# Workers' skill level and information technology: a censored regression model

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***Abstract*** *This paper analyses the link between educational qualification structure and information technology (IT) in the service production process. The analysis is based on 1996 cross-sectional data for approximately 1,000 West German firms. The empirical evidence indicates that IT capital and high-skilled labor are complements in the production process: firms with higher IT investment output ratios employ a larger fraction of high-skilled workers at the expense of unskilled workers. To a lesser extent, the positive IT effect carries through for workers with vocational degrees including masters and technicians. Furthermore, we find that firms' expectations of the future size of their high-skilled workforce are positively related to their initial IT investment output ratio. To account for censoring in the employment variables, the empirical analysis uses Powell's Censored Least Absolute Deviations estimators as well as standard Tobit estimators.*

## 1. Introduction

The large-scale introduction of personal computers for general use as well as the increasing computerization of various production processes in the 1960s led to a public apprehension that computer-controlled machines could gradually erode the demand for blue-collar workers. By the 1990s, public opinion had shifted, recognizing that information technology (IT) could potentially be more threatening to the position of the middle manager (Drucker, 1988). A simple microeconomic justification for this notion points to the lower marginal and total costs exhibited by IT capital relative to human capital. The differences in cost would suggest a substitution of IT capital for the more expensive managerial and clerical workers, assuming similar marginal products of IT and human capital. Similarly, as transaction costs fall due to improved communication technologies, the need for managerial talent decreases further (Malone and Rockart, 1991). Economic theory and informal evidence thus suggest that the spread of IT into all types of enterprises witnessed primarily in the 1980s and 1990s may significantly alter the composition of firms' workforces.

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Bresnahan (1999) presents a theoretical analysis of the impact of the expansion of IT on the qualification structure of the workforce, dividing the role of IT into two separate effects. On the one hand, the fall in demand for low- and medium-skilled labor results directly from the systematic substitution of computers for human decision making. However, only a certain number of unskilled and medium skilled tasks can be replicated by IT, and thus only "limited substitution" takes place. An example of a task that cannot be covered by IT includes front office staff. On the other hand, upon computerization of the production process, the demand for highly skilled workers who can efficiently use newly introduced IT structures rises. The magnitude of restructuring due to computerization may vary by type of organization. Bresnahan argues that the impact of new IT innovations may be limited in "people-based" organizations, which rely strongly on personal communication. Conversely, in software-based production, the same innovation can be easily supplied to all customers and suppliers, leading to an increased marginal product of the creators of new ideas. This process of "organizational complementarity" is likely to be more pronounced at the level of the firm than at the level of the employee. A number of implications for empirical investigations of the role of IT in today's workforce arise. First, the effect of IT should be examined at the firm level since we expect benefits for both the organization and the individual employee. Second, increased reliance on IT may negatively impact the demand for medium and unskilled workers due to limited substitution, though these effects should be relatively small. Lastly, only the highest skill group, in particular professionals and managers, can be expected to benefit from computerization.

The link between information and communication capital and the workforce's skill structure has been empirically analyzed by a number of authors (for a survey of the literature see Chennells and Van Reenen, 1999). The majority of studies relies on industry-level data to relate the rate of change in the employment share of skilled labor to the industry's initial IT capital to total capital (or investment) ratio. In contrast to public opinion, several authors find a complementarity of IT capital and skilled labor. Berman *et al.* (1994) as well as Autor *et al.* (1997) provide US evidence at the four-digit SIC level that the change in the cost share of skilled labor is positively related to the industry's initial investment in computers.

Our analysis of the determinants of firm-level skill intensity is closely related to the approach adopted by Doms *et al.* (1997). The authors examine the effect of computer investment on the share of non-production workers and find a significantly positive relationship. Bresnahan *et al.* (1999) estimate IT capital demand functions for college-educated workers and professionals based on a panel of 311 US firms. Their findings suggest that IT capital is positively correlated with investments in human capital and workforce skills. The authors conclude that skill-IT complementarity is the dominant factor in explaining the demand for skilled labor. While acknowledging that there is a causal relationship running from IT capital to the share of highly skilled technical workers[1], the authors base their analysis on the assumption that the skill level of the workforce drives the demand for IT capital. This assumption may be violated, however, in situations where firms hire more skilled labor to efficiently use the previously installed IT capital. The issue of causality will be addressed further in the following empirical exposition.

This paper focuses explicitly on the role of IT in the service production process. IT has been quickly adopted in the service sector, with the highest adoption rates prevailing in wholesale trade, finance and insurance, and business services (McFetridge, 1992). The IT distribution by service industry suggests vastly differing degrees of importance of IT across the sector, however, and motivates a more detailed study of those industries in which IT capital is highly concentrated.

The data used in the following analysis are derived from the 1997 wave of the Mannheim Service Innovation Panel (MIP-S), which has previously been analyzed by Kaiser (1999). We exclude the subsample of East German firms from the analysis, since the interactions between IT and the workforce's qualification structure cannot be separately identified from dramatic restructuring efforts undertaken by East German industry in recent years. We investigate the link between IT capital and skill intensity for three separate skill types, university graduates, vocational school graduates, and unskilled workers. Data limitations dictate to some extent the econometric approach taken in this paper. The lack of capital stock data and the cross-sectional nature of the data force us to focus on the link between current firm investments in information technology capital and workforce skill structure. Previous work (see Falk and Seim, 1999) justifies the use of IT and non-IT investment as proxies for the underlying capital stocks. To address endogeneity and causality questions arising from the use of same period investment and labor data, we investigate the impact of the initial IT investments on projected future movements in firms' employment of labor by different skill types.

Our econometric work takes into account that a certain fraction of firms in the sample does not employ any workers of a given skill class. We employ Powell's (1984) censored least absolute deviations (CLAD) estimator as well as standard Tobit models. While assuming a functional form for the regression model, Powell's CLAD estimator does not rely on a functional form assumptions for the error process. This estimator is therefore preferable to the standard Tobit estimator in cases of heteroscedastic or non-normally distributed error terms.

The layout of the paper is as follows. Section 2 outlines the econometric models, while section 3 describes and summarizes the data. In section 4, we present the results for the factor demand equations. Section 5 concludes.

## 2. Econometric model

### *2.1 Employment share equations*

The link between IT and workforce skill intensity can be analyzed using a standard firm-level variable cost function framework (examples from the literature using this approach include Doms *et al.* (1997)). The cost function is defined over two quasi-fixed factors of production, IT capital ($IT$) and non-IT capital ($K$), and three variable inputs, university graduates ($H$), vocational school graduates ($M$), and workers without advanced degree including apprentices ($U$). In the case of a homothetic translog cost function exhibiting constant returns to scale and homogeneity of degree one in prices, Shepard's Lemma implies the following cost share equations (see Chennells and Van Reenen, 1999):

$$\frac{\partial \ln C}{\partial \ln P_i} = \frac{P_i X_i}{C} = S_i = \alpha_i + \sum_{j=U,H} \beta_{ij} \ln(P_j/P_M) + \beta_{iK} \ln(K/Q) + \beta_{iIT} \ln(IT/Q) + u_i,$$

where $C$ denotes total cost, $P_i$ the price of input $i$ ($i$ = $H$, $U$), and $X_i$ the conditional factor demand for input $i$. $S_i$ is thus the cost share for the two types of labor, and $Q$ denotes total wage costs in nominal prices as a proxy for value added. We normalize by the factor price of medium-skilled labor, $P_M$, and consequently drop the medium-skilled labor equation because the cost shares sum to unity. The parameters $\beta_{iK}$ and $\beta_{iIT}$ measure the effects of the non-IT capital output ratio ($K/Q$) and the IT capital output ratio ($IT/Q$) on the labor cost shares. A positive coefficient on the capital output ratio in the university graduates share equation ($\beta_{HK} > 0$ ) indicates, for example, that capital is a complement to skilled labor. Since our data do not provide reliable information on firms' capital stocks, we use the investment output ratio as a proxy for the capital output ratio in the two investment sectors, IT and non-IT investment[2].

