Non-technical summary

One of the most notable developments in recent years has been the rising spread of information technology in the overall economy. In the U.S, following the spread of the commercial internet during the beginning of the 90s, investment in information processing equipment as a share of total private equipment investment accelerated by 10 percentage points to 45%. According to the US. Department of Commerce, IT investment covers office computing, accounting machinery, communication equipment, instruments and photocopying equipment. For some industries like insurance or investment brokerages IT equipment constitutes over three-quarters of all equipment investment. In wholesale trade and most business services IT equipment constitutes half of all equipment investment. German figures exhibit similar tendencies.

Therefore the service industries are prone to be severely affected and to experience the most significant changes resulting from the rise of IT. Consistent with the rapidly growth of IT is the acceleration in the relative demand for university graduates. In German service industries during the late 1980s and the 1990s the university graduates employment share accelerated compared to the first half of the 1980s. For business services a further acceleration of the relative demand for university graduates can be observed for the period after 1995. Changes in the educational qualification structure of the work force may also reflect changes in supply. However, supply side explanations fail to explain the shift in demand towards skilled labour. In the US., shifts in labor supply are unable to explain the increase in the return of highly skilled labour. In European countries, the rapid growth in educational levels is not associated with a growing portion of underutilized graduates. For instance, in Germany, the proportion of underutilized graduates has been very stable over time.

This paper investigates the impact of information technology on firms' high-skilled employment share in the German service industry. We use panel data estimation techniques to control for unobservable effects. Coefficients are allowed to vary across four service subindustries: (i) wholesale and retail trade and transport, (ii) banking and insurance, (iii) software, data processing, techni-

cal consultancy and business services, and (iv) other business services and waste disposal. The empirical evidence indicates that firms with a higher IT investment output ratio employ a larger fraction of high-skilled workers. However, the quantitative impact of the IT effect on the skill intensity is rather small. The magnitude of the IT elasticity is found to be substantially larger in banking and insurance. The estimated elasticities can be used to investigate how much of an industry's change in the high skilled labour share from 1991 to 1995 can be explained by accumulation of information technology. Our findings indicate that in the 1990's only a small portion of the aggregate within industry skill upgrading can be explained by IT accumulation. The effect of within industry skill upgrading due to IT accumulation ranges between 6 % in business services and 25 % in banking and insurance.

The Impact of Information Technology on High-Skilled Labour in Services: Evidence from Firm Level Panel Data¹

> Martin Falk² Katja Seim³

ABSTRACT. This paper analyses the link between the high-skilled employment share and information technology (IT) in the service production process. Obviously, not all firms employ university graduates. To account for these zero shares, we apply fixed and random effects tobit models. Coefficients are allowed to vary across subsectors. The analysis is based on an unbalanced panel data set for about 900 West German firms over the period 1994-96. The empirical evidence indicates that firms with a higher IT investment output ratio employ a larger fraction of high-skilled workers. However, the size of the IT effect on the skill intensity is rather small.

Keywords: demand for high-skilled labour, information technology, service sector

JEL-Classification: J23, O33, L8

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1. Introduction

It is well known that the shift in demand towards skilled labour can be explained by within industry shifts, rather than between industries shifts. This holds not only for manufacturing, but also for non-manufacturing industries. In the literature, much of the increase in the demand for skilled labour at the industry level can be explained by the spread of information technology (see Berman et al. 1994 and Autor et al. 1998). In particular, complementarity of human capital with either information and communication technology or other new technologies is the dominant factor explaining the rapid within shift in demand away from unskilled labour and towards skilled labour. However, it remains unclear, how much of the shift in demand towards skilled labour can be explained by the accumulation of information technology.

Some authors claim that the rapid growth in educational levels could lead skilled workers to occupy less skilled jobs (see for example Robinson and Manacorda 1997 and Büchel and Weisshuhn 1997). Calculations based on the GSOEP suggest, however, that the proportion of underutilized university graduates amounts to 25 % and is very stable over the period 1984 to 1997.¹

The link between both information- and communication-capital and the skill structure at the firm level has been empirically analysed by a number of studies (for a survey of the literature, see Chennells and Van Reenen 1999). For the US. several studies based on firm level data show that the greater use of information technology or advanced technologies is associated with a higher employment share of highly educated workers (Doms et al. 1997 and Bresnahan et al. 1999). The results of Doms et al. (1997), however, are not robust when unobservable firm effects are allowed.

This paper investigates the impact of information technology on the firms' high-skilled employment share at the firm level in the service industry. We use panel data estimation techniques to control for unobservable effects. Coefficients are allowed to vary across four service subindustries: (i) wholesale and retail

¹ Many thanks to Thomas Bauer, IZA, for this point.

trade and transport, (ii) banking and insurance, (iii) software, data processing, technical consultancy and business services, and (iv) other business services and waste disposal. Interestingly, one third of all firms does not employ university graduates. Approximately 15 % of the firms employ neither university graduates nor masters and technicians. Since the high-skilled labour share is censored we employ panel tobit models. There are not many studies in the literature which estimate a panel tobit model with fixed or random effects. Hajivassiliou (1993) amongst others proposed a simulated ML estimator for the panel tobit model with random effects. Since the ML estimator for a panel tobit model with fixed effects is inconsistent, Honoré (1992) proposed a semi-parametric fixed effects tobit estimator (see also Grootendorst, 1997, and Chay and Honoré 1998 for recent applications). Dagenais et al. (1997) proposed the use of a generalized tobit model.

We use both the fixed tobit models suggested by Honoré (1992) and standard random effects tobit models. Moreover, we employ panel probit models with random effects to explain the firm's decision to employ university graduates. Population-averaged models estimated by General Estimating Equations (GEE) are used to specify the panel's within-group correlation structure. The data is drawn from the first two waves of the Mannheim Service Innovation Panel (MIP-S) which has previously been analysed by Kaiser (1999). Our estimates of the determinants of the demand for university graduates are based on an unbalanced panel data set of 930 West German firms for the period between 1994 and 1996. Moreover, shift share analysis based on the German Labour Force survey are provided to analyse the within contribution of the shift away from unskilled and towards skilled labour. Following Maurin and Thesmar (1999) we use an extended shift share analysis to allow for functional diversity within sectors and to thereby analyse the role of organisational change. Finally, we conduct some calculations how much of aggregate within skill-upgrading in services can be explained by the IT accumulation, given the estimated elasticities at the firm level.

The layout of the paper is as follows. Section 2 outlines the econometric model.

Data for the study are discussed in section 3. In sections 4, we present the results for the factor demand equations. Section 5 provides a shift share analysis based on industry data using the German Labour Force Survey. Section 6 concludes.

2. Empirical Modelling

2.1 Employment share equation

To investigate the link between information technology and the skill intensity of the firm, we employ factor demand equations. From a theoretical point of view it would be preferable to derive cost share or factor demand equations based on a flexible cost function (for instance the translog cost function). Since wages by skill class are generally not available at the firm level, one can employ the skill-specific employment shares to proxy the unknown cost shares. Assuming constant returns to scale as well as the absence of substitution possibilities between different labour inputs, the high-skilled employment share equation can be written as a function of IT expenditure output ratio, the non-IT expenditure output ratio, as well as a set of appropriate control variables. Furthermore, to account for the large share of firms that report zero expenditures for IT or non-IT investment, we use the level of the IT output ratio and IT output squared rather than the logarithm of the IT output ratio. All coefficients are allowed to vary across industries:

$$EH_{it} = \alpha_i + \beta_{1j}ITQ_{it} + \beta_{2j}ITQ_{it}^2 + \beta_{3j}IQ_{it} + \beta_{4j}IQ_{it}^2 + \beta_{3j}z_{it} + u_{it}$$
(2.1)

where i denotes the firm, j the industry and t the year. The variables are defined as:

EH high-skilled employment share (censored)

ITQ information technology and communication expenditure as % of output

IQ non IT investment as % of output

z 1,...,4 size classes participation in R&D and exporting part of industrial conglomerate

The main hypothesis is that the IT output ratio should be strongly related to the high-skilled employment share $(\partial EH_{it}/\partial ITQ_{it} > 0)$. A positive effect on the investment to output ratio in the high-skilled employment equation indicates that capital is a complement to skilled labour. Note that two measures of the high-skilled share, EH, can be constructed. The first employment share contains workers with a university degree. The second one covers university graduates as well as masters and technicians. The high-skilled employment share equations contains dummy variables, which equals one if the firm qualifies for specific firm characteristics (exporter, participation in R&D and part of industrial conglomerate). In particular, export orientation represents a good control variable because the exporting activity of German firms is concentrated in skill-intensive goods and services.

Given the characteristics of the dataset used for this paper, a number of problems arise. The major problem is that the dependent variable is censored at the lower side of the distribution. Another problem is that gross value added is not available in out dataset. A third data problem arises out of the fact that some firms, in particular among respondents from the banking sector, reported total income rather than total sales. To overcome these problems total wage bill will be used to proxy firm output rather than total sales.

