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New Technologies and the Demand for Medium Qualified Labour in Germany

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Abstract

The literature on skill-biased technological change concentrates on highly skilled and unskilled employees. It is unclear, however, if the employment opportunities of the majority of the labour force in Germany – employees with a degree from the dual apprenticeship system *(Fachkräfte mit Dualer Ausbildung)* – are positively or negatively affected by new technologies. This paper answers this question and it addresses estimation and data problems on the basis of a topical and rich data set. It shows that innovation expenditures and investments in information and communication technologies (IT) lead to lower medium skilled employee shares in most sub-sectors of the West German service sector, whereas other investments frequently lead to higher medium skilled employee shares. The most notable deviation is the banking sector where IT intensive firms have higher shares of medium qualified employees.

Zusammenfassung

Die Literatur zum Einfluss des technologischen Fortschritts auf die Qualifikationsnachfrage konzentriert sich bisher auf die hochqualifizierten Beschäftigten und die Beschäftigten ohne Berufsabschluss. Es ist deshalb unklar, ob die Beschäftigungsmöglichkeiten der Mehrheit der Arbeitskräfte in Deutschland – Beschäftigte mit einer Dualen Ausbildung – positiv oder negativ durch neue Technologien beeinflusst werden. Der vorliegende Beitrag beantwortet diese Frage. Er behandelt außerdem eine Reihe von Schätz- und Datenproblemen auf der Basis eines aktuellen und umfangreichen Datensatzes. Er zeigt, dass Innovationsausgaben und Investitionen in Informations- und Kommunikationstechnologien in den Betrieben fast aller westdeutschen Dienstleistungssektoren zu niedrigeren Beschäftigungsanteilen von Fachkräften mit Dualer Ausbildung führen. Andere Investitionen erhöhen hingegen häufig den Anteil der Fachkräfte an der Gesamtbeschäftigung. Eine deutliche Abweichung von diesem Muster ergibt sich für den Sektor Banken und Versicherungen, in dem Unternehmen, die Informations- und Kommunikationstechnologien stark nutzen, höhere Fachkräfteanteile haben.

JEL codes: C 24, J 23, O 32

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1. Introduction

Traditionally the dual apprenticeship system is the backbone of professional qualification in Germany. In 2000, according to the German federal statistical office, the highest professional qualification of about 53% of the labour force is a degree from the German dual apprenticeship system, Statistisches Bundesamt (2001), p. 378.[1] This share decreased only slightly in recent years. Therefore the dual apprenticeship system is by far the most important institution to acquire a professional degree in Germany, Blechinger and Pfeiffer (2000). Year by year, the German government invests considerable effort in goodwill campaigns in order to promote the willingness of firms to offer apprenticeships, Franz, Steiner, and Zimmermann (2000). As a consequence, the public awareness of the importance of apprenticeship training is high and almost 100% of the German firms accept a social responsibility of the firms to offer apprenticeships, Zwick and Schröder (2001).

Germany takes pride in the qualification results of its extensive and expensive dual apprenticeship system. Three parties, the training firm, the apprentice, and the government finance the mainly three year apprenticeship (Franz and Soskice, 1995, and Harhoff and Kane, 1997). The apprenticeship comprises education in public training schools and theoretical as well as practical training within the company. The dual apprenticeship system is praised even by most German companies that do not offer apprenticeships as an efficient means to obtain qualified personnel with topical and general skills. Few German enterprises indicate that they consider the skill level of their former apprentices to be inadequate, Zwick and Schröder (2001).

Graduates of the dual apprenticeship system *(Fachkräfte mit Dualer Ausbildung)* are well educated in an international comparison, too (Acemoglu and Pischke, 1999), and have a comparable professional position to for example high school graduates in the USA (Harhoff and Kane, 1997). Freeman and Schettkat (1999) stress that literacy and numeracy scores of medium skilled employees in Germany are higher than those of American employees with a college or an associate degree. The apprenticeship diplomas are monitored by the local chambers of commerce and work councils, have the same level for all participating apprentices regardless of the training firm, and entail skills generally applicable in the entire business sector of the apprentice (Franz and Soskice, 1995, and Zwick and Schröder, 2001). Therefore the basic knowledge necessary to acquire an apprenticeship degree in Germany can be labeled as general, well-known for everybody and marketable elsewhere, Franz et al. (2000).

1 We call this group of the labour force medium skilled for convenience in the remainder.

Technological change always implies the necessity to train and therefore employees need a broad background of general skills that allows them to acquire new skills easily in order to benefit from the introduction of new technologies, Bartel and Sicherman (1998) or Acemoglu and Pischke (1999). Nickell and Bell (1996) write: "The very high level of education and training embodied in the vast bulk of the German labor force enables them to respond in a exible manner to demand shifts. As a consequence, in Germany, in contrast to Britain and the United States, we do not find a large segment of the work force who simply cannot cope with the demands placed upon them by technological change". Blechinger and Pfeiffer (2000) state, however, that the contents of the apprenticeship training became obsolete due to technological change in recent years while the transferability of knowledge between professions is frequently very low.

It is therefore unclear if medium skilled employees are flexible enough and have the qualificational background that is necessary to adapt to the qualificational changes implied by investments in new technologies or in other words if they are in a good position to benefit from the chances provided by technological change. From the empirical literature we know that technological change favoured highly skilled employees and replaced unskilled jobs, Acemoglu (2002). The impact of technological change on medium skilled employees in Germany is largely unknown, however, because most papers are based on crude measures of skill[2] or concentrate on the share of highly qualified or unqualified employees[3]. Although it is undisputed that technological changes favour highly skilled employees, it is still unclear which qualification groups can take advantage of technological changes when we differentiate between several qualification levels, or in other words, where the dividing line lies. The aim of this paper is to empirically assess if relative demand for medium skilled employees is positively influenced by the usage of new technologies in German service firms.

This paper is organized as follows. The next section explains the theoretical link between new technologies and qualification demand and the empirical estimation possibilities. Then our data and estimation techniques are described. Finally, we present the estimation results for different subsectors of the West German service sector and provide some conclusions for economic policy.

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[2] Berman, Bound, and Griliches (1994), Autor, Katz, and Krueger (1998) or Askenazy (2000) concentrate on manufacturing versus non-manufacturing employee shares, Machin and Van Reenen (1998) focus on college versus non-college employment shares.

[3] See Machin (1996), Kaiser (1998), or Falk and Seim (2001).