Since factor prices by skill class are not available at the firm level, we employ the skill-specific employment shares to proxy for unknown cost shares[3]. Given the limited availability of wage data at the industry level, we choose to capture the effects of relative wages by including industry dummies in the factor demand equation. Industry dummies will pick up the effects of relative wage differences on labor demand if relative wages, ($P_H/P_M$) or ($P_U/P_M$), are constant within industries, but not across industries. The general specification used in the following empirical implementation thus relates the employment shares of each skill class, $E_i^k$, to the IT investment output ratio, the non-IT investment output ratio, as well as a set of appropriate control variables[4]:

$$E_i^k = \alpha_i + \beta_{1j} ITQ_i + \beta_{2j} ITQ_i^2 + \beta_{3j} IQ_i + \beta_{4j} IQ_i^2 + \beta_{nj} z_i + u_i, \tag{1}$$

where $k = H, M, U$; $i$ refers to the firm and $j$ to the industry. The variables are defined as:

$E^H$ high-skilled employment share (censored at zero).

$E^U$ unskilled employment share (censored at zero).

$E^M$ medium-skilled labor (censored at both sides).

$ITQ$ information technology and communication expenditure as percentage of output.

$IQ$ non-IT investment as percentage of output.

$z$ 1, . . ., 4 firm size classes;
1, . . ., 9 industry dummies;
participation in R&D and exporting activities;
part of industrial conglomerate .

The vector of control variables, $z$, contains sector, size, and other heterogeneity control variables. As a normalization, we exclude one of the industry and size classes each in the estimation. Appropriate control variables, which may affect the skill composition of firms' labor forces, include information on export orientation, participation in R&D, and ownership form (part of industrial conglomerate).

Since factor prices are not included, it is not necessary to impose the conditions of symmetry and linear homogeneity in factor prices. Consequently, each of the three employment share equations can be estimated by single equation methods. The degree of substitutability between different types of labor and information technology cannot be ascertained based on employment shares only. A positive IT coefficient in the employment share equation for high-skilled labor then simply indicates that firms with higher IT investment output ratios have a higher skill intensity. Furthermore, elasticities, defined as the percentage change in the three types of labor associated with a 1 percent increase in IT capital, cannot be estimated. Instead, in the empirical part of the paper, we calculate the elasticity of the employment share with respect to the IT-investment output ratio:

$$\epsilon_{E^k,ITQ} = \frac{\partial E^k}{\partial ITQ}\frac{ITQ}{E^k}, \quad k = H, M, U.$$

The sign of the partial derivative of the different labor inputs with respect to the IT-investment output ratio indicates whether a certain skill class is complementary ($\epsilon_{E^k,ITQ} > 0$) or substitutable ($\epsilon_{E^k,ITQ} < 0$) to IT investment. IT-skill complementarity is found if the partial derivative of unskilled labor with respect to capital is higher than it is for both medium-skilled and high-skilled labor.

We advance five hypotheses concerning the relationship between the worker skill level and information technology, which we proceed to evaluate in the following empirical work:

*H1*: IT-skill complementarity: highly educated labor is complementary rather than a substitute for IT investment. Conversely, IT is a substitute for unskilled labor.

*H2*: A weaker form of IT-skill complementarity implies that the IT employment share elasticities decrease with the skill level: $\epsilon_{E_H,ITQ} > \epsilon_{E_M,ITQ} > \epsilon_{E_U,ITQ}$.

*H3*: The ranking of the IT employment share elasticities holds most strongly in sectors, which rely heavily on information technology, such as banking and insurance.

*H4*: Given the comparative advantage of German exporting industries, we hypothesize that exporters produce human-capital-intensive goods and have a higher educational qualification structure. Therefore, the expected sign on exporting activities is positive for high-skilled labor and negative for unskilled labor.

*H5*: Firms, which undertake R&D projects, can be expected to have a more qualified workforce due to the high skill intensity of R&D.

### *2.2 Estimation procedure*

*2.2.1 Censored regression model of the employment share equation.* The observed data on employment broken down into skill categories contains clusters of zero values leading to censored employment shares. The less frequent case of an employment share that is censored above arises when all workers belong to the same skill class. Under censoring of the dependent variable, OLS estimates are inconsistent. A truncated regression model can be employed instead. In the basic censored regression model with left censoring, the true underlying dependent variable, $y^*$, is a function of a set of independent variables, $x$:

$$y^* = x\beta + \varepsilon \quad \varepsilon \sim N(0, \sigma^2), \tag{2}$$

where $\varepsilon$ denotes the error term and $\beta$ the vector of coefficients. The observed value of the dependent variable, $y$, is given by:

$$y = \begin{cases} L & y^* \leq L \\ y^* = x\beta + \varepsilon & y^* > L \end{cases}, \tag{3}$$

with $L$ the lower censoring bound. The values for $y^*$ if $y^* \leq L$ are unobserved. In this particular application, the employment share for medium-skilled labor is censored from both sides of the distribution, leading to the modified Tobit model with both upper and lower bounds[5]:

$$y = \begin{cases} L & y^* \leq L \\ y^* = x\beta + \varepsilon & L < y^* < U \\ U & y^* \geq U \end{cases}, \tag{4}$$

where $U$ and $L$ denote the upper and lower censoring bounds, respectively. The values for $y^*$ if $y^* \leq L$ or $y^* \geq U$ are unobserved. With normally distributed and homoscedastic errors, both the one- and two-limit Tobit models can be estimated using maximum likelihood methods. Homoscedasticity will be violated, though, if the error variance is, for example, proportional to a function of one of the regressors. Under misspecified error distributions, the ML-estimator of the Tobit model is inconsistent.

