

$$\begin{bmatrix} \Delta L_{1t+1} \\ \Delta L_{2t+1} \\ \Delta L_{3t+1} \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} L^*_{1t+1} - L_{1t} \\ L^*_{2t+1} - L_{2t} \\ L^*_{3t+1} - L_{3t} \end{bmatrix} . \tag{1}$$

where ΔL_{it+1} is the change in labor demand for skill group i ($i = 1, 2, 3$) and L^*_{it+1} is the desired level of employment of skill group i at time $t+1$. In the present context, ΔL_{it+1} is the expected change in employment — depicted on an ordinal scale — of skill group i. Inputs i and j are called *dynamic p–substitutes* (dynamic p–complements) if $\beta_{ik} > 0$ ($\beta_{ik} < 0$) [Hamermesh (1993), ch. 6]. If L_i and L_k are p–complements, a greater disequilibrium for one factor slows the adjustment of the demand for the other.

How can the desired level of variable input factor L_i at time $t+1$, L^*_{it+1}, be described? In the following, I assume a Generalized Leontief (GL) cost function [Diewert (1971)] with one quasi–fixed factor, IT–capital. This function has been introduced by Morrison (1988).[12] For three variable inputs L_i and one quasi–fixed input, x, the GL cost function is given by[13]

$$G = Y \left(\sum_{i=1}^{3} \sum_{j=1}^{3} \alpha_{ij} \, p_i^{1/2} \, p_j^{1/2} \right) + Y^{1/2} \sum_{i=1}^{3} \delta_i \, p_i \, x^{1/2} + \sum_{i=1}^{3} p_i \, \gamma_i \, x, \tag{2}$$

where Y denotes output and p_i denotes the factor price of variable input L_i. The input demand functions for L_i used in the empirical part are derived by application of Shephard's lemma on equation (2):

$$L^*_i = \frac{\partial G}{\partial p_i} = Y \left(\sum_{j=1}^{3} \alpha_{ij} \, (\frac{p_j}{p_i})^{1/2} \right) + \delta_i \, (x \, Y)^{1/2} + \gamma_i \, x \, . \tag{3}$$

Expression (3) is inserted as L^*_{it} into (1). In order to make equation (3) empirically better tractable and to avoid a potential source of heteroscedasticity, it is divided by Y. After rearranging terms, the factor demand equation for skill group i is given by:

$$\frac{\Delta L^*_{it+1}}{Y_t} = C + \psi_{ij} \, (\frac{p_{jt}}{p_{it}})^{1/2} + \psi_{ik} \, (\frac{p_{kt}}{p_{it}})^{1/2} \tag{4}$$
$$+ \zeta_i \, (\frac{x_t}{Y_t}) + \vartheta_i \, (\frac{x_t}{Y_t})^{1/2} - \beta_{ii} \, \frac{L_{it}}{Y_t} - \beta_{ij} \, \frac{L_{jt}}{Y_t} - \beta_{ik} \, \frac{L_{kt}}{Y_t},$$

[12] See Prucha (1990) for a discussion of a related paper by Morrison [Morrison (1990)].
[13] The time subscripts have been dropped for notational simplicity.

where $C = \beta_{ii}\alpha_{ii} + \beta_{ij}\alpha_{ij} + \beta_{ik}\alpha_{ik}$, $\psi_{ij} = \beta_{ii}\alpha_{ij}$, $\psi_{ik} = \beta_{ii}\alpha_{ik}$, $\zeta_i = \beta_{ii}\delta_i + \beta_{ij}\delta_j + \beta_{ik}\delta_k$ and $\vartheta_i = \beta_{ii}\vartheta_i + \beta_{ij}\vartheta_j + \beta_{ik}\vartheta_k$.[14] It is clear from inspection of equation (4) that α_{ij} and α_{ik} can be identified by dividing both ψ_{ij} and ψ_{ik} by β_{ii}. The standard error of the disturbance term, σ_i, which scales all coefficients in ordered probit models, cancels out. In ordered probit models, the variance of the disturbance term is not identified so that all parameters are implicitly scaled by the standard error of the disturbance term.