2.2 Estimation techniques

The presence of zero values for university graduates occurs too frequently to be econometrically ignored. For the university graduates labour group approximately 32 % of firms report zero values.² This presence can be addressed in

For both university graduates and masters and technicians approximately 15 % of firms report zero values.

several ways. Random-effects tobit models using the Gauss-quadrature method can be employed, although the model does not perform well when the within correlation is high. A potential solution are simulated ML estimators for random effects panel tobit models as proposed by Hajivassiliou (1993) amongst others. Another alternative put forth by Honoré (1992) is a semi-parametric fixed effects tobit estimator. This approach is an extension of Powell's (1986) work and is based upon the fact that even in the presence of censored dependent variables the median remains uncensored. Consequently, LAD estimators can be employed. A more general alternative to the fixed effects tobit estimator involves the application of double-hurdle or generalized Tobit models. Labeaga (1999), for instance, employed a double-hurdle model in estimating the demand for tobacco using panel data. Under the double hurdle model, an individual's chosen level of consumption reflects a two-part decision process consisting of the discrete decision to take up smoking and consequently, if smoking has been taken up, how much to smoke. An advantage of the double hurdle model adapted to the present application is that the factors influencing a firm's decision of employing any university graduates can differ from the determinants driving the firm's decision of how many university graduates to employ. One important disadvantage of the two-part modeling is presented by the fact that university graduates make up an essential part of the production process in skill intensive service industries such as computing, banking, or R&D laboratories, and cannot be replaced by less qualified workers. These firms are therefore not faced with the decision of whether or not to employ any university graduates, rather they only decide how many high skilled workers to employ. This logic suggests that the employment decision making process is not uniform across all service firms which engage in activities as varied as retail trade to R&D. To address some of these concerns, we estimate both panel Probit models as well as panel Tobit models.

A univariate, random effects panel probit model can be used to explain the firm's decision to employ university graduates:

$$y_{it}^{*} = \beta' x_{it} + u_{i} + \nu_{it}, \quad i = 1, ..., N; t = 1, ...T.$$

$$y_{it} = 1 \text{ if } y_{it}^{*} > 0$$

$$\text{Var}[u_{i} + \nu_{it}] = \text{Var}[\epsilon_{it}] = \sigma_{u}^{2} + \sigma_{v}^{2}$$

$$\text{corr}[\epsilon_{it}, \epsilon_{is}] = \rho = \sigma_{u}^{2} / (\sigma_{v}^{2} + \sigma_{u}^{2}), s \neq t.$$
(2.2)

where u_i denotes the individual firm effect and ν_{it} is a random error. Under random effects, the assumption that the firm effect u_i is independent of all observable x_{it} for all i and t produces a consistent estimator. When estimating panel probit models with random effects, one estimation problem arises, however, in presence of high within-firm correlation (high value of ρ).³ It can be expected that within any given firm, the employment decision is usually highly correlated over time. In this case random effects panel probit models based on quadrature methods are not adequate to compute the log likelihood and its derivative (for an application, see Butler and Moffit 1982). The reason is that the Gauss-Hermite quadrature method approximates the value of a definite integral only poorly in the presence of high within-group correlation.

As an alternative probability simulation methods (see Hajivassiliou, 1993) or population averaged models can be used We consider here the model proposed by Liang and Zeger (1986):

$$y_{it} = \mu_{it}(\beta) + \epsilon_{it}, \quad i = 1, ..., N; t = 1, ..., T.$$

$$E(y_{it}|x_{it}) = \mu_{it}(\beta), \text{ and } \mu_{it}(\beta) = \phi(x_{it}\beta)$$

$$Var(y_{it}|x_{it}) = g(\beta) \cdot \phi = \mu(x_{it}, \beta) \cdot (1 - \mu(x_{it}, \beta))$$
(2.3)

where ϕ denotes the standard normal distribution function, β the parameter vector to be estimated, and function g is the variance function in generalized linear models. The principal difference to the standard random effects probit model (Butler and Moffit 1982) is that the parameter vector β describes an average population response rather than an individual's response to a change in x's (see Zeger, Liang and Albert 1988). This means that under the population averaged model the average, for instance, exporting or R&D doing firm employ-

This holds also for the conditional logit models with fixed effects.

ing high-skilled labour is compared to the average non exporting or non R&D doing firm employing high-skilled labour. The main advantage of the population averaged models is that they allow us to specify the within-group correlation structure. A population-averaged panel probit model with an AR1 structure would have an error correlation matrix of the following form:

$$R_{t,s} = \begin{cases} 1 & \text{if t=s} \\ \rho^{|t-s|} & \text{otherwise} \end{cases}$$
 (2.4)

where $R_{t,s}$ denotes the working correlation matrix and the serial correlation coefficient ρ diminishes as the lag increases.

We proceed with fixed and random effects tobit models. The tobit model cross-sectional model is adapted to the panel framework with a random effects specification (see Maddala 1987) or fixed effects specification (Honoré 1992). In the censored regression model, the true underlying dependent variable, y^* , is a function of a set of independent variables, x, as well as the random effects, u_i :

$$y_{it}^* = \beta' x_{it} + u_i + \nu_{it} \quad \nu_{it}, u_i \sim N(0, 0, \sigma_v^2, \sigma_u^2)$$
 (2.5)

while the actually observed value of the dependent variable, y, is given by:

$$y_{it} = \begin{cases} L & y^* \le L \\ y_{it}^* = \beta' x_{it} + u_i + \nu_{it} & L < y^* \end{cases}$$

where L denotes the lower censoring bound. The values for y^* if $y^* \leq L$ are unobserved. The panel tobit model also includes time effects, which are common to all firms. If both the residuals, ν_{it} , as well as the random effect, u_i , are normally distributed, equation 2.5 can be estimated by maximum likelihood. Similar to the panel probit model, the Gaussian quadrature method cannot be used to evaluate the product of the standard normal density function when within correlation is high. Moreover, when the disturbances, v_{it} , are non-normal, using the standard random effects tobit model is problematic.

To overcome these problems, Honoré's (1992) trimmed least absolute deviations and trimmed least squares for the censored regression models can be employed. There are no distributional assumption necessary on the error term, v_{it} ,

which is assumed to be independent and identically distributed conditional on the x_{it} and the u_i for all t. Honoré's estimator is defined by minimizing the objective function:

$$\widehat{\beta}_{st} = \arg\min \sum_{i=1}^{n} s(Y_{it}, Y_{is}, \Delta X_i, b)$$
(2.6)

where $\Delta X_{it} = X_{it} - X_{is}$, and the time periods are t=2, s=1. Honoré (1992) shows that the resulting estimator is equivalent to a GMM estimator with the following moment condition:

$$E[\xi(\max\{y_{it}, (\widetilde{x}_{it} - \widetilde{x}_{is})'\beta\} - \max\{y_{is}, (\widetilde{x}_{is} - \widetilde{x}_{it})'\beta\} - \{\widetilde{x}_{it} - \widetilde{x}_{is})'\beta)(\widetilde{x}_{it} - \widetilde{x}_{is})] = 0$$
(2.7)

For a given symmetric convex function, $\Xi(d)$, with derivative $\zeta(d)$ the function s is defined as (Honoré 1992: 537):

$$s(y_1, y_2, \delta) = \begin{cases} \Xi(y_1) - (y_2 + \delta)\zeta(y_1), & \text{if } \delta \le -y_2 \\ \Xi(y_1 - y_2 - \delta), & \text{for } -y_2 < \delta < y_1, \\ \Xi(-y_2) + (y_1 - \delta)\zeta(-y_2), & \text{for } y_1 \le \delta. \end{cases}$$
 (2.8)

The estimates of $\widehat{\beta}_{st}$ depend on the chosen loss-function $\Xi(d)$. If the quadratic loss function, $\Xi(d)=d^2$ is chosen then the function $s(y_1,y_2,\delta)$ equals $\chi(y_1,y_2,\delta)$. If the absolute loss function, $\Xi(y_1)=|d|$, is chosen then the function $s(y_1,y_2,\delta)$ equals $\varphi(y_1,y_2,\delta)$, where χ and φ are defined in Honoré (1992: 538). The polynomial loss function is a combination of the quadratic and the absolute value loss function. The adaptations of the fixed effects tobit estimator used here are based on the symmetric distance function minimizing a quadratic loss function as well as the polynomial loss function where the latter is more robust with respect to outliers (see Campbell and Honoré 1991). Furthermore, the asymptotic variance covariance matrix of $\widehat{\beta}$ can be consistently estimated as long as the number of individuals exceeds 200. In addition, the fixed effects estimator is robust to within correlation of the error terms.

Before proceeding, several caveats should be noted. First, it would be prefer-

able to estimate a dynamic relationship. Unfortunately, the time span covered by the data used in this paper is too short to allow modeling a dynamic relationship. Second, we do not account for censoring in the upper tail of the distribution. However, less than 1 % of the firms report a university graduates share equal to 1.