An alternative estimation procedure for the employment share equations follows Powell's (1984; 1986) semi-parametric estimators for censored regression models, the censored least absolute deviations (CLAD) or symmetrically censored least squares (SCLS) estimators. Both estimators perform, under certain circumstances, better than the standard ML-Tobit model due to robustness to heteroscedasticity or other forms of distributional misspecification. While the SCLS estimator is more efficient than the CLAD estimator, the CLAD estimator is more robust to outliers, which arise very frequently in the case of survey data due to erroneous responses (see Appendix 2 for a further note on Robustness tests). The CLAD estimator can be motivated starting from the basic Tobit model by rewriting equation (3) as:

$$y = \max(x\beta + \varepsilon, L). \tag{5}$$

The CLAD estimator of $\beta$ minimizes the sum of absolute deviations, $|\varepsilon|$, assuming a conditional median restriction on the error term[6]. The objective function can thus be specified as:

$$S_n(\beta) = \min_{\beta}\left\{\frac{1}{n}\sum_{i=1}^{n}|y_i - \max\{L, \beta' x_i'\}|\right\}. \tag{6}$$

The CLAD estimator's performance has been shown to be sensitive to the degree of censoring. In our sample, however, censoring at the lower bound, zero, ranges only from 2.4 per cent to 32.5 per cent, depending on the employment share. The sample's degree of censoring falls, therefore, well within the limits specified by Nawata (1994) and McDonald and Xu (1996), validating the use of CLAD procedures. Paarsch (1984) and Deaton (1997) point to a further weakness of the CLAD estimator, namely its finite sample bias resulting in mean-biased results for small samples ($n < 100$). In such cases, the standard Tobit MLE produces superior results with smaller standard errors than Powell's CLAD. Therefore, we base a comparison of Tobit MLE and CLAD only on the full sample of about 1,000 observations instead of the smaller industry-level sub-samples. A final difficulty arising in the application of the CLAD estimator is computational rather than conceptional. The CLAD estimator involves the minimization of an objective function that is not necessarily convex in $\beta$. Obtaining a global minimum of the objective function using numerical minimization algorithms based on approximations of the first derivative can thus be difficult, and convergence to a global minimum cannot necessarily be guaranteed (see Kahn and Powell, 1999). We consequently employ the Simplex Nelder-Mead algorithm to minimize the objective function using the results from the standard ML Tobit as starting values[7]. Since the estimator's asymptotic variance-covariance matrix (as specified by Powell,

1984) involves the estimation of the density function of the error term, we use bootstrapped estimates of the standard errors. The standard errors are obtained by fixing the independent variables and re-sampling the residual, assuming that the data are a random sample from some population.

Censored regression models, such as the Tobit or CLAD models, are often criticized because they require the independent variables to have the same qualitative impact on both the probability to employ labor of different skill types and the size of the employment share. Generalizations of the standard Tobit model, which address this issue, include double hurdle models and Heckman's selection model (see Greene, 1997). The set-up of the double hurdle model divides the standard Tobit model into a decision equation determining whether labor of a given skill level should be employed and, if so, a second decision of how much of the type of labor to employ. The first decision can be modelled as a Probit model, while a truncated regression model applies in the second stage to those firms that employ at least one worker of the given skill. To allow for flexibility in the distribution of the error terms, we use a generalized Tobit model on a Box-Cox transformation of the dependent variable, the employment shares (see Davidson and McKinnon, 1993). We do not attempt to jointly estimate the first and second stage decisions, however, since we are not able to identify the first stage decision separately from the second stage decision. Our dataset does not contain variables which only affect the decision to employ labor of different types, but not the chosen skill category's share.

*2.2.2 Probit equations explaining the change in the employment of the three skill types*. The previous specification of the employment share equations presumes that causality runs from IT to the respective skill share. Some authors, most notably Bresnahan *et al.* (1998), have argued that the direction of causality between IT capital and skill structure is difficult to sort out. It is most likely that firm choices of IT investment and skill structure are jointly determined. This endogeneity of IT investment is difficult to address using only cross-sectional data. Our dataset only contains information on firms' lagged capital stocks and sales, which are rarely uncorrelated with the error term and have to be ruled out as suitable instruments. Berman *et al.* (1994) suggest correcting for the endogeneity of IT and skill structure by analyzing the relationship between the change in employment of the three skill types and the initial IT investment output ratio[8]. Assuming zero substitution possibilities between different types of labor, the short-run demand system for different types of labor may be described as:

$$\Delta l_{it}^{k} = f_1(\Delta y_{it}, ITQ_{it}; IQ_{it}; \alpha) + \zeta_{it}, \tag{7}$$

where $i$ indexes firms, $\Delta l_{it}^{k}$ denotes the employment growth rate from period $t$ to period $t+1$ for the three different types of labor $k$, $k = U, M, H$, and $\Delta y_{it}$ is the change in firm output from $t$ to $t+1$. The parameter vector to be estimated is denoted by $\alpha$. Since the data do not contain information about employment growth rates, we use categorical information on expected employment and sales growth. The expected employment growth rate between periods 1996 ($t$) and 1997-99 ($t+1$) is approximated by a dummy variable indicating whether firms plan to increase the employment of different types of labor in the short-term horizon[9]. The factor demand system is modified as follows:

$$E[\Delta l_{it}^{k}] = f_2\left(ITQ_{it}, IQ_{it}, E[\Delta y_{it}], \frac{L_{it}^{H}}{L_{it}}, z_{it}; \alpha\right) + \nu_{it} \tag{8}$$

where the variables denote:

| | |
|---|---|
| $E[\Delta l_{it}^{k}]$ | expected growth from 1996 to 1997-1999 in employment of labor of type $k = U, M, H$. |
| $ITQ_{it}, IQ_{it}$ | IT investment and non-IT investment wage bill ratios, 1996. |
| $E[\Delta y_{it}]$ | expected output (sales) growth rate, 1996 to 1997-1999. |
| $L_{it}^{H}/L_{it}$ | skill intensity of firms' activities, measured by university graduates' employment share, 1996. |
| $z_{it}$ | size, sector, and other control variables, 1996. |

## 3. Data description

Our empirical analysis is based on the second wave of the Mannheim Service Innovation panel (MIP-S), which contains information for 1996. This survey has been conducted to shed light on the innovation behavior of service firms (for details see Janz and Licht (1999))[10]. Approximately 2,325 firms participated in the second wave of the panel, of which 1,466 firms are located in the West and 859 in the East. The key variables in this study span two types of investment, output (sales), the skill structure of the workforce, and firms' qualitative characteristics (R&D activities, exports). Since value added is not available, firms' total wage costs are used as a proxy[11]. Skill is measured by the employee's level of educational attainment. High-skilled workers denote employees with a university degree in engineering, natural sciences, business, or social sciences. The medium skilled class includes technical college graduates ("*Fachschulabschluß*") and vocational school graduates. Employees without advanced degree and apprentices are classified as unskilled workers. IT investments are defined as 1996 investment in information and communication technology including computers, peripheral equipment, and software. Total gross investment is also provided. In order to avoid double counting, we subtract IT investment from total investment to obtain non-IT investment. Excluding firms with less than five employees led to a reduction of the sample to 1,373 firms. Incomplete information on key variables further reduced the sample by 414 firms. Finally, 12 typing errors and obvious outliers (investment wage cost ratio exceeds 500 per cent) were removed from the sample.