2.2 Empirical implementation

The data set used in the empirical part of this paper is the Mannheim Innvoation Panel in the Service Sector (MIP–S). This data set was originally collected in order to analyze the innovation behaviour of the German service sector. It is thoroughly described in Ebling et al. (1998).

The MIP–S is a mail survey which was designed and conducted in 1996. The survey's population refers to all firms with more than four employees. The survey design extends the traditional concept of innovation surveys in manufacturing industries as summarized in the OECD Oslo-Manual [OECD (1997)] to the service sector. Information collected in the questionnaire include (1) general information about the firm (size, industry, sales, number of employees, labor costs, exports, strategic management objectives, customers and product characteristics), (2) workforce of the firm and (3) investment in new physical assets and investment in information technologies.

The MIP–S data are used to estimate the system of equations (1). This system of equations is estimated by a trivariate ordered probit model since the MIP–S provides only *ordinal* information on changes in the firms' demand for heterogeneous labor. I take the *expected* change in the demand for the three types of labor as endogenous variable in order to account for the time structure of equation (1). Firms indicate on a three point scale if they plan to adjust their number of employees of a given skill group, to not change or to release labor of a certain skill type. I will abbreviate increased labor demand by “up”, unchanged labor demand by “unchanged” and decreased labor demand by “down” hereafter.

[14] Note that equation (4) is of course not identical to one of the equations in (1). If it were written down in an identical way, the equation would (a) include multicollinear terms (the factor price ratios and their inverses) and (b) be unidentifiable (inclusion of factor price ratios p_j/p_i, p_k/p_i *and* of p_j/p_k).

In the MIP–S, no information on the actual value of the IT–capital stock is given. Instead, IT–capital stock is approximated by IT–investment. The most important inputs in the production of services are labor and IT–capital which depreciates quickly. Proxying IT–capital by IT–investment thus appears as a plausible assumption.
Another shortcoming of the MIP–S is that labor costs are only collected for the total number of employees, not for individual skill groups. However, it is possible to assess labor costs for both individual firms and the three skill groups. The average labor costs per employee for firm m can be written as the following identity:

$$\frac{\Sigma_{i=1}^{3} LC_{im}}{L_m} = \sum_{i=1}^{3} p_{im} \frac{L_{im}}{L_m} \tag{5}$$

where i denotes the ith skill level and p_{im} are labor costs for labor of quality i for firm m. Labor cost for skill group i and firm m are denoted by LC_{im}. L_m denotes the total number of employees of firm m.
I assume p_{im} to be determined by the average labor cost for skill group i across all firms p_i, by sector–specific and regional influences,[15] by labor productivity (total number of employees over sales), investment–intensity (total investment over sales) and a set of firm size dummy variables. These variables are summarized in a vector $\boldsymbol{K_m}$. Thus, p_{im} is assumed to be given by

$$p_{im} = p_i + \boldsymbol{\theta}\ \boldsymbol{K_m} + \epsilon_m, \tag{6}$$

where $\boldsymbol{\theta}$ is a vector which relates $\boldsymbol{K_m}$ to p_{im} and ϵ_m is an i.i.d. distributed error term. Substitution of (6) into (5) leads to

$$\frac{\Sigma_{i=1}^{3} LC_{im}}{L_m} = \sum_{i=1}^{3} p_i \frac{L_{im}}{L_m} + \sum_{i=1}^{3} \boldsymbol{\theta}\ Ka \frac{L_{im}}{L_m} + \epsilon_m \tag{7}$$

Since $\frac{L_{im}}{L_m}$ and $\boldsymbol{K_m}$ are known for all m and i, equation (7) can be estimated by ordinary least squares.[16] The term $\boldsymbol{\theta K_m}\frac{L_{im}}{L_m}$ represents interactions between the elements of $\boldsymbol{K_m}$ with the shares of the three skill levels. In order to avoid multicollinearity, one skill group — I have chosen low skilled labor

[15]Wages are bargained over between trade unions and employers' associations at the sectoral and regional level in Germany. See Franz (1996, ch. 8) for details.