2. New technologies and qualification demand

2.1 Theoretical considerations

There are a number of possible avenues by which new technologies may influence qualification demand and even if we find a clear empirical correlation between the relative demand for medium skilled employees and the usage of new technologies we have to carefully analyse the possible reasons for it in order to be able to draw adequate conclusions from this finding.

There are at least four rival hypotheses on the impact of new technologies on the relative demand for medium skilled employees at the firm level.

1. New technologies are skill-biased and also employment opportunities of medium skilled employees benefit from technological change. They replace low skilled employees.
2. New technologies are skill-biased but only highly qualified employees benefit from technological change.
3. New technologies are skill biased but not towards the formal degree of qualification, but towards access to training and the ability to create new skills by training.
4. Technological change is not biased in the sense that more and higher qualifications but other qualifications are needed.

In this paper, we concentrate on the first two hypotheses by analyzing qualification demand for medium skilled employees of firms that heavily use new technologies. We find that the relative demand for medium skilled employees reacts differently on investment in new technologies in the various service sectors in West Germany. Therefore, we differentiate between four sub-sector groups.

The third hypothesis is advocated by Bartel and Sicherman (1998). They show on the basis of the US National Longitudinal Survey of Youth that training incidence of the low skilled employees aged 14–21 is relatively high in comparison to training incidence of the high skilled in firms facing high rates of technological change. They conclude that probably higher skilled employees need less training because they are in a better position to adapt to changes having received more general training. It is unclear, however, if the higher training incidence increases the employment opportunities of the low skilled youths. In our data set, we do not observe training incidence and therefore, we can not assess the role of training for employability in times of skilled biased technological change.

With regard to the last hypothesis, Blechinger and Pfeiffer (2000) show that the applicability of the apprenticeship training contents of medium skilled employees decreased in the wake of the introduction of new technologies. The effect of this skill obsolescence on the relative demand for medium skilled labour is unclear, however, as it might also affect other qualification groups like computer scientists. Our data do not allow to test this hypothesis, because we do not have information on the work content of the employees. It should be kept in mind, however, that skill obsolescence might contribute to a negative impact of new technologies on the relative demand for the medium skilled.

2.2 Empirical Implementation

The impact of new technologies on the medium skilled labour demand can empirically be analyzed in the framework of factor demand models where labour demand is expressed as a function of several determinants including indicators for the usage of new technologies. The functional form of factor demand models can be derived from firms' profit maximizing behaviour on the basis of flexible production functions like the generalized Leontief or the translog production function (Berndt, 1991, chapter 9, Chennels and Van Reenen, 1999, and Morrison, 1999). These may contain variable factors as well as quasi-fixed factors like capital. By Shephard's lemma, the dual cost functions allow the derivation of factor demand and cost share equations which can be used for an empirical analysis. Important determinants of the factor demand are the prices of the variable factors. In our data, however, we do not observe the average wages paid to the different qualification levels.[4] Therefore, we have to assume that the effects of the relative wages for the different qualification groups are captured by the firm size and sector dummies implying that they are constant within one firm size-sector combination.[5]

A further assumption is that the labour cost shares are independent of the production level of the firm (homothetic production function). This assumption allows us to use capital intensities instead of levels. Theory suggests nonlinear impacts of quasi-fixed factors in factor demand equations. Therefore we include quadratic terms.

It is hard to measure the usage of new technologies directly. Therefore, more or less indirect measures of the innovative behaviour of firms have to

[4] The average wages can be approximated by regressing the total wage sum on the qualification shares (Kaiser, 2000). In explorative estimations the approximated relative wages do not have an impact on qualification shares, however. One could conclude from this that the qualification groups are paid according to their marginal productivity. This result could also be caused by the inaccuracy of the auxiliary regression, however, which has a low R^2 and some inconsistencies.

[5] The same assumption is implied when wages are merged or approximated by a regression on the basis of firm size and sector dummies.

be used. A positive impact of the indicators for innovation activities shows that the share of medium skilled employees and new technologies are complements.

In order to tackle the problem of measuring new technologies and to obtain a differentiated picture of the impact of new technologies on the demand for medium qualified employees in Germany, we use three complementary and direct indicators for innovative activities: innovation expenditures, IT investments, and research and development employees and projects.

An important measure of the usage of new technologies is the ratio of innovation expenditures to turnover which we call innovation intensity in the following. Innovation expenditures are asked according to the Oslo Manual and therefore innovation expenditures have to be related to technological changes, Janz et al. (2001). One problem with this measure is that innovations are hard to define and the costs for innovations are accordingly hard to calculate. Therefore, we expect a substantial subjective component in this variable.

Secondly, the ratio of investments in IT on turnover (IT intensity) is included. We define these technologies as "new" because not all firms use them extensively yet. Their penetration rate increased rapidly in Germany, though. In 1979, 14% of the employees used a computer-based tool (CNC or NC machine, computer, laptop etc.), for example, while in 1999, the share was 62%. The share of medium skilled employees using new technologies was 58% in 1999, while 33% used those technologies as their main tool, Troll (2000). Firms using new technologies in the service sectors are characterized by quick introduction of the latest information and communication technologies. This is mirrored in high expenditures for these technologies. Investments in IT technologies are therefore a good proxy for the use of new technology and it measures the use (and not the production) of new technology, Bartel and Sicherman (1998). While IT captures only one aspect of new technology usage, it seems to be at the core of topical innovations, Berman, Bound, and Machin (1998) and Zwick and Schröder (2001). The IT intensity differs between firms and sectors. In our sample of West-German service sector firms, the IT intensity is on average less than 2% (see Table 5). This intensity varies between 0.7% in retail trade, 3.3% in technical services and 3.7% in electronic data processing (see Table 6).

Research and development (R&D) activities can also be interpreted as an indicator for the usage of new technologies. They are a direct measure of innovative activity in the firm. In contrast to the usage of IT, they measure inputs for and not output of new technologies, Bartel and Sicherman (1998). It is well known that R&D activities are mainly performed by highly skilled employees (Pfeiffer and Falk, 1999). Therefore we have to take into account that the skill structure of firms with large R&D departments might differ from those with no R&D departments in our regressions. Since we only observe the number of R&D employees, but not their qualification structure, we cannot correct the skill shares directly. Instead, we add the share of employees in the R&D department and a dummy if R&D projects have been carried out as control variables to measure the impact of our innovation indicators corrected for R&D activities.