Table AI in Appendix 1 provides some insight into the sample data. Since sample weights are not used, the sample is not representative and should be interpreted with caution. The proportion of university or higher technical college graduates is 15 per cent, 58 per cent of workers are medium-skilled, while workers without any advanced degree account for approximately 26 per cent of the workforce. The relatively high IT to total investment ratio of about 46 per cent highlights the significant role that IT takes in the service production process. Expressed as a percentage of total wage costs, IT investment amounts to 4.2 per cent in 1996. The data set contains a significant number of entries for which investment or IT investment equals zero. Out of the total sample of 959 firms, 110 report zero expenditures for IT investment. Approximately one-quarter of firms only invest in IT (IT-investment share of 100 per cent) and do not make any other capital investments.

Table AII contains information on industry affiliation, size classes, and export behavior. Firm size is defined by number of employees, and firms are divided into five size classes: the reference group contains firms with less than ten employees, the three medium-sized classes are defined as 10-19, 20-49, and 50-249 employees, while large firms have more than 250 employees. In 1996, 37 per cent of West German firms belonged to a corporate group. The share of exporting firms amounts to 28 per cent. The service sector is broken down into ten sub-sectors or industries, primarily defined by NACE two- or three-digit industries. Market services are split up into computer and software firms (NACE 72); R&D labs and technical consultants (NACE 731, 742, 743); business consultants, legal services, and accounting (NACE 741); and other market services including personal services (NACE 744-746, 748, 93).

Table AIII reports the sector-level skill decomposition, which varies considerably across service industries. Among computer and software firms, 42 per cent of employees have a university degree, while only 5 per cent of retail trade employees are university-educated. The most skill-intensive sectors are the computer and software industries, R&D laboratories and technical consulting sectors, as well as business services (consultants, legal services, accounting). In these sectors, the share of university graduates lies between 30 per cent and 45 per cent. Banking and insurance, as well as real estate and community services, can be classified as medium skill-intensive industries. Finally, wholesale and retail trade, transport and other business services (cleaning, advertising) are low skill-intensive, employing primarily medium- and unskilled labor. To verify the reliability of the revealed educational qualification structure, we compare the average skill structure based on the MIP-S data set to the 1996 wave of the German Labor Force Survey ("Micro Census"), a survey at the level of the individual. Summing across Micro Census participants who are employed in one of the service sector industries reveals a similar qualification structure among high- and medium-skilled employees. However, the share of unskilled workers in the MIP-S firm data set exceeds the corresponding figures in the German Micro Census considerably. This bias in the MIP-S data may indicate that a fraction of the workers in the category "other employment" were erroneously categorized as unskilled. An under-reporting of high- and medium-skilled labor may introduce a slight downward bias in the estimated coefficients.

Table AIV shows the breakdown by sector of IT and non-IT investment, both as a percentage of total wage costs. Banking and insurance, computer and software, as well as business services possess the expected higher IT intensity than the remaining sectors. Retail trade as well as other services (including mostly low-skill-intensive personal services) exhibit very low IT investment output ratios. Wholesale trade, transport, and community services (in particular sewage and sanitation) can also be classified as capital-intensive industries. A comparison of the high-skilled shares and IT investment sales ratios provides informal evidence that the sectors which are skill-intensive are the ones that use IT intensively. The table furthermore depicts the percentage of exporters and of firms engaging in R&D, which show that human-capital-intensive industries are more likely to engage in R&D activities and are more export oriented than the remaining sub-sectors.

## 4. Determinants of the skill structure

### *4.1 CLAD estimates for the employment share equations*

In order to quantify the main factors behind firm skill intensity, the employment shares are regressed against the potential determinants discussed above. As noted earlier, 32 per cent of the 959 West German sample firms do not employ high-skilled labor in 1996, causing the employment share to be censored at zero. For unskilled labor and medium-skilled labor, the percentage of zero values are 24.5 and 2.8 per cent, respectively. Of the sample firms, 8.6 per cent solely employ medium-skilled labor, causing the medium-skilled share to be censored at one.

Table I reports the estimation results for the three skill classes[12]. The standard ML Tobit results are displayed in the appendix (see Table AV). Table I also includes a Wald statistic testing the quadratic specification employed in the estimation. We concentrate the interpretation of our results on the CLAD estimations for two reasons. First, the likelihood ratio test statistic, distributed $\chi^2(20)$, which tests the assumption of multiplicative heteroscedastic errors versus the homoscedastic base model, ranges in value between 212 and 423 for the three employment share equations. The heteroscedastic model can therefore not be rejected at the 5 per cent level[13]. Second, the residuals of the standard Tobit model exhibit a large degree of kurtosis questioning the assumption of normal residuals. The Shapiro-Francia (Francia and Shapiro, 1972) statistic for normality of residuals ranges between 7.0 for the high-skilled labor equation and 4.3 for the unskilled labor equation[14]. The clear rejection of two central assumptions on the Tobit model's residuals questions the reliability of the resulting estimates and points towards using more flexible models such as the CLAD.

| | High-skilled labor (1) | High-skilled labor (2) | Medium-skilled labor (3) | Unskilled labor (4) |
|---|---|---|---|---|
| $IT/Q$ | 0.44 | 0.33 | 0.18 | –1.12 |
| | (2.29) | (2.21) | (0.48) | (–2.01) |
| $(IT/Q)^2$ | –0.19 | – | –0.59 | 1.13 |
| | (–0.94) | | (–3.21)} | (1.36) |
| $I/Q$ | –0.07 | –0.06 | –0.02 | 0.15 |
| | (–1.61) | (–1.56) | (–0.08) | (2.14) |
| $(I/Q)^2$ | 0.01 | – | 0.02 | –0.06 |
| | (1.97) | | (0.06) | (–2.07) |
| Exporter | 0.14 | 0.12 | –0.06 | –0.01 |
| | (3.54) | (3.69) | (–1.90) | (–1.64) |
| Ind. group | 0.04 | 0.03 | 0.05 | –0.11 |
| | (1.25) | (1.27) | (0.44) | (–3.15) |
| R&D | 0.15 | 0.17 | –0.01 | –0.06 |
| | (3.49) | (4.15) | (–0.08) | (–0.98) |
| $10 \leq L$ 20 | –0.00 | –0.01 | –0.03 | 0.04 |
| | (–0.34) | (–0.34) | (–0.24) | (0.83) |
| $20 \leq L$ 50 | 0.00 | –0.00 | –0.12 | 0.19 |
| | (0.08) | (0.08) | (–0.82) | (3.47) |
| $50 \leq L$ 250 | 0.03 | –0.03 | –0.18 | 0.26 |
| | (1.21) | (1.21) | (–1.15) | (6.07) |
| $L \geq 250$ | –0.01 | –0.07 | –0.18 | 0.30 |
| | (–0.29) | (–3.16) | (–1.15) | (5.44) |
| Wholesale trade | –0.18 | –0.19) | –0.07 | 0.23 |
| | (–3.77) | (–4.47) | (–0.59) | (5.01) |
| Retail trade, repairs | –0.16 | –0.20 | 0.03 | 0.06 |
| | (–1.26) | (–2.40) | (0.20) | (1.25) |
| Transport | –0.29 | –0.33 | –0.13 | 0.26 |
| | (–2.71) | (–4.33) | (–0.88) | (3.66) |
| Real estate, renting | –0.01 | –0.33 | –0.15 | 0.17 |
| | (–0.26) | (–3.48) | (–0.51) | (2.16) |
| Computer, software | 0.19 | 0.16 | –0.28 | –0.04 |
| | (2.99) | (2.60) | (–1.92) | (–1.24) |
| Tech. consultants | 0.16 | 0.25 | –0.31 | 0.00 |
| | (4.50) | (4.23) | (–7.76) | (–0.37) |
| Business services | 0.21 | 0.17 | –0.28 | 0.04 |
| | (4.10) | (3.67) | (–2.97) | (1.44) |
| Other services | –0.17 | –0.20 | –0.42 | 0.45 |
| | (–3.00) | (–4.49) | (–1.65) | (4.82) |
| Sewage, sanitation | 0.01 | –0.06 | –0.36 | 0.30 |
| | (0.78) | (–2.45) | (–0.70) | (2.66) |
| Constant | 0.02 | 0.07 | 0.88 | –0.05 |
| | (0.84) | (3.01) | (6.83) | (–1.37) |
| Wald-Test: $IT/Q, (IT/Q)^2 = 0$ | 4.64** | | 10.81* | 5.89* |
| Wald-Test: $I/Q, (I/Q)^2 = 0$ | 3.29 | | 0.01 | 5.11** |
| $\partial(E^k/\partial(IT/Q)$ | 0.42** | 0.33* | 0.13* | –1.13* |