[16]The REGRESS option of the software package STATA5.0 was used for this purpose. All other estimations were run by using my own GAUSS procedures which are based on the MAXLIK application module.

— has to serve as the base category. Estimation results of equation (7) are presented in Table A in the appendix. Descriptive statistics for the variables used in the estimation of equation (7) and the following equation are displayed in Table B.
The factor prices are finally calculated separately for each of the skill groups from the fitted values of equation (7).
Due to the likely simultaneous determination of factor prices and factor inputs, labor costs have to be instrumented. Fortunately, in the MIP–S some questions, such as those on skill structure and labor cost, were asked retrospectively so that lagged labor costs — calculated in analogy to equation (7) — were used as instruments.

3 Results

Estimation results of the system of equations (1) are presented in Table 1. The direction of the effect of IT on the demand for heterogeneous labor cannot be inferred from the coefficients displayed in Table 1 alone since the estimation equation contains both IT–investment and its square root (both scaled by sales). An exception is the labor demand equation for low skilled labor where both the linear and the square root term are negative, indicating that increased expenditures in IT lead to a decreased demand for low skilled labor. For the other two equations, marginal effects have to be calculated.[17]
These marginal effects — evaluated at the means of the independent variables — are presented in Table 2. It turns out that the marginal effect of an increase in IT–intensity is positive and significant for the probability of expecting increased demand for both high and medium skilled labor. The effect is larger for the demand for high skilled than for the demand for medium skilled labor. The effects on the other two categories "unchanged" and "down" are negative and significant for both skill groups.
Since the marginal effects are crucially dependent on the means of the dependent variables, I have also calculated the share of firms for which a one percent increase in IT–intensity leads an increased probability of indicating increased expected demand for labor. For 96.2 (92.3) percent of the firms in the sample, this effect is positive for the demand for high (medium)

[17]Standard errors for the marginal effects are obtained by using the "delta method" [Greene (1997), pp. 278].

skilled labor. The effect is negative for all firms for the demand for low skilled labor.
Since investment in IT has a positive impact on the demand for high and medium skilled labor and has a negative effect on the demand for low skilled labor, evidence in favor of skill–biased technical change is found.
Although γ_i and δ_i cannot be identified, it is possible to calculate the elasticity of labor demand with respect to a change in IT–investment intensity (IT over sales). Rewriting equation (4) in matrix notation for all skill groups, multiplying it by sales (Y_t, and replacing $\boldsymbol{x_t}$ by $\boldsymbol{x_t}/Y_t$ (IT–investment intensity) leads to

$$\boldsymbol{\Delta}\ \boldsymbol{L_{t+1}} \ = \ \boldsymbol{M_t} \ + \ \boldsymbol{\zeta}\ \boldsymbol{x_t}^{1/2}\ Y_t \ + \ \boldsymbol{\vartheta}\ \boldsymbol{x_t}\ Y_t \ - \ \boldsymbol{\beta}\ \boldsymbol{L_t}, \tag{8}$$

where $\boldsymbol{M_t}$ contains all elements apart from the lagged number of employees of skill group i and the IT–variables of equation (1). $\boldsymbol{\zeta} \ = \ (\zeta_1 \ \ \zeta_2 \ \ \zeta_3)'$, and $\boldsymbol{\vartheta} \ = \ (\vartheta_1 \ \ \vartheta_2 \ \ \vartheta_3)'$. In long–run equilibrium, $\boldsymbol{\Delta}\ \boldsymbol{L_{t+1}} \ = \ 0$, $\boldsymbol{L_t} = \boldsymbol{L}$, $\boldsymbol{x_t}=\boldsymbol{x}$, $\boldsymbol{M_t}=\boldsymbol{M}$ and $Y_t = Y$. Solving for $\boldsymbol{L}$ leads to

$$\boldsymbol{L} \ = \ \boldsymbol{\beta}^{-1}\ \boldsymbol{M}\ Y \ + \ \boldsymbol{\beta}^{-1}\ \boldsymbol{\zeta}\ \boldsymbol{x}^{1/2}\ Y \ + \ \boldsymbol{\beta}^{-1}\boldsymbol{\vartheta}\ \boldsymbol{x}\ Y. \tag{9}$$