Non-IT investments over turnover (non-IT intensity) is taken as a measure for the replacement of obsolete capital by new but not necessarily innovative equipment. The share of investments induced by innovations among non-IT can be expected to be substantially smaller than among IT investments. If the firm's investment budget is fixed, IT and non-IT investments might as well be substitutes.

New technologies might affect the demand for medium skilled employees differently in the various sub-sectors of the service sector. Some occupations that are predominant in certain sub-sectors might be able to cope with changes incurred by new technologies more easily than others. We find indeed that different sub-sectors behave differently and therefore present estimations for four coherent sub-sectors.

In addition, the size of the firm is included in the list of explanatory variables. The estimation equation can therefore be written as follows:

$$\frac{E}{B} = \alpha + \beta_{IN}\frac{IN}{Q} + \beta_{IN2}\left(\frac{IN}{Q}\right)^2 + \beta_{IT}\frac{IT}{Q} + \beta_{IT2}\left(\frac{IT}{Q}\right)^2 + \beta_{NIT}\frac{NIT}{Q} + \beta_{NIT2}\left(\frac{NIT}{Q}\right)^2 + \beta_{AFE}\frac{AFE}{B} + \beta_{FE}d_{FE} + \sum_{m=1}^{4}\beta_{FGm}d_{FGm} + \sum_{j=1}^{9}\beta_{WZ_j}d_{WZ_j} + \varepsilon\,.$$

Hereby, E is the number of employees whose highest professional degree is an apprenticeship in the dual system, B is the total number of employees, IN are innovation expenditures and IT are investments in information and communication technology, NIT are non-IT investments, Q is the turnover, AFE is the number of employees in the R&D department, d_{FE} is a dummy that equals one for firms that had R&D projects in the last three years before the interview was held, d_{FGM} is a dummy for firm size, d_{WZ_j} is a dummy for the sector (see the list of sectors in the appendix), and ε is a stochastic error term.

The basis of estimation are those firms that provided information on the qualification share of their employees on a 5 level scale. We define three qualification levels: unskilled employees[6], medium skilled employees (having a degree from the dual apprenticeship system as their highest professional qualification) and highly skilled employees (employees with master / technician degree, university or polytechnic diploma).

3. Data and Estimation Technique

The data basis of the estimation is the Mannheim Innovation Panel for service firms (MIP-S) with its 1995, 1997 and 1999 waves that are available at that moment. The three waves contain answers for the years 1994 until 1998. The Mannheim Innovation Panel captures different dimensions of the innovative behaviour of service firms in Germany. Mainly technology oriented innovations that are either introduced into the market or used within the production process are included. The MIP-S is a representative sample of most commercial service sectors and excludes health care, government services and non-profit sectors. It very closely reflects the national averages for the variables used, Falk and Seim (2001). An in-depth description of the panel can be found in Janz et al. (2001).

In the nineties substantial differences in the structure and behavior of firms located in East and West Germany can be expected because the transition process after the German re-unification is not finished. A Chow test rejected the equality of coefficients indicating behavioral differences. Most regressions for the East German service sector were not satisfying because the signal-noise ratio was small and therefore only few coefficients were significant. In addition, small sample sizes were problematic. Therefore we present only regressions for West German firms.

We find that the demand for medium skilled employees differs between sub-sectors of the service sectors. The number of observations per sub-sector is too small and therefore we aggregate sub-sectors to relatively homogeneous groups (see the average shares in Table 5 in the appendix). Wholesale trade and retail trade are merged to "trade", banks, insurance, real estate, and renting are merged to "banks and real estate", electronic data processing and technical services are merged to "IT and technical services", and transport, business services, and social and personal services are merged to "transport, business and personal services".

Of those 6917 observations with 5 or more employees we have to exclude 3152 because only firms that stated to have introduced an innovation during the last three years, or at least have tried to but failed, were asked about their innovation expenditures and R&D employees and projects. After drop-

[6] In the data there is no category for employees without professional degree, but there is one summary category for all employees not in the list mentioned above.

ping observations with missing or implausible[7] values we are left with 1864 observations. Table 5 shows that variable means before and after the reduction of the sample are quite similar. This indicates that we do not have a serious selection problem.

The structure of the data would allow for the use of a panel estimator in order to control for unobservable heterogeneity (Chennels and Van Reenen, 1999). Exploratory random effects tobit estimations analogous to the cross section regressions presented in this paper encountered problems with the Gauss-Hermite quadrature approximation, however. The results were not robust with respect to the number of quadrature points and therefore the estimations are not reliable. To avoid this problem, Honoré's fixed effects tobit estimator seems to be a promising choice. We leave the implementation of this estimator for future work. A major drawback of using panel techniques here might be measurement errors, however. In a pooled data set, measurement errors are less severe because the true variation is likely to be greater across firms than within firms over time, Bartel and Sicherman (1998). An additional problem is that the indicators for innovative behaviour of the firms are ratios of two separate variables which may further increase the noise and the impact of measurement errors in a panel regression.

Our regressions contain pooled data with observations from all five years, leaving us with 449 cases for the trade sub-sector, 377 for banks and real estate, 359 for IT and technical services, and 679 for transport, business and personal services. Descriptive statistics of the endogeneous and exogeneous variables can be found in the appendix in Tables 5 and 6.

The share of medium skilled employees can only be between zero and one and the endogeneous variable is censored. Therefore an ordinary least squares estimation is inconsistent and the coefficients are biased towards zero (that means their absolute value is too small). The bias increases with the share of censored firms (Greene, 1997, chapter 20). In the data used, 4.9% of the firms do not employ medium skilled employees and 2.2% only employ medium skilled employees. Therefore estimation techniques should be applied that take account of the censoring on both sides of the endogeneous variable.

We assume a model with a latent endogeneous variable y_i^* that may be interpreted as the unobservable qualification demand of firm i for medium skilled employees:[8]

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[7] We regard observations with an innovation intensity greater than one, with IT investments greater than total investments and with a non-IT intensity greater than 2 as implausible.