*(continued)*

**Table I.**
Censored least absolute deviations estimates, educational qualification shares

Table I.

| | High-skilled labor | | Medium-skilled labor | Unskilled labor |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\partial \ln(E^k/\partial \ln(IT/Q)$ | 0.12** | 0.09* | 0.01* | –0.16* |

**Notes:**
* Significant at 5 per cent level
** Significant at 10 per cent level
$T$-statistics in parentheses. Dep. var.: Share of workers of respective educational qualification. Reference group for sector dummies is banking/insurance, for size classes size 1 (less than ten employees). The CLAD standard errors are bootstrapped estimates from re-sampling 500 times

The central result to be drawn from the CLAD as well as Tobit estimations is the significant relationship between firms' skill structure and their IT investment output ratios. For medium and unskilled labor, Wald tests indicate that both the IT investment output ratio and its square are jointly significant at the 5 per cent level. In the case of the high-skilled labor share, the Wald test rejects the quadratic specification of the high-skilled labor equation in the CLAD model. Re-estimating the CLAD model excluding the squared IT investment output ratio for the high-skilled employment share results in an IT-coefficient of about 0.33 with a $t$-statistic of 2.2. The derivative of the unskilled employment share with respect to the IT investment output ratio of (–1.03) indicates that IT serves as a substitute to unskilled labor[15]. Conversely, both medium- and high-skilled labor are complementary to IT-investment with a positive derivative of the employment shares with respect to the IT investment output ratio[16]. The magnitude of the IT effect on the high-skilled employment share is rather small, however, as indicated by the elasticity of 0.06[17]. Similarly, the IT effect on unskilled labor is also relatively low in absolute terms, with an elasticity of the unskilled employment share with respect to the IT investment output ratio of –0.11[18]. An increase in the IT investment output ratio of 2.4 per cent or approximately 0.1 percentage points per year would thus only yield an increase in the average high-skilled labor share by 0.2 percentage points over the course of five years, from 15.4 per cent in 1996 to 15.6 per cent in 2001[19]. Applying these results to the actual and interpolated evolution of the high-skilled employment share from the German Labor Force Survey shows that less than 10 per cent of the observed increase in the high-skilled share of about 0.5 percentage points per year can be explained by the rising IT share (see Table AVI)[20].

The negative relationship between the IT investment output ratio and unskilled labor, on the one hand, and the increasing positive relationship between IT investment relative to output and the two upper skill levels, on the other hand, indicates a complementarity between IT capital and the educational qualification structure of firms' workforces. The low quantitative effects of IT investment on the employment shares suggests that other factors besides capital intensity may play an important role in explaining service firms' skill intensity. One such explanation points to the importance of differing output elasticities at the firm level, which are likely to be increasing in skill levels, thereby providing an incentive to shift the skill composition towards more skilled labor (see Hammermesh, 1993). Furthermore, unskilled labor is more likely to be replaced by process innovations, including a large number of innovations focusing on other aspects of the production process besides improvements in information technology (see Chennells and Van Reenen, 1999).

In contrast to IT investment, non-IT investment does not appear to be an important determinant of the employment shares, except for unskilled labor. The significantly positive relationship between the non-IT investment output ratio and the unskilled employment share highlights the fact that capital-intensive firms employ a larger fraction of unskilled workers. Furthermore, we find that exporting reinforces the positive relationship found between IT investment and firms' skill structure in the case of high-skilled labor. This finding is consistent with our conjecture that exporting firms concentrate extensively on human-capital-intensive products relative to firms that do not engage in exporting activities. The coefficient on the ownership dummy indicates that members of large industrial conglomerates use less unskilled labor than their counterparts. Firms' R&D activities may also provide an incentive to employ more skilled labor.

In order to examine whether coefficients vary across service sector industries beyond purely linear effects captured by sector dummies, we separately estimate the share equations for four different sub-samples:

(1) retail and wholesale trade;

(2) banking, insurance and real estate;

(3) business services, including computer and software as well as technical consultants; and

(4) other personal services.

The CLAD results for the different industries are qualitatively similar[21]. The impact of information technology on the unskilled labor share remains significantly negative across all four sub-samples. For high-skilled labor, higher than average elasticities can be found for retail and wholesale trade as well as for banking, insurance and real estate. Surprisingly, the lowest IT impact arises for business services, which include technical consultants and computer/software firms. This finding can partly be explained by the heterogeneous composition of this sub-sector. It includes firms with vastly differing processes and products, ranging from computer and software firms to accounting and legal services. Upon splitting up this sub-sector further to include only technical consultants and computer and software firms, the IT impact remains positive.

*4.2 Probit estimates for expected employment movements*

To account for the endogeneity of IT investment and employment shares, we relate the expected change in each skill type's employment share to the initial