The long–run elasticity of IT–investment intensity is

$$\eta_{\boldsymbol{L},\boldsymbol{x}} \ = \ \frac{\partial\ \boldsymbol{L}}{\partial\ \boldsymbol{x}}\ \frac{\boldsymbol{x}}{\boldsymbol{L}} \ = \ (\boldsymbol{\beta}^{-1}\ \boldsymbol{\zeta}\ 1/2\ \boldsymbol{x}^{-1/2}\ Y \ + \ \boldsymbol{\beta}^{-1}\ \boldsymbol{\vartheta}\ Y)\ \frac{\boldsymbol{x}}{\boldsymbol{L}}. \tag{10}$$

At the mean of the variables, the long–run elasticity of a one percent increase in IT–investment intensity is

$$\eta_{\boldsymbol{L},\boldsymbol{x}} = \begin{pmatrix} 1.0364 \\ 0.9758 \\ -1.2756 \end{pmatrix}, \tag{11}$$

which indicates a long–run complementarity between IT–investment intensity and both high and medium skilled labor and a substitutability to low skilled labor. The effect of IT–investment is quite similar for high and medium skilled labor. It is difficult to find comparable elasticities in existing papers since most studies use the traditional translog approach (with all factors variable) with the associated share equations. Dewan and Min (1998) also proxy technical progress by IT capital and find an elasticity of 1.063 between homogeneous labor and IT capital for a CES–Translog function.

The signs of the diagonal elements of the β–matrix are positive for all skill groups as required by the dynamic factor demand model. It is, however, insignificant for high skilled labor. Signs and significancies of the lagged labor inputs indicate p–complementarities between medium and low skilled and p–substitutabilites between high and medium as well as between medium skilled and low skilled labor.

The marginal effects of an increase in own labor costs are displayed in Table 3. The effect on the probability of expecting increased (decreased) employment is negative (positive) and significant for high and low skill labor. It is disappointing that the reverse is true for medium skilled labor. The condition for the own–price elasticity of factor L_i to be negative is that $-\alpha_{ij} \;/\; \alpha_{ik} \;>\; (p_k/p_j)^{(1/2)}$ if $\alpha_{ik} > 0$ and $-\alpha_{ij} \;/\; \alpha_{ik} \;<\; (p_k/p_j)^{(1/2)}$ if $\alpha_{ik} < 0$. The matrix of the relative price coefficients, $\boldsymbol{\alpha}$, is given by (standard errors in parenthesis):[18]

$$\boldsymbol{\alpha} = \begin{pmatrix} \text{n.a.} & \underset{(234.0905)}{261.6576} & \underset{(116.0392)}{-125.3066} \\ \underset{(10.7786)}{2.7345} & \text{n.a.} & \underset{(57.0548)}{-148.5697} \\ \underset{(57.6819)}{125.4075} & \underset{(65.9502)}{67.6268} & \text{n.a.} \end{pmatrix} \tag{12}$$

The elements of the diagonal of $\boldsymbol{\alpha}$ cannot be identified without imposing further restriction on the system of equations (1).

The error terms of the labor demand equation for high and medium as well as those of medium and high skilled, but not those for high and low skilled labor are significantly correlated with one another. Correlation coefficients are 0.4074 and 0.3906, respectively. This implies that a separate estimation of equation (1) would have led to inefficient estimates of the variance–covariance matrix. The parameters would still have been consistently estimated.

[18]The variances of the elements of $\boldsymbol{\alpha}$ are calculated by using the formula $Var[X/Y] = (\mu_x/\mu_y)^2\ (Var[X]/\mu_X^2 + Var[Y]/\mu_Y^2 - 2\,Cov[X,Y]/\mu_x\mu_y)$ [Mood et al. (1974), p. 181].