[8] This implies the assumption that for the decision to employ no medium skilled employees, to employ a certain share of medium skilled employees or to employ only

$$y_i^* = x_i\beta + \varepsilon_i \ .$$

For the observable share of medium skilled employees y_i we obtain:

$$y_i = \begin{cases} 0 & \text{if} \quad y_i < 0 \\ y_i^* & \text{if} \quad 0 \le y_i^* \le 1 \\ 1 & \text{if} \quad y_i > 1 \end{cases} .$$

For normally distributed and heteroscedastic error terms $\varepsilon_i \sim N(0, \sigma_i^2)$, we obtain the heteroscedastic tobit model.[9] Assuming that $\sigma_i = \varepsilon^{z_i\gamma}$ we maximize the log likelihood function

$$\begin{aligned} \hat{\beta}_{ML} &= \underset{\beta,\gamma}{\operatorname{argmax}} \quad \ln L \\ &= \underset{\beta,\gamma}{\operatorname{argmax}} \sum_{i=1}^{N} (1 - C0_i - C1_i) \left\{ -\frac{1}{2} \left[\ln(2\Pi) + \ln(\varepsilon^{z_i\gamma})^2 + \left(\frac{y_i - x_i\beta}{\varepsilon^{z_i\gamma})} \right)^2 \right] \right\} \\ &\qquad\qquad + C0_i \quad \ln\left[1 - F\left(\frac{x_i\beta}{\varepsilon^{z_i\gamma}} \right) \right] \\ &\qquad\qquad + C1_i \quad \ln\left[F\left(\frac{x_i\beta - 1}{\varepsilon^{z_i\gamma}} \right) \right] , \end{aligned}$$

with $C0_i$ and $C1_i$ indicating if the endogenous variable is censored at 0 or 1, while z_i are variables explaining heteroscedasticity and γ is the corresponding coefficient vector.

Wald-, LR- and LM-tests reject the assumption of homoscedasticity. To test the normality assumption we apply an information matrix (IM) test developed by White (1982), which was adjusted for heteroscedasticity. Normality is rejected but simulation studies by Davidson and MacKinnon (1992) and Orme (1992) reveal the weak performance of the IM test which in finite samples rejects the true null hypothesis much too often even in the homoscedastic case and with few variables. As can be expected, own simulations show that this problem increases considerably in the heteroscedastic case. To check the reliability of the heteroscedastic tobit estimation that

medium skilled employees the same decision process applies. A double hurdle model explicitly explaining the decision to hire medium skilled employees in a first regression and the share of the medium skilled employees in a second step is not possible, because the number of censored firms is too small and we do not have suitable additional identifying variables.

9 Alternative and closely related estimation procedures are logit or normit, see Greene (1997), p. 895. The main difference to the tobit model is that these techniques assume a nonlinear S-bended relationship between y_i^* and $x_i\beta$. A problem arises with logit or normit estimations if – as in our case – some y_i equal 0 or 1. These firms would either have to be dropped or their shares would have to be changed ad hoc.

hinges on the normality assumption, we therefore apply two semiparametric methods developed by Powell (1984, 1986) that do not rely on this assumption: the censored least absolute deviation (CLAD) estimator and the symmetrically censored least squares (SCLS) estimator. They come at the cost of being less accurate than the tobit estimates if the error terms are in fact normally distributed and heteroscedasticity is explained completely by the scedastic equation $\sigma_i = \varepsilon^{z_i \gamma}$.

The CLAD estimator models the conditional median of $y_i|x_i$[10] instead of its expectation. Therefore, comparing CLAD and tobit coefficients one implicitly assumes that the distribution of $y_i|x_i$ is symmetric. Being a quantile regression, CLAD minimizes the sum of the absolute deviations $|\hat{\varepsilon}_i|$. The minimizing problem with two-sided censoring at zero and one can be written as:

$$\hat{\beta}_{CLAD} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N} |y_i - \max\{0; \min\{1; x_i\beta\}\}| \ .$$

It is not easy to directly optimize the objective function, because it is not differentiable. Therefore we use the iterative procedure proposed by Buchinsky (1994).[11] Powell (1984) shows that $\hat{\beta}_{CLAD}$ also is consistent and asymptotical normally distributed if we have a non-normally distributed and heteroscedastic error term.

The SCLS estimator is based on the OLS estimator that also is consistent under heteroscedasticity. It needs symmetric error terms, however. Assume that the true value of β is known. For observations $\{i|0 \leq x_i\beta \leq 1\}$ we obtain the following deviations:

$$\tilde{\varepsilon}_i = y_i - x_i\beta \ ,$$

for the case of censoring at zero and one, we get:

$$-x_i\beta \leq \tilde{\varepsilon}_i \leq 1 - x_i\beta \ .$$

10 Other quantiles can be modeled depending on the number of censored values.

11 The implementation of the iterative calculation is straightforward if the computer estimation package allows for median regressions. In iteration t the procedure uses a median regression for the observations that have an estimated value in $t-1$ between zero and one. The procedure is iterated until the coefficients do not change any more which means that the estimated sample is stable (Jonston and DiNardo, 1997, p. 445). Fitzenberger (1994) shows that the iterative procedure is under certain conditions less likely to converge than alternative algorithms and that convergence does not even guarantee a local maximum. He suggests other optimization methods and compares their performance in simulation studies (Fitzenberger, 1997, and Fitzenberger and Winker, 1999). In our case with few censored observations the iterative procedure can be expected to converge to the maximum, however.

Due to this censoring the variable $\tilde{\varepsilon}_i$ is usually correlated with x_i. If ε_i is symmetrically distributed, we obtain consistent OLS estimators by trimming such that $\tilde{\varepsilon}_i|x_i$ is also symmetric around zero and we then obtain $E(\tilde{\varepsilon}_i|x_i) = 0$. The following condition must hold:

$$\max\{-x_i\beta, -1 + x_i\beta\} \leq \tilde{\varepsilon}_i \leq \min\{x_i\beta, 1 - x_i\beta\}$$

This can be obtained by transforming y_i as follows:

$$\tilde{y}_i = \min\{-1 + 2x_i\beta, \max\{y_i, 2x_i\beta\}\} \ .$$

Figure 1 demonstrates the trimming of y_i and $\tilde{\varepsilon}_i|x_i$, respectively, which is symmetrically distributed around $x_i\beta$.

The SCLS estimator can be calculated iteratively by a series of OLS estimations (Jonston and DiNardo, 1997, p. 443). Powell (1986) shows that the SCLS estimator is consistent and asymptotical normally distributed if ε_i is symmetrically distributed.