IT-investment output ratio. As dependent variables, we use three binary variables indicating whether firms plan to increase employment of high-skilled, medium-skilled, or unskilled labor between 1997 and 1999. Table II shows the results for the three types of labor[22]. The IT investment output ratio and its square are jointly significant at the 6 per cent level in explaining the probability of expected increased employment of high-skilled labor, conforming with results for the high-skilled employment share equation from the previous section. The positive, significant IT impact does not carry through to medium-skilled labor, though. Export participation, skill intensity (as measured by the high-skilled employment share) and sales expectations are, however, consistently strong predictors of the probability of increasing the employment

| | Expected evolution of workforce, 1997-1999 | | |
|---|---|---|---|
| | High-skilled labor | Medium-skilled labor | Unskilled labor |
| $IT/Q$ | 3.75 | 0.58 | –0.79 |
| | (2.35) | (0.77) | (–0.55) |
| $(IT/Q)^2$ | –5.47 | – | – |
| | (–2.03) | | |
| $I/Q$ | –0.01 | 0.17 | 0.15 |
| | (–0.09) | (1.37) | (1.03) |
| Exporter | 0.33 | 0.15 | 0.06 |
| | (2.40) | (1.16) | (0.40) |
| Ind. group | 0.19 | 0.21 | 0.01 |
| | (1.48) | (1.81) | (0.05) |
| R&D | –0.08 | –0.03 | –0.20 |
| | (–0.49) | (–0.21) | (–0.91) |
| $H$-share | 1.82 | –1.21 | –1.36 |
| | (5.12) | (–3.67) | (–2.64) |
| Exp. $\Delta$ in sales | 0.47 | 0.58 | 0.77 |
| | (3.87) | (5.33) | (5.25) |
| $10 \leq L < 20$ | –0.02 | 0.21 | –0.29 |
| | (–0.07) | (0.99) | (0.83) |
| $20 \leq L < 50$ | 0.40 | –0.06 | –0.33 |
| | (1.75) | (–0.30) | (–1.25) |
| $50 \leq L < 250$ | 0.55 | 0.22 | –0.06 |
| | (2.43) | (1.17) | (–0.26) |
| $L \geq 250$ | 1.11 | 0.07 | –0.18 |
| | (4.62) | (0.32) | (–0.69) |
| Industry dummies | Yes | Yes | Yes |
| Constant | –1.71 | –0.61 | –1.92 |
| | (–6.15) | (–2.66) | (–5.59) |
| Wald-Test: $IT/Q, (IT/Q)^2 = 0$ | 5.55** | 2.12 | 0.30 |
| Wald-Test: $I/Q, (I/Q)^2 = 0$ | 0.02 | 1.79 | 1.06 |
| Obs. | 638 | 638 | 638 |

**Notes:**
** Significant at the 10 per cent level
$T$-statistics in parentheses

**Table II.**
Probit estimates, firms' employment expectations

of either of the three skill types in expectation. As expected, skill-intensive firms are less likely to expand employment for both medium- and unskilled labor.

## 5. Conclusions

This paper analyses the link between skill intensity and information technology in the service production process. The service sector exhibits large differences in tasks' skill intensity, including firms from human-capital-intensive sectors such as computing, banking and insurance, but also from low-skill-intensive sectors such as community services and retail trade. The service sector therefore represents an excellent opportunity to study not only the contributions of information technology in changing the employment structure of the sector, but also the role of firm and sector heterogeneity in mitigating that production factor's impact on organizational change. Our results largely confirm theoretical hypotheses regarding the interactions of IT capital and the workforce's skill structure.

In particular, we find that IT capital serves as a complement to high-skilled labor as well as medium-skilled labor in the production process, while it can be used to substitute for unskilled labor. As predicted, the elasticity of the high-skilled labor share with respect to IT exceeds the elasticity of medium-skilled labor, indicating that IT is a stronger complement to high-skilled labor than to medium skilled labor. We do not find, however, that the elasticity of high-skilled labor exceeds, in absolute value, the elasticity of unskilled labor with respect to the IT investment output ratio. This finding is therefore not in line with the prediction of limited substitutability between unskilled labor and IT investments. In contrast, we find that the degree of substitutability between unskilled labor and IT exceeds the degree of complementarity between high-skilled labor and IT. These results have to be interpreted with some caution, however, since the MIP-S dataset overstates the unskilled labor share slightly relative to other datasets, which are representative of the German economy. The misclassification of some workers as unskilled may drive, to some extent, the lower IT impacts on high-skilled workers relative to unskilled workers. Overall, the contributions of IT in changing the employment structure at the firm level are found to be small and fall short of results previously found in the literature (see Bresnahan *et al.*, 1999). Our results point towards other factors besides IT innovations, which have to be held responsible for driving the rise in the high-skilled employment share over the last decade.

The impact of IT on the employment structure is strongly dependent on firm heterogeneity. We find that the IT effect on high-skilled and unskilled labor is reinforced for exporters, which tend to produce more human-capital-intensive products, as well as firms which actively engage in R&D activities. As predicted, the link between exporting and the relative utilization of medium-skilled labor is not as clear-cut: we find, for example, that the share of workers with vocational certificates is lower for exporting firms relative to their non-exporting counterparts. Finally, our findings indicate that the IT effect is strongest in information technology intensive industries such as banking and insurance, as well as in industries with a history of high IT adoption rates, such as retail and wholesale trade.

## Notes

1. See Figure 1 in Breshnahan *et al.* (1999).
2. The use of investment flows to proxy capital stock data is appropriate provided there is a relatively constant investment ratio. The use of IT investment as a proxy variable for IT capital can be justified further by the high depreciation rate of IT such that current period investments represent most of the value of the firm's IT capital stock.
3. We obtained industry-level information on wages for different skill groups from official wage and salary statistics. Unfortunately, only wholesale and retail trade, transport and banking and insurance are covered by the official German wage statistics. A second source of wage statistics, the employment register of social security statistics, is limited in coverage to the period 1975-1995 and thus does not ovelap with our 1996 data.
4. The above described cost share equations have to be adapted to the current problem where a sizable fraction of firms does not invest in either IT or non-IT capital in the given period. The traditional logarithmic specification would lead to a significant reduction in observations, so that we chose a quadratic specification instead.
5. We do not consider censoring in the upper tail of the distribution for either the unskilled or high skilled employment shares since the percentage of right-censored observations is negligible (approximately 1 per cent of all observations).
6. The left censored CLAD can esily be extended to allow for censoring in the upper and lower tails which was used in estimating the medium-skilled labor share equation.
7. We apply the Nelder-Mead simplex algorithm included in the GMAXIM Gauss package.
8. We thank an anonymous referee for this suggestion.
9. A negligible number of firms reported plans to decrease the number of employees of a given skill. Due to the small number of such responses, they were combined with the "no change" respondents.
10. The MIP 1997 is a stratified sample, firms belonging to small industries such as computer and software are slightly over-represented.
11. Sales were discarded as a proxy for value added since a large number of firms appear to be reporting their income statement's balance in place of total sales.
12. CLAD estimates of the parameters were computed using both GAUSS and MATLAB programs. We thank Johannes Ludsteck for providing us with the MATLAB program.
13. In the current application, all variables except for the constant are included in the heteroscedascity function and the heteroscedastic model is tested against the heteroscedastic based model.
14. Similarly, a normality test based on conditional moment restrictions proposed by Pagan and Vella (1989) implies a LM statistic for larger than the critical value.
15. The corresponding value based on standard MI Tobit is –0.71 (see Appendix).
16. Note that the linear specification for the high-skilled employment share resulted in a negative but insignificant coefficient for the IT-investment output ratio.
17. The coefficients represent the effect on the observed truncated variable, rather than the true underlying dependent variable. A scale factor can be used to convert coefficients into marginal effects by scaling the parameters by the probability of falling in the uncensored part of the distribution. For the censored regression model with censoring at zero, the scale factor is given by $\Phi(\beta' x_i'/\sigma)$, where $\Phi$ denotes the standard normal cdf and $\sigma$ the estimated

variance. The scale factor is evaluated at the means of the independent variables. The elasticity is computed as $\epsilon_{E^k,IT} = (\beta_{IT/Q} + 2\beta_{(IT/Q)^2}\overline{IT}/\overline{Q})(\overline{IT}/\overline{Q})/\overline{E}^k$, where $\overline{IT}/\overline{Q}$ and $\overline{E}^k$ denote the sample means of the IT investment output share and the employment share, $k = U, M, H$, based on the full sample. Given a scale factor of 0.66, the elasticity in the case of the high-skilled employment share is (0.66)(0.09) = 0.06.