4 Conclusions

This paper shows that a decline in the relative demand for unskilled labor is also present in the fast growing business–related services sector. The paper presents evidence that skill–biased technical change is an explanation for this phenomenon.

Starting from a dynamic factor demand framework, a structural approach for an analysis of the impact that new technologies have on the demand for heterogeneous labor in the business–related services sector is derived. The "optimal" number of workers as an ingredient of the dynamic factor demand system is assumed to be determined by a Generalized Leontief cost function with one quasi–fixed factor, IT capital stock which is proxied by investment in IT. The model is estimated by a trivariate ordered probit model.

It turns out that investment in IT has a significantly positive impact on the demand for high and medium skilled labor and a significantly negative effect on the demand for low skilled labor. Thus, evidence for skill–biased technical change is found.

Thus, lowering wages for the low–skilled may contribute to an improvement in the employment prospects of the low skilled. However, even if low skilled wages were driven down to a very low value, firms would be hesitant to hire workers whose abilities do not fit the current needs. It is therefore important to care for a proper education within Germany's dual system and to try to keep track on the technical progress by providing workers with additional training.

Table 1
Estimation Results of Equation (1)
(standard errors in parentheses)

Parameters	High skilled	Medium skilled	Low skilled
$(p_j/p_i)^{1/2}$	6.6695	0.0643	1.3531
	(0.2751)	(0.2501)	(0.3384)
$(p_k/p_i)^{1/2}$	-3.194	-3.4929	0.7297
	(0.9149)	(0.2323)	(0.6572)
IT/Y	-8.1339	-8.5004	-0.5889
	(0.2046)	(0.3884)	(0.1391)
$(IT/Y)^{1/2}$	4.415	3.7067	-0.9982
	(0.5155)	(0.3849)	(0.3297)
$L^{high\ skilled}/Y$	0.0255	-0.096	-0.0046
	(0.0228)	(0.0215)	(0.0213)
$L^{medium\ skilled}/Y$	-0.0284	0.0235	0.0141
	(0.0097)	(0.0089)	(0.0093)
$L^{low\ skilled}/Y$	-0.0023	0.0021	0.0108
	(0.0044)	(0.004)	(0.0041)
1st threshold	1.9104	-3.7699	2.056
	(0.4156)	(0.1662)	(0.3034)
2nd threshold	3.9226	-2.4426	3.8294
	(0.4113)	(0.1658)	(0.3046)

Table 1 presents trivariate ordered probit results of the extended equation (4). Time subscripts have been surpressed for notational simplicicity. The number of observations was 678. The units of measurement of the relative labor cost variable, of IT–investment (IT) and of sales (Y) is 1 bn DM. The IT–intensity variables (IT/Y) and $(IT/Y)^{(1/2)}$ have both been multiplied by 10 for numerical reasons. The correlation coefficient of the error terms between high skilled and medium skilled labor demand is 0.4074 (0.0413) — standard errors in parenthesis, for the medium and low skilled equation it is 0.3906 (0.0401), and for that of the high and low skilled equation, 0.0744 (0.0473). 62.2/46.9/61.3 percent of the actual outcomes were correctly predicted in the demand equations of high/medium/low skilled labor. The mean of the log–likelihood function was -2.6215.

Table 2
Marginal Effects of an Increase in IT–Investment
(standard errors in parentheses)

	probability to indicate...		
	"down"	"unchanged"	"up"
high skilled	-2.2736	-3.4696	5.7432
	(0.0452)	(0.1438)	(0.1438)
medium skilled	-2.7655	-2.0088	4.7743
	(0.3856)	(0.4973)	(0.4973)
low skilled	1.8011	-0.2634	-1.5377
	(0.5777)	(0.1640)	(0.1640)

Table 2 displays the effects of a one percent increase in IT–intensity on the probabilities of indicating an increase ("up"), decrease ("down") or no change in their demand for the respective skill group.