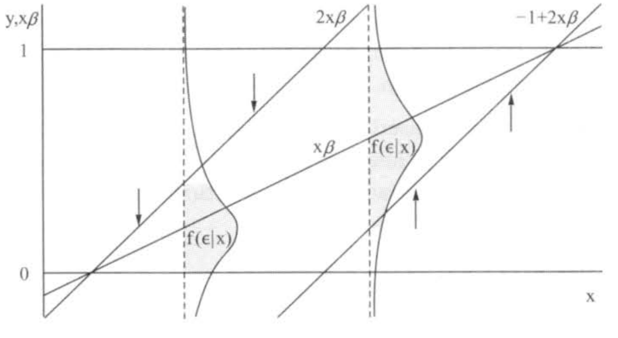

Figure 1: Transformation of the endogeneous variable in the SCLS estimation

Many firms in our data set report lack of suitably qualified personnel as a main obstacle to innovation. This points to potential endogeneity of our innovation intensities. We can not control for this as we do not have good instruments correlated with the IT and innovation intensities but not with the medium skilled share.

We apply the three cross section regression methods described above for the sub-sectors separately. The heteroscedastic tobit is efficient if its restrictive assumptions normality and fully explained heteroscedasticity are correct and inconsistent otherwise. SCLS is consistent under heteroscedasticity but requires symmetric errors. *CLAD* is consistent under the most general conditions and robust to outliers, but it models the conditional median instead of the expectation of the medium skilled share. Therefore all of these methods have their advantages and drawbacks. Their common application serves as a robustness check for our results.

4. Estimation Results

Tables 1 – 4 present the results of the CLAD, SCLS and heteroscedastic tobit estimations for several West German service sub-sectors. We find a similar pattern of the impacts of innovation intensity, IT intensity and non-IT intensity on medium skilled labour demand in most sub-sectors. The higher the innovation intensity and the IT intensity the lower is the share of medium skilled employees. The higher the non-IT intensity the higher is the share of medium skilled employees. The significance of the impacts differs, however. Innovation intensity only has a significantly negative impact in the banks, insurances, and real estate sectors as well as the technical services sector. IT intensity is not significant in the transport, business, and social services sectors. This pattern is also found by Berman et al. (1994) who state for US-American manufacturing that those sub-sectors with the highest shares of expenditures in IT experience the strongest increase in demand in highly qualified employees. The positive impact of non-IT intensity is not significant in the trade, banks, insurances, and real estate sectors. As all indicators are also included as squares, we plotted the nonlinear effects in Figure 3 in the appendix. In Figure 4 confidence intervals for the tobit estimators are added. We plotted the effects for intensity values smaller than 0.5 because only few firms have higher values. The distribution of the innovation indicators is plotted in Figure 2.

There is one notable deviation from these results in the banks and real estate sector. Here IT intensity has a significantly positive impact on the demand for medium skilled employees.

Our second main result is that the estimation results are robust with regard to the choice of the estimation method. In the case of contradictory results, we would have had the problem that there is no ranking with respect to the reliability of the estimators as they depend on different assumptions.

According to other findings in the literature, Pfeiffer and Falk (1999), the share of employees in the R&D departments has a negative impact on the share of medium skilled employees (except for the IT and technical services sector).

The share of employees in the R&D departments is also an important factor in the scedastic equation of the tobit model in most sub-sectors. One explanation is that firms with a large R&D department tend to report more carefully than others. The dummy indicating if R&D projects have been carried out in the enterprise has different signs in the sub-sectors regarded. In the banks and real estate sector, the few establishments with own research and development projects have a significantly higher share of medium skilled employees.

Firm size has the expected negative impact on the share of medium skilled employees (Zwick and Schröder, 2001) in all sectors except trade. The larger the firm the lower the share of the endogeneous variable. Firm size has an impact in the scedastic equation. Small firms have larger error variances. This is in part due to the discrete character of this variable. The lower the number of employees, the larger is the range between possible skill shares, and the stronger is the impact of indivisibility effects. Year dummies do not have a significant impact on the estimation results, but they play a role in the scedastic equation of some sub-sectors. Therefore they are only included in the scedastic equations.

Summing up, hypothesis 1 is rejected for all sectors apart from the bank, insurance and real estate sector. Medium skilled employees in Germany are no complements for new technologies and have a lower share in information intensive and innovative firms although they have a relatively high qualification level.

Therefore the dividing line between the qualification levels that benefit from the introduction of new technologies in Germany and those that loose is above the employees with a degree from the dual apprenticeship system. In the bank and retail sector, IT intensive establishments and establishments with R&D expenditures demand relatively many employees with medium skills, however.

Table 1

Estimation of the medium skilled employees share, trade

Independent variables	CLAD	SCLS	Tobit	
			regression equation	scedastic equation
Innovation intensity	-0.452	-0.840	-0.545	
	(0.804)	(0.669)	(0.527)	
Innovation intensity squared	0.879	1.294	0.908	
	(2.103)	(1.134)	(0.986)	
IT intensity	-5.926*	-5.825**	-6.978**	
	(2.537)	(2.170)	(2.341)	
IT intensity squared	33.643	36.799	49.819	
	(33.102)	(21.353)	(29.665)	
Non-IT intensity	0.386	0.588	0.381	
	(0.785)	(0.477)	(0.398)	
Non-IT intensity squared	-0.180	-0.133	0.144	
	(3.936)	(0.517)	(0.662)	
Share employees in R&D department	-0.831*	-0.612	-0.811**	0.237
	(0.393)	(0.325)	(0.296)	(0.740)
R&D project has been carried out	-0.007	-0.014	-0.001	
	(0.050)	(0.031)	(0.035)	
Firm size (reference: 5 – 9 employees)				
Firm with 10 – 49 employees	0.060	0.060	0.056	0.122
	(0.043)	(0.039)	(0.038)	(0.118)
Firm with 50 – 249 employees	0.052	0.040	0.029	-0.090
	(0.051)	(0.039)	(0.038)	(0.120)
Firm with more than 250 employees	-0.025	0.014	0.009*	-0.202
	(0.052)	(0.040)	(0.038)	(0.126)
Sector (reference: Wholesale trade)				
Retail trade	0.146**	0.104**	0.093**	-0.111
	(0.035)	(0.024)	(0.023)	(0.075)
Year (reference: 1994)				
1995				-0.036
				(0.112)
1996				-0.067
				(0.102)
1997				-0.047
				(0.130)
1998				-0.015
				(0.098)
Constant	0.506**	0.509**	0.522**	-1.346**
	(0.047)	(0.037)	(0.036)	(0.127)
Number of observations	449	449	449	

Notes: Standard deviations are shown in brackets. For the CLAD estimators they are obtained by bootstrapping. Draws for which the iterative estimation procedure did not converge were replaced. Significance levels of the variables are: * < 0.05 and ** < 0.01.