18. Given a scale factor of about 0.71, the elasticity is (0.71)(–0.61) = –0.11.
19. According to the European Information Technology Observatory (EITO) the II investment share out of GDP rose by 0.1 percentage points per year from 1996 onwards.
20. Between 1991 and 1998, the high-skilled employment share increases from 11.7 in 1991 to 16.0 in 1998, by about 4.5 per cent per year.
21. Results for the employment share equations for four different subsamples based on the CLAD and Tobit model are available on request.
22. The different sample size compared with the employment share equations is due to missing information on the employment expectations.

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## Appendix 1. Descriptive statistics and further estimation results

| | Mean[a] | Median | Std dev. | Min. | Max. | $x = 0$ (%) | $x = 100$ (%) |
|---|---|---|---|---|---|---|---|
| High skilled share (%) | 15.4 | 4.1 | 23.5 | 0 | 100.0 | 31.8 | 0.7 |
| Medium skilled share (%) | 58.4 | 62.5 | 29.7 | 0 | 100.0 | 2.8 | 8.6 |
| Unskilled share (% ) | 26.1 | 15.0 | 29.0 | 0 | 100.0 | 24.5 | 0.8 |
| IT investment, percentage of total investment | 46.0 | 38.5 | 39.0 | 0 | 100.0 | 5.7 | 22.2 |
| Non-IT investment, percentage of sales | 4.4 | 0.8 | 11.4 | 0 | 156.0 | 22.4 | |
| IT investment, percentage of sales | 1.3 | 0.4 | 2.8 | 0 | 33.0 | 11.5 | |
| Non-IT investment, percentage of wage costs | 18.5 | 3.7 | 45.1 | 0 | 452.0 | 22.4 | |
| IT investment, percentage of wage costs | 4.2 | 1.7 | 7.7 | 0 | 96.8 | 11.5 | |

**Note:**
[a] Arithmetic means

**Source:** Mannheim Service Innovation Panel (1997)

**Table AI.** Summary statistics, 959 West German firms

| | |
|---|---|
| *Sector distribution (NACE classification in parenthesis)* | |
| Wholesale trade (51) | 14.0 |
| Retail trade and repairs (50, 52) | 14.0 |
| Transport (60, 61, 62, 63, 64) | 13.9 |
| Banking and insurance (65, 66, 67) | 13.6 |
| Real estate activities and renting (70, 71) | 5.1 |
| Computer and related software (72) | 8.7 |
| R&D labs, technical consultants (731, 742, 743) | 7.1 |
| Business consultants, legal, accounting (741) | 7.6 |
| Other business activities, cleaning, advertising (744-746, 748, 93) | 11.8 |
| Sewage, sanitation (90, 921-924) | 4.4 |
| *Size distribution in terms of total employees,* L | |
| Size 1: $5 \leq L < 10$ | 14.7 |
| Size 2: $10 \leq L < 20$ | 18.7 |
| Size 3: $20 \leq L < 50$ | 20.8 |
| Size 4: $50 \leq L < 250$ | 27.5 |
| Size 5: $L \geq 250$ | 18.4 |
| *Other indicators* | |
| R&D performer, 1996 | 13.1 |
| Exporter, 1996 | 27.6 |
| Part of industrial conglomerate, 1996 | 36.7 |
| *Business expectations (increase=1, unchanged/decrease=0)* | |
| Ex. university graduates employment growth | 34.5 |
| Ex. medium skilled labor employment growth | 46.8 |
| Ex. unskilled labor employment growth | 15.8 |
| Ex. sales growth | 49.8 |

**Notes:**
West German firms ($N$ = 959). Performance indicator dummies: exporter = 1 if firm has earned positive revenues from exports for 1996. Part of industrial conglomerate = 1 if firm is parent to or subsidiary of another firm in 1996. R&D = 1 if firm employs at least one R&D worker

**Source:** Mannheim Service Innovation Panel (1997)

**Table AII.** Summary statistics, dummy variables (percentage share of total)

**Table AIII.** Qualification structure in German service Industries, 959 West German firms

| | Qualification structure (means in \% ) | | | | | | |
|---|---|---|---|---|---|---|---|
| | MIP-S '97 | | | | Micro Census '96 | | |
| | H | M | U | Obs. | H | M | U |
| Wholesale trade | 7.9 | 64.2 | 27.9 | 134 | 8.4 | 74.0 | 17.6 |
| Retail trade, repairs | 3.6 | 73.7 | 22.7 | 134 | 5.1 | 75.9 | 19.0 |
| Transport | 3.3 | 56.6 | 40.0 | 133 | 8.5 | 72.8 | 18.7 |
| Banking, insurance | 14.5 | 72.9 | 12.6 | 130 | 13.3 | 76.4 | 10.2 |
| Real estate, renting | 10.7 | 64.7 | 24.6 | 49 | 15.9 | 69.8 | 14.3 |
| Computer, software | 42.2 | 49.7 | 8.1 | 83 | 43.8 | 46.5 | 9.7 |
| Tech. consult. | 43.3 | 43.6 | 13.0 | 68 | 45.4 | 44.2 | 10.4 |
| Business services | 37.2 | 49.5 | 13.2 | 73 | 32.4 | 55.7 | 11.9 |
| Other services | 6.2 | 41.7 | 52.0 | 113 | 10.6 | 64.4 | 25.0 |
| Sewage, sanitation | 12.9 | 45.2 | 41.8 | 42 | 28.9 | 53.2 | 18.0 |

**Notes:**
$H, M, U$ refer to the high-skilled, medium-skilled and unskilled employment shares, respectively. The statistics are based on the German Micro Census Public Use File, which contains 70 per cent of the complete Micro Census. The data refer to April 1996. The German Micro Census is based on a 1 per cecnt sample of the German population. Employment shares by educational category are calculated as the proportion of total workers (including self-employees, apprentices and workers earning less than the social security threshold) in each of the three educational categories

**Sources:** Mannheim Service Innovation Panel (1997); Micro Census 1996 Public Use File

**Table AIV.** IT and non-IT investment, R&D and exporters, 959 West German firms (means in %)

| | IT inv. share | Non-IT inv. share | Exporter | R&D | Obs. |
|---|---|---|---|---|---|
| Wholesale trade | 3.0 | 16.5 | 43.3 | 13.4 | 134 |
| Retail trade, repairs | 2.2 | 14.9 | 21.6 | 4.5 | 134 |
| Transport | 2.3 | 37.1 | 33.8 | 12.0 | 133 |
| Banking, insurance | 8.4 | 11.8 | 14.6 | 5.4 | 130 |
| Real estate, renting | 3.4 | 67.6 | 12.2 | 2.0 | 49 |
| Computer, software | 8.1 | 7.8 | 37.3 | 33.7 | 83 |
| Tech. consult. | 4.4 | 7.8 | 41.2 | 29.4 | 68 |
| Business services | 5.5 | 5.3 | 27.4 | 21.9 | 73 |
| Other services | 1.8 | 5.0 | 19.5 | 8.8 | 113 |
| Sewage, sanitation | 4.5 | 38.8 | 16.7 | 9.5 | 42 |