3. Data description

The data set employed for the subsequent empirical analysis contains the first two waves of Mannheim Service Innovation panel 1995 and 1997 (MIP-S) covering the period 1994-1996. The survey's main intention was to investigate the innovation behaviour of service firms (for details see Janz and Licht 1999). Approximately 2550 and 2220 firms, respectively, participated in the first two waves of MIP-S from which we removed East German firms. Since the second wave contains retrospective information for some continuous variables, an unbalanced panel consisting of three years can be constructed. The key variables covered by the study are total output (total sales or total wage bill), different types of investment, the educational qualification structure of the work force, R&D expenditures as well as R&D staff and a large number of qualitative variables. Since value added is not available, the firm's total wage bill can be used as a proxy for value added since total wage costs represent a better proxy for value added than total sales in the service sector. The original data base distinguishes between five educational qualifications, including two types of university graduates. The first group consists of employees having attained a university degree in engineering or natural science and the second group contains graduates with a degree in social sciences or other fields. Following Kaiser (1999), the engineering/natural science and the social science group are combined into a single category of university graduates. Two measures of the high-skilled labour share can be constructed. The first high-skilled employment share measures the share of university educated employees out of total employees. The second measure extends this definition to also include masters and technicians. Each high-skilled share is expressed as that group's share of total employees, that is the sum of employees across all five skill groups. IT is defined as investment in information and communication technology and includes expenditures on 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.⁴

The initial sample for West German firms contains 4428 observations on 2460 firms. For the empirical analysis we use a reduced sample for which all variables are available. Incomplete information on gross investment, IT investment, employees by skill class, or firm characteristics led to a reduction of the sample to 3353 observations (for details see table A3 in the Appendix). Exclusion of firms which belong to either the manufacturing or construction sectors reduces the sample by 23 observations. Furthermore, about 50 obvious typing errors were corrected. Extreme values in the growth rates of the number of employees, total sales per employee and total wage bill per employee in excess of 300 % have been dropped. Observations were also excluded when the ratio of total investment to total labour costs exceeded 300 %. In total, 212 observations were dropped on the basis of the chosen selection criteria. From a total of 2962 observations an unbalanced sample of 1762 West German firms remained. To be able to employ panel data techniques, we furthermore restricted the sample to firms for which two firm year observations were available leaving us with 2193 observations on 933 firms. While the loss in observations was large, Table 1 shows that most variables (IT output ratio or high-skilled employment share) have a mean that is very similar to the complete sample.

Table 1 reports averages of the key variables for the subsample used in the estimation based on firms with two or more observations. In addition, the full sample was included as a reference. For the restricted sample, firms report that of their employees, on average 15 % have obtained a university or higher technical college degree. The masters and technicians' employment share averages to about 11 % which is slightly below that group's corresponding share in the German

In some cases, firms report positive IT expenditures, but zero total investment expenditures such that IT expenditures exceed total investment expenditures. In these cases, the resulting negative non-IT investment has been replaced by zero.

Labour Force Survey. The restricted sample's combined high-skilled labour share (masters and technicians as well as university graduates) amounts to 26.7% in 1996 and 25.6% in 1995. Firms have been divided into five size classes based on their total number of employees: the reference group has less than 10 employees, the three medium-sized classes are defined as 10-19, 20-49, and 50-249 employees, while large firms are defined to have more than 250 employees. The share of firms with less than 10 workers ranges from 13 % in 1994 and 15 % in 1996. Over the period between 1994 and 1996 36 % of West German firms in the sample belonged to a corporate group. The share of exporting firms ranges from 23 to 26 %. The percentage of R&D doing firms ranges from 20% in 1994 and 13% in 1996, suggesting that the sample's composition is changing over time.

The service sector is broken down into 10 subsectors. These subsectors do not entirely correspond to the NACE 2 digit classifications. Some regrouping of industries was found to be necessary and sectors with a large number of firms such as market services were split up into computer, related software and data processing (NACE 72); R&D labs and technical consultants (NACE 731, 742, 743); business consultants, legal services, and accounting (NACE 741); and other business activities including cleaning and advertising (NACE 744-746, 748). To examine the representativeness of the MIP-S survey participants, the sectorial employment distribution in the 1995 wave of the German Labour Force Survey ('Micro Census'), a survey at the level of the individual, was examined by computing sectorial weighted averages across participants employed in the service industries. A comparison of the Micro Census and the MIP-S' employment distribution reveals that the MIP-S sample is somewhat skewed towards firms in the following sectors: (1) software and data processing, (2) wholesale trade, (3) transport and communication, (4) real estate and renting, as well as (5) banking and insurance (see Table A6 in Appendix).

Table 2 presents a sectorial breakdown of the high-skilled employment share, IT investment output ratio, non-IT investment ratio, and the participation in exports as well as in R&D. The service sector can be differentiated on the basis of the activities' knowledge intensity (measured as an industry's share of

Table 1: Summary Statistics, 1994-96, West German firms

	Means in $\%$					
	ful	full sample restricted same				
	94	95	96	94	95	96
University grad. empl. share	14.4	14.5	15.2	14.9	14.4	14.9
Masters/tech. empl. share	11.5	11.1	11.5	12.0	10.8	11.3
Non-IT investment sales ratio	5.2	5.0	4.5	5.1	5.0	4.5
IT investment sales ratio	1.1	1.1	1.3	1.2	1.1	1.2
Non-IT inv. wage bill ratio	21.5	22.0	19.6	20.9	21.9	19.6
IT inv. wage bill ratio	4.6	3.9	4.2	4.2	3.7	4.2
Exporters	23.8	23.9	26.5	22.6	22.7	26.4
R&D activities	17.8	12.4	12.5	20.3	12.5	12.5
Part of industrial group	36.4	35.2	36.4	28.4	35.8	36.0
L < 10	12.9	15.3	14.4	13.8	14.7	14.3
$10 \le L < 20$	19.9	18.6	19.1	23.8	18.6	18.6
$20 \le L < 50$	19.7	21.4	20.8	24.1	21.2	21.0
$50 \le L < 250$	25.5	27.4	27.7	23.8	27.7	28.0
L > 250	21.9	17.3	18.0	14.6	17.7	18.2
Total number of observations	1054	946	962	349	919	925

Notes: The means given in the table are arithmetic means. Employment shares: The proportion of eihter university graduates or masters and technicans in % of the sum of the five educational qualification groups.

Source: Mannheim Service Innovation Panel 1995, 1997, own calculations.

Table 2: Summary Statistics: University graduates share, IT and Non IT wage bill ratio and participation in exports and R&D by sector

	Univers.	IT inv.	Non IT-	Participat	tion (%)	Cases
	grad.	share	inv.	Export-	R&D	•
	share		share	ers		
		M	eans (in %	(i, 1994-96)		
Wholesale trade	8.7	2.7	18.1	40.3	13.5	325
Retail trade and repairs	4.1	2.1	20.8	17.7	5.1	311
Transport, comm.	3.7	2.5	35.4	33.1	12.6	302
Banking, insurance	13.6	7.4	12.6	12.2	8.9	304
Real estate, renting	8.5	3.5	78.7	8.7	1.7	115
software, data process.	41.1	7.8	7.6	33.9	36.8	174
R&D labs, tech. cons.	42.5	4.2	10.1	36.8	29.2	144
Business services	33.6	4.4	5.9	22.0	20.2	173
Other business scvs.	5.9	2.9	7.1	13.5	10.2	266
Waste disposal	16.2	4.3	50.5	16.5	8.9	79
		Zero	values (in	%, 1994-9	6)	
Wholesale trade	36.3	17.8	20.0			325
Retail trade, repairs	54.0	20.9	20.9			311
Transport, communic.	47.0	15.6	15.6			302
Banking, insurance	23.4	5.9	20.1			304
Real estate, renting	39.1	10.4	21.7			115
software, data process.	7.5	3.4	28.2			174
R&D labs, consult.	4.2	3.5	20.8			144
Business services	10.4	6.4	19.1			173
Other business scvs	38.0	19.5	29.3			266
Waste disposal	19.0	6.3	8.9			79
All service ind.	31.8	12.7	20.9			2193

Notes: Exporter t=1 if firm has earned positive revenues from exports in t=1994, 1995 or 1996. Missing values in 1995 have been replaced when export information is available for 1994 and 1996. R&D = 1 if firm employs at least one R&D worker.

Source: Mannheim Service Innovation Panel 1995, 1997, own calculations.

workers with completed higher education out of total workers). The most skillintensive sectors are computer, software and data processing, R&D laboratories and technical consultants, as well as business services (consultants, legal services, accounting). In these sectors, the share of university graduates lies between 30% and 45 %. Banking and insurance, real estate, and waste disposal can be classified as medium-skill-intensive industries. Finally, wholesale and retail trade, transport, and other business services (cleaning, advertising) can be classified as low-skill-intensive. Wholesale and retail trade and other business service activities tend to occupy primarily medium- and unskilled labour. The sectorial breakdown reveals that software and data processing, R&D labs, and banking and insurance possess the expected higher IT intensity than the remaining sectors. A comparison of the high-skilled labour share and IT investment to sales ratio provides informal evidence that the sectors which are skill-intensive are the ones that use IT intensively. Participation in exports is highest in (1) wholesale trade, (2) R&D labs and technical consultancies, (3) computer, software and data processing and (4) transport and communication. Furthermore, as expected, participation in R&D is more pronounced in skill-intensive industries. In computer, software and data processing, in R&D labs, the percentage of observations with one or more R&D employees is 40% and 30 %, respectively. Table 2 also indicates that the percentage of firms with zero reported university graduates ranges from 4~% in technical consultancies to 54~% in retail trade.