Table 2

Estimation of the medium skilled employees share, banks, insurances and real estate

Independent variables	CLAD	SCLS	Tobit regression equation	Tobit scedastic equation
Innovation intensity	-2.515**	-1.573*	-1.447**	
	(0.955)	(0.666)	(0.514)	
Innovation intensity squared	2.870	1.622	1.353	
	(4.307)	(0.872)	(0.903)	
IT intensity	3.386*	2.273*	2.280*	
	(1.577)	(0.952)	(0.902)	
IT intensity squared	-7.092	-4.510*	-4.527*	
	(4.784)	(1.875)	(1.920)	
Non-IT intensity	-0.046	-0.004	0.077	
	(0.373)	(0.302)	(0.251)	
Non-IT intensity squared	0.111	-0.017	-0.104*	
	(0.374)	(0.276)	(0.281)	
Share employees in R&D department	-0.545	-0.493	-0.817*	-4.280 *
	(0.854)	(0.407)	(0.360)	(1.715)
R&D project has been carried out	0.137*	0.107**	0.128**	
	(0.059)	(0.039)	(0.042)	
Firm size (reference: 5 – 9 employees)				
Firm with 10 – 49 employees	-0.091	-0.178*	-0.223**	-0.190
	(0.099)	(0.070)	(0.070)	(0.174)
Firm with 50 – 249 employees	-0.098	-0.170*	-0.216**	-0.487**
	(0.099)	(0.068)	(0.069)	(0.176)
Firm with more than 250 employees	-0.063	-0.139	-0.195**	-0.598**
	(0.101)	(0.071)	(0.071)	(0.182)
Sector (reference: Banks and insurance)				
Real estate and renting	0.008	0.033	0.000	-0.117
	(0.057)	(0.050)	(0.040)	(0.107)
Year (reference: 1994)				
1995				0.039
				(0.120)
1996				-0.028
				(0.115)
1997				-0.047
				(0.130)
1998				0.045
				(0.153)
Constant	0.626**	0.687**	0.737**	-1.050**
	(0.099)	(0.068)	(0.069)	(0.119)
Number of observations	377	377	377	

Notes: Standard deviations are shown in brackets. For the CLAD estimators they are obtained by bootstrapping. Draws for which the iterative estimation procedure did not converge were replaced. Significance levels of the variables are: * < 0.05 and ** < 0.01.

Table 3

Estimation of the medium skilled employees share, IT and technical services

Independent variables	CLAD	SCLS	Tobit	
			regression equation	scedastic equation
Innovation intensity	-0.452	-0.613**	-0.442*	
	(0.309)	(0.231)	(0.226)	
Innovation intensity squared	0.528	0.689**	0.556*	
	(0.410)	(0.259)	(0.242)	
IT intensity	-0.817	-1.168	-1.515**	
	(1.109)	(0.693)	(0.508)	
IT intensity squared	0.268	1.019	1.611	
	(6.245)	(1.008)	(0.981)	
Non-IT intensity	1.230	0.883**	0.683*	
	(0.645)	(0.305)	(0.299)	
Non-IT intensity squared	-0.627	-0.355	-0.238	
	(1.312)	(0.256)	(0.361)	
Share employees in R&D department	0.168	0.083	-0.063	-0.955**
	(0.111)	(0.080)	(0.056)	(0.197)
R&D project has been carried out	-0.046	-0.054	-0.037	
	(0.043)	(0.034)	(0.034)	
Firm size (reference: 5 – 9 employees)				
Firm with 10 – 49 employees	-0.098	0.008	-0.015	-0.446*
	(0.077)	(0.074)	(0.065)	(0.176)
Firm with 50 – 249 employees	-0.064	0.006	-0.006	-0.702**
	(0.081)	(0.076)	(0.064)	(0.178)
Firm with more than 250 employees	-0.073	-0.015	-0.028*	-0.413*
	(0.088)	(0.084)	(0.079)	(0.210)
Sector (reference: Electronic data processing)				
Technical services	0.007	0.006	0.036	-0.182*
	(0.038)	(0.030)	(0.029)	(0.091)
Year (reference: 1994)				
1995				0.256
				(0.136)
1996				0.274*
				(0.132)
1997				0.365*
				(0.179)
1998				0.422**
				(0.128)
Constant	0.369**	0.329**	0.356**	-0.950**
	(0.082)	(0.081)	(0.067)	(0.188)
Number of observations	359	359	359	

Notes: Standard deviations are shown in brackets. For the CLAD estimators they are obtained by bootstrapping. Draws for which the iterative estimation procedure did not converge were replaced. Significance levels of the variables are: * < 0.05 and ** < 0.01.

Table 4

Estimation of the medium skilled employees share, transport, business and personal services

Independent variables	CLAD	SCLS	Tobit regression equation	Tobit scedastic equation
Innovation intensity	-0.434	-0.476	-0.403	
	(0.388)	(0.269)	(0.266)	
Innovation intensity squared	0.746	0.677*	0.552	
	(0.508)	(0.298)	(0.362)	
IT intensity	-2.280	-1.259	-1.364	
	(1.450)	(0.766)	(0.858)	
IT intensity squared	9.591	3.429	4.159	
	(7.625)	(3.169)	(3.798)	
Non-IT intensity	0.985**	0.393*	0.420*	
	(0.342)	(0.179)	(0.176)	
Non-IT intensity squared	-0.887*	-0.254	-0.268	
	(0.354)	(0.156)	(0.151)	
Share employees in R&D department	-0.643	-0.717**	-0.673**	-0.914
	(0.303)	(0.266)	(0.157)	(0.612)
R&D project has been carried out	-0.022	0.035	0.038	
	(0.057)	(0.033)	(0.030)	
Firm size (reference: 5 – 9 employees)				
Firm with 10 – 49 employees	-0.060	-0.122*	-0.121**	-0.109
	(0.074)	(0.052)	(0.050)	(0.128)
Firm with 50 – 249 employees	-0.123	-0.155**	-0.132**	-0.167
	(0.083)	(0.053)	(0.050)	(0.127)
Firm with more than 250 employees	-0.144*	-0.166**	-0.152**	-0.242
	(0.084)	(0.056)	(0.051)	(0.127)
Sector (reference: Transport)				
Business services	-0.113**	-0.101**	-0.082**	-0.074
	(0.042)	(0.027)	(0.027)	(0.064)
Personal services	-0.121	-0.070	-0.065	-0.111
	(0.066)	(0.038)	(0.036)	(0.097)
Year (reference: 1994)				
1995				0.095
				(0.086)
1996				0.107
				(0.083)
1997				0.214*
				(0.107)
1998				0.095
				(0.083)
Constant	0.574**	0.617**	0.597**	-1.129**
	(0.078)	(0.057)	(0.053)	(0.134)
Number of observations	679	679	679	

Notes: Standard deviations are shown in brackets. For the CLAD estimators they are obtained by bootstrapping. Draws for which the iterative estimation procedure did not converge were replaced. Significance levels of the variables are:* < 0.05 and** < 0.01.