Table 3
Marginal Effects of an Increase in Own Labor Cost
(standard errors in parentheses)

	probability to indicate...		
	"down"	"unchanged"	"up"
high skilled	2.0796	3.1737	-5.2533
	0.9487	2.8517	1.7835
medium skilled	-4.7662	-3.4620	8.2283
	1.2457	1.0942	0.1514
low skilled	9.1030	-1.3314	-7.7716
	1.7652	6.1518	4.3865

Table 3 shows the effects of a one percent increase in own labor cost on the probabilities of firms indicating an increase ("up"), decrease ("down") or no change in their demand for the respective skill group.

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A Labor cost decomposition (1996 labor cost)

	Coeff.	Std. err.
Constant (p_3)	0.0516	0.0048
High skilled share (p_1)	0.0485	0.0097
Medium skilled share (p_2)	0.0161	0.0071
East German firm	-0.0099	0.0038
East German firm · high skilled share	-0.0178	0.0093
East German firm · medium skilled share	-0.0092	0.0082
Productivity	0.0109	0.0041
Productivity · high skilled share	0.0002	0.0002
Productivity · medium skilled share	0.0001	0.0001
Investment intensity	0.0068	0.0036
Investment intensity · high skilled share	-0.0007	0.0005
Investment intensity · medium skilled share	0.0004	0.0003
19 — 50 employees	0.0020	0.0062
19 — 50 employees · high skilled share	0.0093	0.0098
19 — 50 employees · medium skilled share	-0.0002	0.0093
50 — 250 employees	-0.0080	0.0055
50 — 250 employees · high skilled share	0.0378	0.0137
50 — 250 employees · medium skilled share	0.0157	0.0114
more than 250 employees	-0.0145	0.0061
more than 250 employees · high skilled share	0.0177	0.0348
more than 250 employees · medium skilled share	0.0164	0.0178

Table A displays ordinary least squares regression results of equation (7). The dependent variable labor cost per capita is in 1 bn DM. That is, the average payroll costs across all firms for an unskilled worker are $0.0485 \cdot 1e6 = 48,500\ DM$. The number of observations is 1,113, the adjusted R^2 is 0.1789.

B Descriptive statistics

Variable	Mean/share	Std. Dev.
Labor cost decomposition		
per capita labor cost	0.0729	0.0550
High skilled share (p_1)	0.2392	0.2932
Medium skilled share (p_2)	0.5121	0.3155
East German firm	0.4159	-
East German firm · high skilled share	0.1221	0.2444
East German firm · medium skilled share	0.2260	0.3350
Productivity	0.3038	0.5995
Productivity · high skilled share	6.5595	25.2300
Productivity · medium skilled share	15.2159	41.8822
Investment intensity	0.0522	0.2640
Investment intensity · high skilled share	1.0548	6.1757
Investment intensity · medium skilled share	3.3041	15.4020
19 — 50 employees	0.2135	-
19 — 50 employees · high skilled share	0.0534	0.1705
19 — 50 employees · medium skilled share	0.1196	0.2668
50 — 250 employees	0.2825	-
50 — 250 employees · high skilled share	0.0630	0.1739
50 — 250 employees · medium skilled share	0.1350	0.2663
more than 250 employees	0.1595	-
more than 250 employees · high skilled share	0.0200	0.0940
more than 250 employees · medium skilled share	0.0594	0.1870
Labor demand equation		
Exp. change in high skilled labor demand	1.2212	0.5737
Exp. change in medium skilled labor demand	1.2581	0.6980
Exp. change in medium skilled labor demand	0.9528	0.6203
p_2/p_1	0.8011	0.0234
p_3/p_1	0.6791	0.0338
p_3/p_1	0.8464	0.0309
IT–investment over sales	0.0132	0.0212
(IT–investment over sales)·5	0.0889	0.0729
number of high skilled employees over sales	1.4000	2.0823
number of medium skilled employees over sales	3.8273	4.7154
number of low skilled employees over sales	3.7548	10.5659

Table B shows descriptive statistics for the variables used in the estimations. The dimension of per capita labor cost, IT–investment and sales is 1 bn DM. The number of observations is 1,113 for the labor cost and 678 observations for the labor demand equations.