To investigate the sample's representativeness of the German service sector as a whole, the average high-skilled employment share has been compared to 1995 data derived from the German Labour Force Survey ('Micro Census'). A comparison of the university graduates employment share at the sectorial level indicates that the MIP-S sample very closely reflects the Micro Census' national averages. In skill intensive service industries such as software design and data processing, technical consultancies and business services, the university employment share ranges between 34% and 44 %, comparable to the 34% and 43 % shares revealed by the German Labour Force Survey (see Table A4 in Appendix). Across sectors, however, the share of masters and technicians in the MIP-S firm data set considerably exceeds the corresponding figures in the German Micro Census.

4. Determinants of the Demand for High-Skilled Labour

4.1 Panel Probit Results for all Service Industries

We first start with estimates of the panel probit model which identifies factors influencing the firm's decision of whether or not to employ university graduates. As noted earlier, approximately one third of the firms in our estimation sample did not employ university graduates and 14.7 % of firms did not employ neither university graduates nor masters and technicians. Table A10 in the Appendix shows the results for different estimators of the panel probit random effects model, where column (i) contains the results for the panel probit random effects model estimated by population-averaged methods and the specification in column (ii) allows for a first-order autoregressive correlation coefficient. Both specifications' t-statistics are based on robust standard errors.

The results shows that the firm's decision regarding the employment of university graduates can be attributed to its IT-investment share as well as individual firm characteristics (exporting and R&D activities, firm size and sector). A Wald test supports the hypothesis that the effect of the IT investment output ratio and its square are jointly significantly different from zero. However, we cannot reject the hypothesis that the effect of the non-IT investment is significantly different from zero. Moreover, the positive sign of the IT investment output ratio combined with the negative sign on its square maintained in both specifications indicates a concave relationship between the IT investment wage bill ratio and the probability of employing high-skilled labour. The probability of employing university graduates is increasing in the IT output ratio and peaks at an IT investment output ratio of over 100%. The coefficients on firm size are positive and significant at the 5 %-level, suggesting that the probability of employing university graduates depends on the firm's size. Exporting and R&D activities also contribute to a higher probability of employing university graduates. The coefficients on the industry effects are as expected with a higher probability of employing high-skilled labour being associated with R&D labs, technical consultancies followed by computer and software design as well as business services.

Some additional sensitivity checks are presented. The first point concerns the measurement of the IT investment output ratio. Unreported regression results indicate that employing sales as a measure of value added when computing the investment sales ratios does not alter the results significantly. A second sensitivity test addresses the definition of the dependent variable. As it is unclear which employees a firm would consider to be highly skilled based on their educational record, we investigate the robustness of our results using a broader definition of high-skilled labour which in addition to university graduates includes masters and technicians as well. Reestimating the panel probit model using the broader definition of high-skilled labour again indicates a concave relationship between the decision to employ high-skilled labour and the IT investment output ratio.

4.2 Panel Tobit Results for all Service Industries

Table 3 shows the results for the fixed and random effects panel tobit models. For the fixed effects Tobit model two specifications are used: the estimated coefficients in column (i) are based on a quadratic loss function while the results displayed in column (ii) use a polynomial loss function. Note that the results based on polynomial loss function are more robust in the presence of outliers (see Campbell and Honoré 1991). Column (iii) contains the results from a random effects tobit model. Since time effects are not significant at the 5 % level they are not included. The coefficients of the random effects model, however, should be interpreted with caution. Refitting the panel probit model with an eight point Hermite and 16 point Hermite integration shows that the effect of the IT investment output ratio changed by 30 % while the effect of its square changed by nearly 50 %. This is clearly related to the high within correlation coefficient $(\rho = 0.90)$ causing the quadrature approximations to be inaccurate.⁵

⁵ An alternative method is the simpson's rule to compute an approximate value of the integral.

Table 3: Fixed and Random effects tobit models for the EH-share

-		FE Tobit				RE Tobit			
	Quad	ratic	Polyn	omial					
	Loss f	unct.	Loss	funct.					
	(i	(i)		i)	(ii	i)	(iv)		
	coeff	t-stat	coeff	t-stat	coeff	t-stat	coeff.	t-stat	
ITQ	0.26	1.85	0.18	1.56	0.52	7.70	0.43	6.27	
ITQ^2	-0.21	-1.35	-0.12	-0.96	-0.45	-4.44	-0.33	-3.09	
IQ	-0.003	-0.23	0.010	0.27	-0.002	0.17	0.002	0.24	
IQ^2	0.000	0.45	0.002	0.04	0.000	0.36	-0.001	-0.30	
Exporters							0.02	3.21	
Ind. Congl.							-0.00	-0.56	
R&D							0.04	5.05	
$10 \le L < 20$							0.00	-0.58	
$20 \le L < 50$							-0.03	-2.11	
$50 \le L < 250$							-0.03	-2.03	
$L \ge 250$							-0.04	-2.30	
Ind. dummies					ne	0	ye	\mathbf{S}	
Constant					0.12	25.64	0.13	8.18	
Wald tests: ^a									
$ITQ=ITQ^2=0$	4.	7	3	.3	87	.4	57	.3	
$_{\mathrm{ITQ,ITQ}^{2}},$									
$_{IQ,IQ}^2=0$	7.	5	7	.2	88	.6	58	.1	
ho					0.9	90	0.8	39	
Object. funct									
value/log-L	11.	93	113	3.38	251	5	532	.30	
$arepsilon_{EH,ITQ}$	0.0	44	0.0	030	0.0	86	0.0	72	
$arepsilon_{EH,IQ}$					0.0		0.0	02	
obs./firms	2193,	/933	2193	5/933	2193,	/933	2193,	/933	

Notes: West German Service firms, for the period between 1994 and 1996. Dependent variable: university graduates employment share. Obs. summary for the Tobit models: 697 left-censored observation with EH = 0. $\mathcal{E}_{EH,ITQ}$: see expression 4.1.

For the fixed effects tobit model based on Quadratic loss function, the Wald test with a chi-squared statistic of 4.7 with two degrees of freedom indicate that the IT investment output ratio and IT investment output ratio squared are jointly significant at the 10 % level. We again find a concave quadratic relationship between IT investment output ratio and the university graduates employment share. The predicted high-skill labour share reaches a maximum at an IT investment wage bill ratio of more than 60% for specification (i) and 75 % for specification (ii), well above the mean IT investment wage bill ratio of 4.0%. The quantitative impact of the IT investment output ratio on the university graduates share, however, is very low. The elasticity of the university graduates share with respect to the IT expenditure output ratio can be calculated as follows:⁶

$$\varepsilon_{EH,ITQ} = SF \times \beta_1 \overline{ITQ} + SF \times 2 \times \beta_2 \times \overline{ITQ}/\overline{EH})$$
 (4.1)

where β_1 denotes the estimated IT coefficient and β_2 its square. \overline{ITQ} , \overline{EH} are the sample means of the IT output ratio and the university graduates share. The scale factor, SF, can be used to convert coefficients into marginal effects. For the fixed effects tobit model, the scale factor is unknown. Given the scale factor of the pooled tobit model of about 0.66, we observe relative low elasticities from 0.030 to 0.044 depending on the specification. Thus an increase in the IT investment output ratio by 50% from 4.0% to 6.0% would only raise the average firm's high-skilled labour share by 0.03 percentage points from 14.7% to 15.0%.

Unreported results shows, as expected, that in the presence of firm-specific effects, pooled Tobit appears to give upward biased estimates of the IT-coefficients. For the period between 1994 and 1996, the pooled tobit model yields an IT coefficient of 0.77 and a coefficient of -0.46 for IT squared. The coefficients translates into an IT elasticity equal to 0.13, which is significantly higher than the IT elasticity based on the fixed effects tobit model.

The random effects model allows us to include time-invariant variables. The

Note in a censored regression model, the magnitude of the coefficients is not interpretable as the marginal effect on the observed dependent variable of changes in the regressors.

coefficient on the exporter dummy indicates that exporting firms use more skill-intensive labour than their counterparts. 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. A firm's R&D activities may also induce it to employ a more skilled labour force as the positive coefficient on R&D shows.

4.3 Differences among Sectors

In order to account for differences in the service production process and differences in the employment decision process, we reestimate the panel tobit models for four broad subsectors. The top panel of Table 4 shows the results for wholesale and retail trade and transport. The lower panel shows the results for banking and insurance. Table A11 in Appendix shows the results for high-skilled intensive service industries. The coefficients of primary interest are those on the IT investment output ratios. We again find a significant relationship between the share of university graduates and the IT investment output ratio. Wald tests support the hypothesis that the effects of the IT investment sales ratio and its square are jointly different from zero. For wholesale, retail trade and transport based on the polynomial loss function the value of the Wald statistic is 5.6, which has a p-value (marginal significance level) of 0.06. For banking, insurance and real estate, the value of the test-statistic ranges between 4.8 for the quadratic loss function and 4.7 for the polynomial loss function. The corresponding p-values are 0.091 and 0.097, respectively. To compare the IT effect across sectors, the scaling factor of the pooled tobit model is used to convert the IT coefficients into marginal effects. The size of IT elasticity differs across industries. The magnitude of the IT elasticity is found to be substantially larger in banking and insurances than in other services industries. The IT elasticity evaluated at sample means equals to 0.13 which is more than twice the elasticity based on all service industries.⁷ For skill intensive service industries a consistently low value is found for the IT elasticity across both models (see Table A11 in Appendix).