5. Conclusions

This paper shows that the share of employees with a degree from the dual apprenticeship system in most West German service sub-sectors is lower in establishments with high innovation expenditures and in establishments with high IT investments. Non-IT investments that are interpreted as proxies for replacement efforts have a positive impact on medium qualification demand, however. We therefore conclude that West German firms heavily using new technologies not only replace low skilled employees but also employees with a degree from the dual apprenticeship system by higher skilled employees.

New technologies and especially IT investments are crucial for the growth of the economy, Jorgenson and Stiroh (1999), and the main employment potentials can be found in information intensive and innovative firms like business services[12] (Kaiser, 1998, or Zwick and Schröder, 2001). Therefore the negative impact of innovations and IT investment on medium skilled labour demand is a worrying sign for decreased job opportunities for more than half of the German labour force in the most promising sectors of the economy.

It is not clear, however, why German IT intensive and innovative service firms demand relatively few medium skilled employees. One reason might be that these firms offer jobs that traditionally require highly skilled employees and investments in new technologies did not decrease qualification demand. Another reason may be that investments in new technologies require qualifications that are not met by medium skilled employees. This question is not resolved yet. First evidence for the second hypothesis is given in representative enterprise interviews in the German service sector[13]. Especially the information intensive and innovative business service enterprises indicated that one of the main reasons for the low share of medium skilled employees are gaps in qualifications. Typical qualificational bottlenecks identified were computer skills, qualifications around new information technologies and foreign languages. Most frequently these qualification gaps were indicated in commercial professions that have a high employment share in services, Zwick (2001). Also the self assessment of apprentices points in the same direction: Employees programming or working with personal computers apply less of their apprenticeship training relative to colleagues who do not use these tools, Blechinger and Pfeiffer (2000), p. 265.

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12 These are: Renting, electronic data processing and data bases, research and development and other business services.

13 In April 2000, more than 1500 enterprises in this sector have been extensively asked about their perception of the dual apprenticeship system, Zwick and Schröder (2001) and Zwick (2001).

A notable exception from this pattern are banks, insurances and real estate businesses. A superficial interpretation of the deviating results in the banks and insurances sector also seems possible from the findings of the enterprise interviews mentioned above. In comparison to other sectors, banks and insurances indicate more often that the specific professions mainly demanded in this sector (qualified bank or insurance clerk, *Bankkaufmann / frau, Versicherungskaufmann / frau*) are adequate and up-to-date and that they think that the qualification level obtained by the apprentices during their dual apprenticeship is sufficient (Zwick and Schröder, 2001). It seems that the IT skills in these specific professions that have been modernized in 1996 and 1997 are sufficient even for IT intensive establishments and the few establishments that carry out research and development in this sector.

For the other sub-sectors in the West German service sector it seems to be a viable option to increase medium skill employment shares in information intensive enterprises by bridging the skill gaps identified by the enterprises. The German state also has a direct impact on the qualification of the apprentices, because it sets the minimum requirements that have to be fulfilled in order to pass the exams. In addition, it is responsible for the financial and personal endowment of the public professional schools *(Berufsschulen)* that are an essential part of the dual apprenticeship system. A more adequate qualification of the medium skilled employees therefore can increase the attractiveness of the German dual apprenticeship system and the job opportunities of the majority of employees in a crucial employment sector.

References

Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market. Journal of Economic Literature, 40, 7 – 72.

Acemoglu, D. / *Pischke,* J.-S. (1999). Beyond Becker: Training in Imperfect Labor Markets. Economic Journal, 109, 112-142.

Askenazy, P. (2000). Organisational Innovations, Computerisation and Employment. In M. Vivarelli and M. Pianta (Eds.), Employment Impact of Innovation: Evidence and Policy. Routledge.

Autor, D. / *Katz,* L. / *Krueger,* A. (1998). Computing Inequality: Have Computers Changed the Labor Market? Quarterly Journal of Economics, 113, 1169-1213.

Bartel, A. / *Sicherman,* N. (1998). Technological Change and the Skill Acquisition of Young Workers. Journal of Labor Economics, 16, 718-763.

Berman, E. / *Bound,* J. / *Griliches,* Z. (1994). Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers. Quarterly Journal of Economics, 109, 367-397.

Berman, E. / *Bound,* J. / *Machin,* S. (1998). Implications of Skill-biased Technological Change: International Evidence. Quarterly Journal of Economics, 1245-1279.

Berndt, E. R. (1991). The Practice of Econometrics: Classic and Contemporary. Sydney: Addison-Wesley.

Blechinger, D. / *Pfeiffer,* F. (2000). Technological Change and Skill Obsolescence: The Case of German Apprenticeship Training. In H. Heijke and J. Muysken (Eds.), Education, Training and Employment in the Knowledge Based Economy (pp. 243-278). Basingstoke: Macmillan.

Buchinsky, M. (1994). Changes in the U.S. Wage Structure 1963 – 1987: Application of Quantile Regression. Econometrica, 62, 405-458.

Chennels, L. / *Van Reenen,* J. (1999). Technical Change and the Structure of Employment and Wages: A Survey of the Micro-Economic Evidence (Discussion Paper 99 / 27). Institute for Fiscal Studies, London.

Davidson, R. / *MacKinnon,* J. G. (1992). A New Form of the Information Matrix Test. Econometrica, 60, 145-157.

Falk, M. / *Seim,* K. (2001). The Impact of Information Technology on Highskilled Labor in Services: Evidence from Firm-Level Panel Data. Economics of Innovation and New Technology, 10, 289-323.

Fitzenberger, B. (1994). A Note on Estimating Censored Quantile Regressions (Discussion Paper 14). Konstanz University.

– (1997). A Guide to Censored Quantile Regressions. In G. Maddala and C. Rao (Eds.), Handbook of Statistics, Vol. 15: Robust Inference (pp. 405-437). Amsterdam: North-Holland.