**Source:** Mannheim Service Innovation Panel (1997)

| | High-skilled labor | Medium-skilled labor | Unskilled labor |
|---|---|---|---|
| $IT/Q$ | 0.51 | 0.29 | –0.80 |
| | (2.41) | (1.09) | (–2.75) |
| $(IT/Q)^2$ | –0.18 | –0.85 | 1.04 |
| | (–0.53) | (–1.92) | (2.15) |
| $I/Q$ | –0.07 | –0.03 | 0.13 |
| | (–1.62) | (–0.64) | (2.53) |
| $(I/Q)^2$ | 0.02 | 0.02 | –0.05 |
| | (1.49) | (1.15) | (–2.90) |
| Exporter | 0.08 | –0.05 | -0.01 |
| | (4.20) | (–2.20) | (–0.54) |
| Ind. group | 0.04 | 0.06 | –0.08 |
| | (2.42) | (2.59) | (–3.56) |
| R&D | 0.14 | –0.04 | –0.11 |
| | (5.75) | (–1.24) | (–3.21) |
| $10 \leq L < 20$ | –0.00 | –0.04 | 0.06 |
| | (–0.11) | (–1.13) | (1.75) |
| $20 \leq L < 50$ | 0.00 | –0.12 | 0.18 |
| | (0.10) | (–3.41) | (5.03) |
| $50 \leq L < 250$ | 0.03 | –0.16 | 0.26 |
| | (1.06) | (–4.81) | (7.27) |
| $L \geq 250$ | 0.04 | –0.18 | 0.32 |
| | (1.27) | (–4.86) | (7.88) |
| Industry dummies | Yes | Yes | Yes |
| Constant | 0.02 | 0.84 | –0.05 |
| | 0.52) | (20.67) | (–1.21) |
| $F$-test: $IT/Q, (IT/Q)^2 = 0$ | 8.14* | 2.56** | 3.91* |
| $F$-test: $I/Q, (I/Q)^2 = 0$ | 1.32 | 1.00 | 4.21* |
| S-F normality test | 6.98* | | 4.29* |
| $\partial(E^k)/\partial(IT/Q)$ | 0.49** | 0.22** | –0.71* |
| $\partial \ln(E^k)/\partial \ln(IT/Q)$ | 0.13** | 0.02** | –0.11* |

**Notes:** See notes under Table I
* Significant at 5 per cent level
** Significant at 10 per cent level
The 5 per cent critical value of the $F$-test is $F(2,939) = 3.0$. The reported normality test statistic is the Shapiro-Francia test statistic

**Table AV.**
Tobit ML estimates, educational qualification shares

| | Impact of 2.4 per cent increase of the $IT/Q$ (1) | Reference case: exogenous increase $\Delta E^H/E^H = 0.044$ (2) | $\Delta E^H/E^H = 0.027$ (3) |
|---|---|---|---|
| 1996 | 15.40 | 15.40 | 15.40 |
| 1997 | 15.43 | 16.08 | 15.82 |
| 1998 | 15.46 | 16.79 | 16.24 |
| 1999 | 15.49 | 17.52 | 16.68 |
| 2000 | 15.52 | 18.29 | 17.13 |
| 2001 | 15.55 | 19.10 | 17.59 |
| Change | 0.15 | 3.70 | 2.19 |

**Table AVI.**
Impact of increase in the IT investment output ratio on the high-skilled employment share

**Appendix 2. Robustness tests**

The results for the three employment share equations were tested for robustness. An initial test of robustness concerned the use of wage costs as a proxy for value added. The use of sales as an alternative proxy yielded similar IT elasticities for those industries where sales could be used as a reliable proxy for value added. As stated in section 2, the truncated regression models presume that the right-hand side variables have equal impacts both on the probability of employing labor of certain skill class and on the resulting employment share. To verify the CLAD results, we estimate a Probit model, which identifies the factors that influence firms' decision to employ university graduates.

Furthermore, as discussed above, we separately estimate the second stage decision of how much of each type of labor to employ by estimating a Box-Cox model for the non-zero employment shares. Table AVII shows the results of these models in the case of the high-skilled employment share, which are representative for the two other skill classes. The conclusions from the results for medium and unskilled labor are similar to those for high-skilled labor. The results were omitted due to space constraints, but are available from the authors on request. Only minor differences emerge as a result of separating the decision to employ high-skilled labor from the decision over the size of the high-skilled workforce. Most explanatory variables have the same sign as previously reported results based on the Tobit and CLAD models. Firm size, however, is found to influence the decision to employ high-skilled labor very differently from the decision over the size of the pool of high-skilled workers. The probability to employ high-skilled labor is higher in larger firms, but the high-skilled employment share decreases with firm size for those firms that employ high-skilled labor.

| | H-share (0/1) | | H-share > 0 | |
|---|---|---|---|---|
| | Coeff. | *t*-stat | Coeff. | *t*-stat |
| $IT/Q$ | 3.61 | 2.41 | 1.00 | 2.94 |
| $(IT/Q)^2$ | –3.02 | –1.17 | | |
| $(I/Q)$ | –0.12 | –0.48 | 0.02 | 0.33 |
| $(I/Q)^2$ | 0.07 | 0.82 | | |
| Exporter | 0.47 | 3.71 | 0.14 | 2.33 |
| Ind. group | 0.53 | 4.42 | 0.04 | 0.60 |
| R&D | 0.60 | 2.68 | 0.47 | 6.19 |
| $10 \leq L < 20$ | –0.10 | –0.64 | –0.17 | –1.50 |
| $20 \leq L < 50$ | 0.23 | 1.47 | –0.46 | –4.42 |
| $50 \leq L < 250$ | 0.81 | 5.11 | –0.71 | –7.10 |
| $L \geq 250$ | 1.80 | 8.01 | –1.07 | –9.89 |
| Industry dummies | | Yes | | Yes |
| Constant | –0.20 | –1.05 | –1.23 | –10.78 |
| Lambda | | | 0.14 | |
| Pseudo $R^2$/Adj. $R^2$ | | 0.31 | | 0.55 |
| Wald-test:$IT/Q, (IT/Q)^2 = 0$ | | 8.83 | | |
| Obs. | | 9.59 | | 654 |
| $\partial \ln(E^k)/\partial \ln(IT/Q)$ | | | | 0.28 |

**Notes:** The Ml Box Code in column 2 is used to estimate the high-skilled employment share equation: $(E^H)^\lambda = X\beta + \varepsilon$, where $\lambda$ is estimated value of the normality transformation of $\varepsilon$. Only firms employing at least one university graduate are considered

**Table AVII.** Probit and Box-Cox transformed model, high-skilled employment share