⁷ The scale factor of the pooled model is used to convert coefficients into marginal effects.

Table 4: Fixed and Random effects tobit models for the EH-share, subgroups

		FE tobit				RE Tobit	
	(i		(i	i)	(ii	ii)	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	
Wholes	sale and	retail tr	ade, tra	nsport			
ITQ	0.21	1.12	0.25	1.80	0.50	4.41	
$ m ITQ^2$	-0.43	-1.12	-0.56	-2.26	-0.84	-3.69	
IQ^2	0.004	0.12	0.02	0.70	0.01	0.79	
IQ^2	0.00	0.05	0.00	-0.35	0.00	-0.82	
Exporter					0.02	1.92	
Ind. congl.					0.09	9.62	
R&D					0.04	4.13	
Constant					-0.03	-2.01	
Objective funct./Log-L	2.7	77	278	3.73	283	3.1	
$ITQ=ITQ^2$	1.	6	5	.6	19.44		
$ITQ=ITQ^2=IQ=IQ^2$	1.	8	6	.1	20.	.85	
∂ eh/ ∂ itq $\cdot \overline{ITQ}/\overline{EH}$	0.0	39	0.0)47	0.0	96	
∂ eh/ ∂ iq $\cdot \overline{IQ}/\overline{EH}$	0.0	14	0.0)33	0.0)23	
Obs/firms	938/	397	938,	938/397		938/397	
Bank	ing and i	nsuranc	e, real e	state			
ITQ	0.40	1.86	0.35	1.92	0.37	3.39	
$ m ITQ^2$	-0.29	-1.48	-0.26	-1.60	-0.22	-1.76	
IQ	0.00	0.03	0.002	-0.10	0.04	2.49	
IQ^2	0.00	0.10	0.00	0.24	0.00	-1.71	
Exporter					0.00	-0.11	
Ind. group					0.09	5.80	
R&D					-0.03	-1.65	
Constant					0.01	0.67	
Objective funct./Log-L	1.6	38	195	6.10	181	.40	
$ITQ=ITQ^2$	4.	8	4	.7	19.	.12	
$ITQ=ITQ^2=\underline{IQ}=\underline{IQ}^2$	7.	5	8	.1	21.	.75	
∂ eh/ ∂ itq $\cdot \overline{ITQ}/\overline{EH}$	0.1	32	0.1	.16	0.1	.25	
∂ eh/ ∂ iq $\cdot \overline{IQ}/\overline{EH}$	0.0	01	0.0	000	0.061		
Obs/firms	419/	'175	419_{1}	/175	419/175		

Notes: see Table 4.1. The number of left-censored observations with EH = 0 is 428 and 116, respectively. The scale factor is 0.48 and 0.71 based on pooled tobit model, respectively. The random effects specification includes both industry and size dummies. The within correlation coefficient is 0.86 and 0.85, respectively.

Table 5: Fixed and Random effects models for the log EH-share, subgroup: software, data processing, R&D labs, business services

	F	FE .	R	E	RE, AR(1)		
	coeff	t-stat	coeff	t-stat	coeff	t-stat	
ITQ	0.67	1.97	0.72	2.13	0.72	2.25	
$ITQ \times software$	-0.94	-1.68	-0.88	-1.59	-0.70	-1.40	
IQ	0.11	0.37	-0.03	-0.11	0.09	0.62	
$IQ \times business scvs.$	-0.47	-1.37	-0.33	-1.06	-0.44	-2.46	
exporter			0.16	2.19	0.14	1.62	
ind. cong.			-0.26	-1.70	-0.28	-1.69	
R&D			0.17	2.46	0.13	1.11	
$10 \le L < 20$			-0.16	-1.54	-0.16	-2.50	
$20 \le L < 50$			-0.05	-0.37	-0.04	-0.41	
$50 \le L < 250$			-0.14	-0.96	-0.11	-0.90	
$L \ge 250$			-0.61	-2.71	-0.61	-2.32	
software			0.13	0.72	0.12	0.65	
business scvs			0.28	1.62	0.28	1.59	
d_{95}	0.08	2.17	0.09	2.33	0.09	1.41	
d_{96}	0.12	3.26	0.12	3.26	0.13	2.00	
constant	-1.32	-35.08	-1.33	-8.20	-1.33	-8.13	
Hausmann test	6	.54					
$ ho_1/ ho_2$			0.	0.94		0.96/0.93	
∂ eh/ ∂ itq $\cdot \overline{ITQ}/\overline{EH}$	0.	.04	0.04		0.04		
obs/firms	445	/192	445_{0}	445/192		/192	

Notes: Dependent variable: logarithm of the university graduates employment share. Hausman test:

To compare the RE and FE model time-invariant variables are not included in the RE model. Critical value for the Hausman test is $\chi^2[4]_{.95}=9.49$.

To check the robustness of the results for the high-skilled intensive service industries, we exclude firms reporting a zero university graduates share and relate the logarithm of the university graduates share to IT and IT squared. In skill intensive services such as software and data processing, technical consultancy and business services less than 8 % of the firm report a zero university graduates employment share. Excluding observations with a zero university graduates employment share reduces the estimation sample from 491 to 455 observations. By taking the logarithm of the university graduates employment share, we accommodate the skewness of the employment share. The employment share equation can also be estimated by population averaged model estimated by GEE. As already mentioned, the main advantage of population-averaged models is the more general within correlation structure. Table 5 shows the results for the determinants of the log university graduates employment share based on the restricted sample. Since IT and IT squared are not significant at the five percent level, we only include the IT investment ratio. Column (ii) shows the results for the fixed effects models. Column (ii) and (iii) shows the results for random effects models, whereas specification (ii) assumes constant within coefficient and specification in column (iii) relax this assumption by specifying the within-group correlation as an AR (1) process. T-statistics are based on robust standard errors. Table 5 also includes the Hausman test statistics. The null hypothesis cannot be rejected, so that the random effects estimator seems to be the appropriate method to estimate the determinants of the log high-skilled employment share. The main result is the significant relationship between the share of university graduates and IT investment sales ratio. With regard to the size of the IT impact on the university graduates share, we again find a consistently low value for the IT coefficient across both the random effects and fixed effects model which is somewhat surprising. The IT coefficient on the log university graduates employment share of 0.72 translates into an IT elasticity of 0.04%.8 For the third specification allowing for an AR (1) error structure, the IT impact is 0.057 %. Thus

⁸ The IT-impact evaluated at sample means is $0.72 \times 0.057 = 0.04$, where 0.057 is the sample mean for the IT output ratio based on the restricted sample in skill intensive services (software, techn. consultancy, bus. scvs.).

an increase in the IT investment to output ratio by 50% (from 5.7% to 8.6%) would only raise the firm's high-skilled employment labour share by almost one percentage points which is an increase from 42.0% to 42.9%. For the one third of firms which export over the period 1994-96, we find that exporting reinforces the positive relationship found between IT investment and the employment of high-skilled labour.

5. Determinants of the shift in skill structure

5.1 Within versus. between industry shifts

This chapter analyses the factors behind the shift towards skilled labour. A standard way to evaluate the contribution of changes in the industrial structure is to decompose these shifts into changes that occurred between industries and those that occurred within industries. Since the time period of the firm-level data set covers only 3 years, the shift-share analysis is carried out using data drawn from the German Labour Force Survey and the Employment Register of the Federal Labour Office. To carry out this decomposition, we distinguish between three educational qualification classes. Following the framework used by Berman, Bound and Grilliches (1994) the change in the aggregate high skilled employment share can be written as:

$$\Delta \frac{L_{Ht}}{L_t} = \sum_{s=1}^{S} \Delta \left(\frac{L_{st}}{L_t}\right) \cdot \frac{\overline{L_{Hst}}}{L_{st}} + \sum_{s=1}^{S} \frac{\overline{L_{st}}}{L_t} \Delta \left(\frac{L_{Hst}}{L_{st}}\right)$$
 (5.1)

where s=1,...,S denotes sectors, L_H high skilled labour, and L the total labour force. A bar denotes the variable's mean over time. $\frac{L_{Hst}}{L_{st}}$ measures the share of high-skilled workers in an industry, $\Delta \frac{L_{Ht}}{L_t}$ is the change in the high-skilled employment share in the economy as a whole and $\frac{L_{st}}{L_t}$ is the sectorial employment share. The above equation thus decomposes the change in the high-skilled employment share into two effects. The first term measures the contribution to total change which results from employment shifts between sectors of different skill intensity. If there is a substantial reallocation of labour to the skill-intensive

Table 6: Decomposition analysis of the change in employment share of different educational classes

	emplo	oyees/	employment		total	between	within	within
	wor	kers	sh	are	change	change	change	change
	(100	00s	in	%	perce	entage p	oints	in $\%$
Based on Micro Census (S=20), private sector,1991-95								
	1991	1995	1991	1995	95/91	95/91	95/91	95/91
unskilled	4412	4345	19.3	17.8	-1.4	-0.3	-1.1	81.6
voc. school	15875	16656	69.3	68.4	-0.8	-0.4	-0.4	52.8
univer. grad.	2619	3343	11.4	13.7	2.2	0.6	1.5	70.7
Based on emp	loyment	statisti	cs (S=	269), pr	rivate se	ctor,199	1-95	
	1991	1995	1991	1995	95/91	95/91	95/91	95/91
unskilled	5288	4375	27.1	23.3	-3.7	-0.6	-3.2	84.8
voc. school	13088	13060	67.0	69.6	2.7	0.4	2.2	84.3
univer. grad.	1167	1322	6.0	7.0	1.1	0.1	0.9	86.2
Based on emp	loyment	statisti	cs (S=	269), pr	rivate se	ctor, 19'	78-96	
	1978	1996	1978	1996	96/78	96/78	96/78	96/78
unskilled	6097	4163	36.0	22.6	-13.4	-1.6	-11.8	87.9
voc. school	10221	12925	60.3	70.0	9.7	1.0	8.7	89.6
univer. grad.	631	1371	3.7	7.4	3.7	0.6	3.1	83.5

a high-skilled: university/polytechnical degree; medium-skilled: workers having completed vocational training; unskilled: no qualification. S denotes the number of industries.

Source: Federal Employment Office, own calculations.

sectors then this effect should be large. The second term measures the contribution to total change which results from the shift towards skilled workers within a sector.

Table 6 lays out the result of this decomposition for the three different types of labour as well as two different data sources (Micro Census and Employment Register of the Federal Labour Office). For the latter, we also report results for two different time periods. The last column shows the within shift as a proportion of the total change. For university graduates, 71% of the total 2.2 percentage point increase can be attributed to within industry changes during the period between 1991 and 1995. Thus, nearly all industries have experienced increases in the share of university graduates. The corresponding figure for workers with vocational degrees and workers without any formal degree is 52% and

83%, respectively. A similar picture holds true for the United States and United Kingdom (Berman et al. 1994, Machin, Van Reenen 1998), where the between effect also accounts for a very small part of the overall shift. Using a sample of 140 US industries, Autor et al.(1998) attributed 87% of the skill-upgrading to a within industries shift over the period 1990-1996.

Based on the social security statistics the contribution of the within component is somewhat higher. For 249 West German industries for the 1991-95 period, 86% of the change in employment share of university graduates share can be attributed by within industry shifts. For the longer period between 1978 and 1996 the within component also accounts for 83% of the rise in the high-skilled labour share. The results for the shift-share analysis based on the social security statistics should be interpreted with caution. Because both self-employed workers and workers who earn less than a minimum threshold are not covered from this data base, the industry share of other services is substantially underestimated.⁹

5.2 Role of organisational change

The shift towards university graduates can be attributed to within and between shifts as well as to shifts away from production activities towards service activities. The next step in the analysis is to examine whether the shift in demand towards high-skilled labour is uniform across all fields/activities. To determine how much of the skill-upgrading is attributable to industry change as well as organisational change, we use an industry-organisation matrix. Thus, an additional layer of disaggregation is added by assigning firms to industrial sectors and grouping their activities into several functions. The production process is divided into three activities: production, service activities and research and development. Service activities are further divided into selling, clerical and other service activities. Table A12 in Appendix documents the shift away from unskilled production activities and towards service activities over time. In manufacturing, employment directly related to production activities accounted for

Based on the social security statistics employment in market services (NACE 710-799) accounts for 24 % of total employment in 1995. Based on the micro census, the corresponding figure is 32 % (see Table 7.7 in Appendix).

49.2% in 1991 and 47.3% in 1995. Furthermore, R&D and design has the largest share of university graduates amounting to 35 %. In contrast, skill requirements are much lower in production activities as well as selling, trading and repairing. These tasks require only a small numbers of workers with a university degree. Furthermore, in non-manufacturing as well as manufacturing the shift towards high-skilled labour is uniform across occupations/fields. This contrasts with the results presented by Maurin and Thesmar (1999) who found that the share of skilled workers has remained stable within most occupations/fields.

Following Maurin and Thesmar (1999) the simple shift share analysis can be extended to account for the diversity of occupations within sectors:

$$\Delta \frac{L_{Ht}}{L_t} = \sum_{s=1}^{S} \Delta \left(\frac{L_{st}}{L_t}\right) \cdot \frac{\overline{L_{Hst}}}{L_{st}} + \sum_{s,f}^{S} \frac{\overline{L_{st}}}{L_t} \frac{\overline{L_{fHst}}}{L_{fst}} \Delta \left(\frac{L_{fst}}{L_{st}}\right) + \sum_{s,f}^{S} \frac{\overline{L_{st}}}{L_t} \frac{\overline{L_{fst}}}{L_{st}} \Delta \left(\frac{L_{fHst}}{L_{fst}}\right)$$
(5.2)

where f denotes the activities/occupations, $\frac{L_{fHst}}{L_{fst}}$ is the high-skilled employment share in each activity within industries, and $\frac{L_{fst}}{L_{st}}$ is the activity's employment share within industries. The first component measures the between effect. The second component measures the magnitude of the within sector reallocation. The remaining third component measures the residual within components (see Maurin and Thesmar, 1999). Table 7 shows the results for the extended shift-share analysis.

Table 7: University graduates employment share by activity/field

	emplo	yment	total	between	with. funct	within	within
	sha	are	change	change	change	change	change
in $\%$				percenta	age points	3	in $\%$
Based on micro census (S=20), private sector, 1991-95							
	1991 1995 95/91 95/91 95/91 95/91						
unskilled labour	19.3	17.8	-1.4	-0.3	-0.1	-1.0	70.2
univer. grad.	11.4	13.7	2.2	0.7	0.2	1.4	62.5

Notes: West German private sector.

Source: German Labour Force Survey (micro census), 91,93,95; 70 percent sample.

For university graduates 0.2 percentage points of the total 2.2 % increase

can be attributed to within functional change. Thus, the shift towards more-skilled intensive functions within industries cannot explain the shift in demand towards high-skilled labour. The shift towards skilled labour is uniform across occupations/fields within industries.

5.3 Contribution of IT accumulation to skill-upgrading

The shed some light on the quantitative impact of the estimates, we also calculated how much of the aggregate change in the university graduates share during the period between 1991 and 1995 can be explained by IT accumulation. Two scenarios are considered. The first scenario assumes that the change in the IT output ratio amounted to 5 % per year during the period from 1991 to 1995. This is not unrealistic given the 5.3% increase in the per capita IT expenditure for the total economy based in EITO figures. The second scenario assumes that the change in the IT output ratio amounted to 10 % per year.

Table 8 shows the results for the calculations for three service subsectors: (i) wholesale, retail trade and transport, (ii) banking, insurance and real estate and (iii), software, technical consultancy and business services. The IT elasticities are based on previous estimates. Our calculations suggests that in banking and insurance, for the given elasticity, $\varepsilon_{EH,IT}$, and the 5 % increase in the IT ratio, one fourth of the shift in demand towards university graduates can be explained by the IT accumulation. For the skill intensive industries as well as retail and wholesale trade only 6 % of the increase in the university graduates share can be attributed by IT accumulation.

Table 8: Contribution of IT accumulation to skill upgrading, 1991-95

	1991	1995	% change ^a	
Per capita IT expend., ECU	845	1038	5.3	
IT $\%$ GDP	4.3	4.6	2.0	
	1991	1995	% change ^a	% within
				${\rm change}^a$
Wholesale, retail trade, transp.	5.0	6.4	6.4	3.9
Banking and insurance	9.8	11.1	4.5	2.7
Business services	26.7	31.5	4.2	2.6
	% cha	nge in ITQ:	$arepsilon_{EH,IT}$	
	5%	10%		
Wholesale, retail trade, transp.	0.2	0.4	0.039	
Banking and insurance	0.7	1.4	0.132	
Business services	0.2	0.3	0.030	
	IT im	pact in % of	the within cl	hange
	5%	10%		
Wholesale, retail trade, transp.	6	12		
Banking and insurance	26	52		
Business services	6	12		

Notes: a average annual growth rate during the period 1991 and 1995. $\mathcal{E}_{EH,IT}$ is the elasticity of the university graduates employment share with respect to the IT output ratio based on the fixed effects tobit estimator (see Table 4.2 and Table 7.7).

 $Source: EITO, \ various \ issues, \ German \ Labour \ Force \ Survey, 91,93,95; \ 70 \ percent \ sample, \ own \ calculations.$

6. Conclusions

This paper has presented a number of factor demand models to investigate the link between skill intensity and information technology at the firm level in service industries. Our econometric model allows for censoring at the lower parameters of the employment share as well as for unobserved firm heterogeneity. We also examine the sensitivity of the results with respect to model specification. The most important result is the positive relationship between the share of highskilled workers and information technology, after controlling for size, industry, other heterogeneity controls and unobserved firm characteristics. Firms that have a higher proportion of information technology in total output employ more university graduates. However, the size of the IT effect on the skill intensity is rather small. A consistently low value is found for the IT elasticity across The magnitude of the IT elasticity is found to be substantially all models. larger in banking and insurance. In the 90's in business industries 6 % of the within industry skill upgrading can be explained by IT accumulation given the elasticities at the firm level. The corresponding figure for banking and insurance is 25 %. A more detailed study of the factors which affect firms' skill structure indicates that firms' export orientation, R&D and ownership characteristics have positive effects on the chosen skill intensity.

Finally, various decomposition analyses are provided based on the German Labour Force Survey. Most importantly, the shift in demand towards high-skilled labour can be explained by within industry shifts as well as by between industry effects rather than the increasing role of growing service activities in all sectors of the economy.

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Appendix

and Data Description: Micro Census **Employment** Register: Data for the shift share analysis come from two sources. The employment register of the Federal Labour Office and the German Labour Force survey. In both data sources, three educational categories could be defined: workers without any vocational training and apprentices are categorised as low-skilled or unskilled; workers with a certificate from the dual vocational school are categorised as medium-skilled or skilled; and finally, workers with a university or technical university degree are categorised as high-skilled workers. The first data source contains information on employment by educational qualification and by industry as of 30 June 1999 for all employees paying social security contributions for the 1975-1996 period. Note, that for approximately 5\% of the employees, the educational qualification is not available. Employment shares by educational category have been calculated as the category's share of total workers (excluding self-employed individuals and workers earning less than DM 630 per month). The data disaggregates the West German economy into 294 sectors. After excluding both the agricultural sector, state-run enterprises, as well as non-profit organisations 269 sectors remain.

The second data source is the German Labour Force Survey (Micro Census, see Table A7). A 70 % sample of the complete Micro Census is used for the analysis. The survey is limited to employed workers during the survey reference week April. The data disaggregates the West German economy into 213 sectors based on Nace classification in 1995 and 153 industries on previous sector classification. One data-related problem is the introduction of the Nace classification in 1995. We corrected for the change the sector classification by aggregating into 20 sector groups. Moreover, repairs (electrical appliances and vehicles) are regrouped into the corresponding manufacturing industry. Employment shares by educational category are calculated as the proportion of total workers (including self-employees and workers earning less than DM 630 per month). Information is also available on occupation. In the original data 9 occupations are available. These are regrouped into 5 occupations/fields.

Table A2: Definition of Service Sectors

		Definition of Service Sectors
Sector	3-dgt nace	Description
Wholesale	511	Wholesale on a fee or contract basis
trade	513	Wholesale of food, beverages and tobacco
	514	Wholesale of household goods
	515	Wholesale of non-agricultural intermediate
	516	Wholesale of machinery, equipment & supplies
	517	Other wholesale
Retail	501	Sale of motor vehicles
trade	502	Maintenance and repair of motor vehicles
	503	Sale of motor vehicle parts and accessories
	504	Sale, maintenance and repair
		of motorcycles and related parts
	505	Retail sale of automotive fuel
	521	Retail sale in non-specialized stores
	522	Retail sale of food, beverages and tobacco
	524	Other retail sale of new goods
	525	Retail sale of second-hand goods
	526	Retail sale of mail order
	527	Repair of household goods
Transport	601	Transport via railways
Storage and	602	Other land transport
Communi-	603	Transport via pipelines
cation	611	Sea and coastal water transport
	612	Inland water transport
	631	Cargo handling and storage
	632	Other supporting transport activities
	633	Activities of travel agencies
	634	Activities of other transport agencies
	641	Post and courier activities
	642	Telecommunications
Financial	651	Monetary intermediation
Intermediation	652	Other financial intermediation

continued Table A2

Sector	3-dgt NACE	Description
	660	Insurance
	671	Activities auxiliary to financial intermediation
	672	Activities auxiliary to insurance and pension funding
Real Estate	701	Real estate activities with own property
and Rental	702	Letting of own property
Activities	703	Real estate activities on a fee or contract basis
	711	Renting of automobiles
	713	Renting of machinery and equipment
Computing	721	Hardware consultancy and supply
	722	Software consultancy and supply
	723	Data processing
	724	Data base activities
	725	Maintenance and repair of office,
		accounting and computing machinery
	726	Other software related activities
Research &	731	Research & development on
development,		natural sciences, engineering
technical	742	Architectural and engineering activities
consultants	743	Technical testing and analysis
Consulting	741	Legal, accounting, book-keeping
(business scvs)		and auditing activities
Other business	744	Advertising
services	745	Labour recruitment, provision of personnel
	746	Investigation and security activities
	747	Industrial cleaning
	748	Miscellaneous business activities
	930	Other service activities (hairdressing)
Community	900	Sewage and refuse disposal, sanitation
social and	911	Business, employers and prof. organizations
personnel	913	Activities of other membership organizations
services	921	Motion picture and video activities
	922	Radio and television activities
	923	Other entertainment activities
	924	News agency activities

Table A3: Data cleaning process, West German firms 1994-1996

	Respondents miss						
	MIP-S 95	MIP	-S 97	MIP-S 95	MIP-	-S 97	
	1994	1995	1996	1994	1995	1996	
Participating firms	1629	1399	1400	0.0	0.0	0.0	
Total sales	1589	1398	1399	2.5	0.1	0.1	
Total workers	1629	1399	1400	0.0	0.0	0.0	
Total wage costs	1528	1319	1323	6.2	5.7	5.5	
University graduates, H	1433	1235	1249	12.0	11.7	10.8	
Gross investment, incl. IT	1498	1302	1312	8.0	6.9	6.3	
Inv. in communic. and IT	1492	1307	1321	8.4	6.6	5.6	
R&D employees	1566	1363	1366	3.9	2.6	2.4	
Exporter	1590	660	1355	2.4	52.8	3.2	
Part of ind. conglomerate	1613	1388	1389	1.0	0.8	0.8	
Entire sample	1183	1071	1099				
less manuf. firms	0	10	13				
less firms with $1 \le L < 5$	51	61	67				
less outliers	78	64	70				
Remaining sample	1054	946	962	35.3	32.4	31.3	
Restricted sample	349	919	925				

Source: Mannheim Service Innovation Panel 1995, 1997, own calculations.

Table A4: Comparison of high-skilled employment shares

	Micro	o Census	1995^{a}		M	IP-S 97	
	univ.	mast./	high-	obs	univ.	mast./	high-
	grad	tech.	skilled		grad.	tech.	skilled
	4/95	4/95	4/95		95	95	95
Wholesale trade	7.6	6.8	14.4	136	7.8	10.4	18.1
Retail trade, repairs	5.0	6.9	11.9	131	4.0	9.3	13.4
Transport	7.7	5.7	13.4	130	3.5	8.3	11.8
Banking, insurance	11.4	6.6	18.0	131	13.3	12.7	26.0
Real estate, renting	12.3	8.1	20.4	51	8.4	15.3	23.6
software, data proc.	39.0	10.3	49.3	78	40.4	16.3	56.7
R&D labs, consult.	43.6	10.3	53.9	63	42.9	13.7	56.6
Business services	34.4	4.8	39.2	72	33.8	12.7	46.6
Other business scvs.	10.5	10.4	20.9	118	5.7	8.7	14.5
Waste disposal	17.2	5.2	22.4	36	14.4	6.4	20.8
Total				946	14.5	11.1	25.6

Notes: a Total employment includes apprenticies as well as self-employees.

Source: German Labour Force Survey, '95 wave; 70 % sample; Mannheim Service Innovation Panel 1997, own calculations.

Table A5: Evolution of the university graduates employment share in services

	Universit	y grad. en	nploy. sh.		% change in EH ^a				
	wholes.,	banking,	business		wholes.	banking,	business		
	retail	insur-	services		retail	insur-	services		
	trade	ance			trade,	ance			
	transp.				transport				
80	1.5	3.6	9.6						
85	1.9	4.6	10.0	85/80	4.1	5.1	0.7		
90	2.4	6.0	11.4	90/85	5.1	5.5	2.7		
95	3.0	8.0	12.8	95/90	5.1	5.9	2.3		
96	3.2	8.3	13.2	96/95	5.5	4.4	3.1		
97	3.4	8.7	13.8	97/96	5.9	4.9	4.7		

Notes: West Germany, only workers who are legally required to pay social security taxes. a Annual average growth rate.

 $Source: Federal statistical office. Employment by educational qualification: \\ http://194.95.119.6/zeitreih/dok/sgz2197.htm, own calculations.$

Table A6: Sectoral Distribution: MIP-S and Micro Census

		MIP-S	l)	Micro Census ^a		
	distribution in $\%$			employment	distrib.	
			1000s	in $\%$		
	94	95	96	95	95	
Wholesale trade	15.5	14.7	14.7	986	9.8	
Retail trade, repairs	14.9	13.9	14.2	3369	33.4	
Transport, comm.	13.8	13.8	13.7	1404	13.9	
Banking, insurance	15.2	13.6	13.6	1190	11.8	
Real estate, renting	4.9	5.3	5.3	187	1.9	
software, data process	7.2	8.2	8.0	184	1.8	
R&D labs, consultancy	5.4	6.8	6.8	419	4.2	
Business services	9.2	7.5	7.8	497	4.9	
Other business services	11.2	12.4	12.2	1170	11.6	
Waste disposal	2.9	3.8	3.7	668	6.6	
Observations	349	919	925			
Total	100	100	100	10074	100	

Notes: West German Germany. a Total employment includes apprenticies as well as self-employees. Source: German Labour Force Survey, '95 wave; 70 % sample; Mannheim Service Innovation Panel 1995, 1997, own calculations.

Table A7: Cleaning process: Micro Census

	Employment weighted						
	by sample weights, 1000s						
	1991	1993	1995				
total employment	30243	30330	29779				
degree not available	3321	3334	1618				
degree available	26922	26996	28160				
private sector							
excluding agriculture	25756	25951	25747				
degree not available	2850	2881	1403				
degree available	22906	23070	24344				

Notes: West Germany 1991-1995, Total employment includes apprenticies as well as self-employees.

Source: German Labour Force Survey, '91, '93, '95 waves; 70 % sample, own calculations.

Table A8: Evolution of university graduates share and IT output ratio

	university				IT-wage			cases	
	gra	duates	sh.	bill ratio					
	94	95	96	94	95	96	94	95	96
Full sample									
Wholesale trade	8.7	7.8	8.2	4.3	2.4	2.9	193	136	141
Retail trade, repairs	4.1	4.0	4.1	3.2	1.9	2.1	142	131	132
Transport	4.4	3.5	3.7	2.5	2.3	2.7	145	130	131
Banking, insurance	13.6	13.3	14.6	6.6	7.3	8.3	162	131	131
Real estate, renting	14.5	8.4	10.2	9.1	3.6	2.8	61	51	52
Software, data process.	44.0	40.4	41.6	7.4	8.3	8.2	73	78	79
R&D labs, consult.	43.9	42.9	42.4	5.4	4.0	4.0	51	63	65
Business services	33.2	33.8	35.7	4.7	3.8	5.1	64	72	75
Other business scvs.	8.9	5.7	6.5	2.6	2.9	3.1	139	118	118
Waste disposal	16.4	14.4	14.4	5.3	3.5	4.3	24	36	38
All service ind.	14.4	14.5	15.2	4.6	3.9	4.2	1054	946	962
Restricted sample (T>1	.)								
Wholesale trade	11.4	7.8	8.4	3.2	2.4	2.9	54	135	136
Retail trade, repairs	4.2	4.0	4.1	3.0	1.9	2.0	52	128	131
Transport	4.4	3.5	3.7	3.4	2.3	2.2	48	127	127
Banking, insurance	12.4	13.4	14.3	5.6	7.0	8.5	53	125	126
Real estate, renting	10.2	8.1	8.3	6.1	3.2	2.8	17	49	49
Software, data process.	41.8	40.6	41.4	6.9	7.5	8.4	25	75	74
R&D labs, consult.	41.7	42.9	42.4	5.0	4.0	4.1	19	62	63
Business services	29.6	33.9	35.0	4.1	3.8	5.0	32	69	72
Other business scvs.	7.9	5.3	5.9	2.3	2.8	3.2	39	114	113
Waste disposal	23.1	14.8	15.5	6.9	3.6	4.2	10	35	34
All service ind.	14.9	14.4	14.9	4.2	3.7	4.2	349	919	925

Source: Mannheim Service Innovation Panel 1995, 1997, own calculations.

Table A9: University graduates share and sectoral employment share

		Sector's share in		University	
		total employ. (%)		grad	uates
		$[S_i = 1]$	$L_i/\Sigma L_i]$	share	$[PS_i^H]$
WZ 79	Sector	1991	1995	1991	1995
100-118	electricity, gas, water supply	1.8	1.8	7.7	9.9
200-205	chemical industry, petrolium	3.3	2.5	13.0	14.7
210	rubber and plastics	1.3	1.2	4.5	4.8
221-227	mineral products	1.2	1.0	4.0	5.6
230-239	basic metals	3.2	2.4	3.8	5.0
240-241	iron and steel	1.7	1.3	4.5	5.8
242	machinery	5.0	4.2	9.6	12.4
244-249	vehicles and repairs	5.1	4.3	6.6	8.4
250	electric appliances	4.4	2.7	14.4	18.0
252 - 254/243	optical and precison instr.	1.3	1.4	10.9	17.5
256-259	metal products, musical inst.	1.6	2.2	3.0	4.4
260-269	wood, pulp, paper, printing	4.0	3.7	2.8	3.6
270-279	textile, wearing app., leather	2.6	1.7	2.9	4.2
280-299	food, beverages, tobacco	3.0	2.8	3.0	3.8
300-310	construction	7.9	8.6	5.2	6.2
401-439	wholesale and retail trade	14.2	15.8	4.7	5.9
511-516	transport, communication	6.7	6.3	5.7	7.7
600-657	banking and insurance	4.4	4.6	9.6	11.5
710-775	personal services,				
	education and health	21.8	25.3	24.8	25.2
780-799	business related services	5.5	6.5	26.7	31.5

Notes: West German private sector. Includes self-employed individuals and workers earning less than a DM 630 threshold.

Source: German Labour Force Survey (Micro Census), '91, '95 waves; 70 % sample, own calculations.

Table A10: Population-averaged panel probit model for the firms' decision to employ university graduates

		robit			
	coeff	t-stat	_	t-stat	
ITQ	3.51	4.04	2.86	3.56	
ITQ^2	-1.51	-1.38	-0.84	-0.80	
IQ	0.01	0.14	-0.02	-0.20	
IQ^2	0.01	0.49	0.02	0.95	
Exporter	0.23	2.40	0.23	2.76	
Ind. group	0.68	5.93	0.72	6.25	
R&D	0.49	2.04	0.48	1.78	
$10 \le L < 20$	0.06	0.56	0.09	1.04	
$20 \le L < 50$	0.14	1.14	0.15	1.30	
$50 \le L < 250$	0.68	4.99	0.62	4.66	
$L \ge 250$	1.29	7.20	1.15	7.13	
Wholesale trade	-0.28	-1.66	-0.24	-1.42	
Retail trade	-0.61	-3.68	-0.61	-3.73	
Transport	-0.62	-3.67	-0.63	-3.80	
Real estate	-0.22	-0.97	-0.22	-1.00	
Software, data process.	0.89	3.27	1.02	3.70	
R&D labs	1.19	3.63	1.34	3.62	
Business svcs	0.91	3.73	0.90	3.54	
Other svcs	-0.43	-2.36	-0.41	-2.30	
Comm. svcs.	0.37	1.22	0.35	1.17	
Constant	-0.18	-1.12	-0.35	-0.39	
ho	0.	82	0.88/0.76		
$Wald-test:itq,itq^2$	22	2.4	18.8		
Wald-test:itq,itq 2 ,iq,iq 2	25	5.2	22.6		
Obs./firms	2193	/933	2193/933		

Notes: West German firms 1994-96. Dependent variable, university graduates=1, zero otherwise. Reference group for sector dummies is banking/insurance, for size classes size 1 (less than 10 workers). L denotes the number of workers which equals the sum of the three educational qualification groups. Specifications in column (i) and (ii) are based on robust standard errors.

Table A11: Fixed and Random effects tobit models for the EH-share, skill intensive service industries

		Tobit	RE Tobit		
	coeff.	t-stat	coeff.	t-stat	
software, data processir	ng, R&D	labs, bu	ısiness s	ervices	
ITQ	0.26	0.59	0.76	4.99	
$ m ITQ^2$	-0.21	-0.33	-0.83	-3.01	
IQ	-0.06	-0.98	-0.13	-2.69	
IQ^2	0.01	0.90	0.03	1.94	
Exporters			0.07	5.12	
Ind. Congl.			-0.02	-1.14	
R&D			0.12	8.28	
Ind.+size d.					
Constant			0.31	18.64	
Objective funct./Log-L	5.	66	181	.40	
ρ			0.9	90	
$_{\mathrm{ITQ=ITQ}}^{2}$	1	.1	40	0.8	
∂ ен/ ∂ іт $\mathbf{Q} \cdot \overline{ITQ} / \overline{EH}$	0.031		0.086		
∂ eh/ ∂ iQ $\cdot \overline{IQ}/\overline{EH}$	-0.011		-0.	024	
Obs/firms	491,	/211	491,	/211	

Notes: West German firms, 1994-96. Dependent variable: University graduates employment share. 37 left-censored observations with EH = 0.The scale factor equal to 0.91 is based on pooled to bit model. FE Tobit model is based on the polynomial loss function.

Table A12: University graduates employment share by activity/field

	university			share of			
	grad. employ-			-	function		
	men	t shar	e, %	emp	oloyment, %		
Activities/occupation	'91	'93	'95	'91	'93	'95	
			Manu	ıfacturiı	ng		
Production, processing							
Constructing, making	1.3	1.7	2.0	49.1	48.0	47.3	
Trading, selling and repairing	4.0	4.6	4.8	14.8	15.5	15.6	
Clerical, supporting management	15.8	17.4	18.0	19.9	20.4	20.7	
Research, Development, Design	29.6	32.7	35.1	7.9	8.0	8.1	
Other service activities a	3.7	4.2	4.1	8.4	8.2	8.2	
All activities/fields	7.0	8.0	8.6	100.0	100.0	100.0	
	Non-manufacturing						
Production, processing,							
Constructing, making	2.3	2.6	2.9	13.6	13.7	13.5	
Trading, selling and repairing		4.4	4.8	22.3	21.0	21.0	
Clerical, supporting management		14.2	15.5	24.5	24.6	24.2	
Research, Development, Design		44.7	47.0	3.9	4.2	4.3	
Other service activities a		23.7	24.2	35.7	36.6	36.9	
All activities/fields	14.2	15.3	16.1	100.0	100.0	100.0	

Notes: West German private sector, Agriculture and public services are excluded. b Education, welfare and health, cleaning, catering.

Source: German Labour Force Survey (micro census), 91,93,95; 70 percent sample.