Fitzenberger, B. / *Winker,* P. (1999). Improving the Computation of Censored Quantile Regressions (Discussion Paper 568-99). Mannheim University.

Franz, W. / *Soskice,* D. (1995). The German Apprenticeship System. In F. Butler, W. Franz, R. Schettkat, and D. Soskice (Eds.), Institutional Framework and Labor Market Performance (pp. 208-234). Routledge, London and New York.

Franz, W. / *Steiner,* V. / *Zimmermann,* V. (2000). Die betriebliche Ausbildungsbereitschaft im technologischen und demographischen Wandel. Baden-Baden: Nomos.

Freeman, R. / *Schettkat,* R. (1999). The Role of Wage and Skill Differences in US-German Employment Differences. Jahrbücher für Nationalökonomie und Statistik, 219, 49-66.

Greene, W. H. (1997). Econometric Analysis. London: Prentice-Hall.

Harhoff, D. / *Kane,* T. (1997). Is the German Apprenticeship System a Panacea for the U.S. Labor Market? Journal of Population Economics, 10, 171-196.

Janz, N. / *Ebling,* G. / *Gottschalk,* S. / *Niggemann,* H. (2001). The Mannheim Innovation Panels (MIP and MIP-S) of the Centre for European Economic Research (ZEW). Schmollers Jahrbuch, 121, 123-129.

Jonston, J. / *DiNardo,* J. E. (1997). Econometric Methods. New York: MacGraw-Hill.

Jorgenson, D. / *Stiroh,* K. (1999). Information Technology and Growth. American Economic Review, 89, 109 – 115.

Kaiser, U. (1998). The Impact of New Technologies on the Demand for Heterogenous Labour: Evidence from the German Business-Related Services Sector (Discussion Paper 98-26). ZEW (Centre for European Economic Research Mannheim).

– (2000). A Note on the Calculation of Firm-specific and Skill-specific Labour Costs from Firm-level Data. Zeitschrift fur Wirtschafts- und Sozialwissenschaften, 220, 541-551.

Machin, S. (1996). Changes in the Relative Demand for Skills. In A. Booth and D. Snower (Eds.), Acquiring Skills (p. 129 – 147). Cambridge University Press.

Machin, S. / *Van Reenen,* J. (1998). Technology and Changes in Skill Structure: Evidence from seven OECD Countries. Quarterly Journal of Economics, 113, 1215-1243.

Morrison, C. J. (1999). Cost Structure and the Measurement of Economic Performance. Boston Dordrecht London: Kluwer Academic Publishers.

Nickell, S. / *Bell,* B. (1996). Changes in the Distribution of Wages and Unemployment in OECD Countries. American Economic Review, 86, 302- 308.

Orme, C. (1992). The Sampling Performance of the Information Matrix Test. In L. Godfrey (Ed.), The Implementation and Constructive Use of Misspecification Tests in Econometrics. Manchester: Manchester University Press.

Pfeiffer, F. / *Falk,* M. (1999). Der Faktor Humankapital in der Volkswirtschaft: Berufliche Spezialisierung und technologische Leistungsfähigkeit. Baden-Baden: Nomos.

Powell, J. L. (1984). Least Absolute Deviations Estimation for the Censored Regression Model. Journal of Econometrics, 25, 303-325.

– (1986). Symmetrically Trimmed Least Squares Estimation for Tobit Models. Econometrica, 54, 1435-1460.

Statistisches Bundesamt. (2001). Statistisches Jahrbuch 2001. Stuttgart: Metzler-Poeschel.

Troll, L. (2000). Die Arbeitsmittellandschaft in Deutschland im Jahre 1999. In W. Dostal, R. Jansen, and K. Parmentier (Eds.), Wandel der Erwerbsarbeit: Arbeitssituation, Informatisierung, berufliche Mobilität und Weiterbildung (pp. 125-150). Nürnberg: IAB.

White, H. (1982). Maximum Likelihood Estimation of Misspecified Models. Econometrica, 50, 1-25.

Zwick, T. (2001). Beschäftigungsmöglichkeiten von Fachkräften mit Dualer Ausbildung in informationsintensiven Dienstleistungsunternehmen. Mitteilungen aus der Arbeitsmarkt- und Berufsforschung, 34, 74-81.

Zwick, T. / *Schröder,* H. (2001). Wie aktuell ist die Berufsbildung im Dienstleistungssektor? Baden-Baden: Nomos.

Appendix

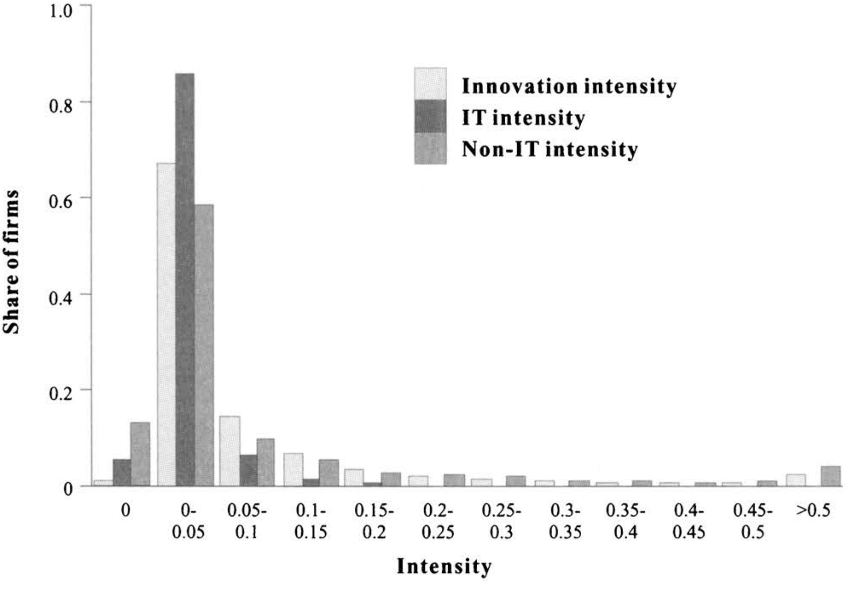

Figure 2: Distribution of innovation, IT and non-IT intensities

Figure 2 displays the share of firms in several categories of innovation, IT investments and non-IT investments divided by turnover (the innovation, IT and non-IT intensities). More than 60% of the firms have an innovation intensity between 0 and 0.05, for example. Only few firms have innovation and non-IT values above 0.5.

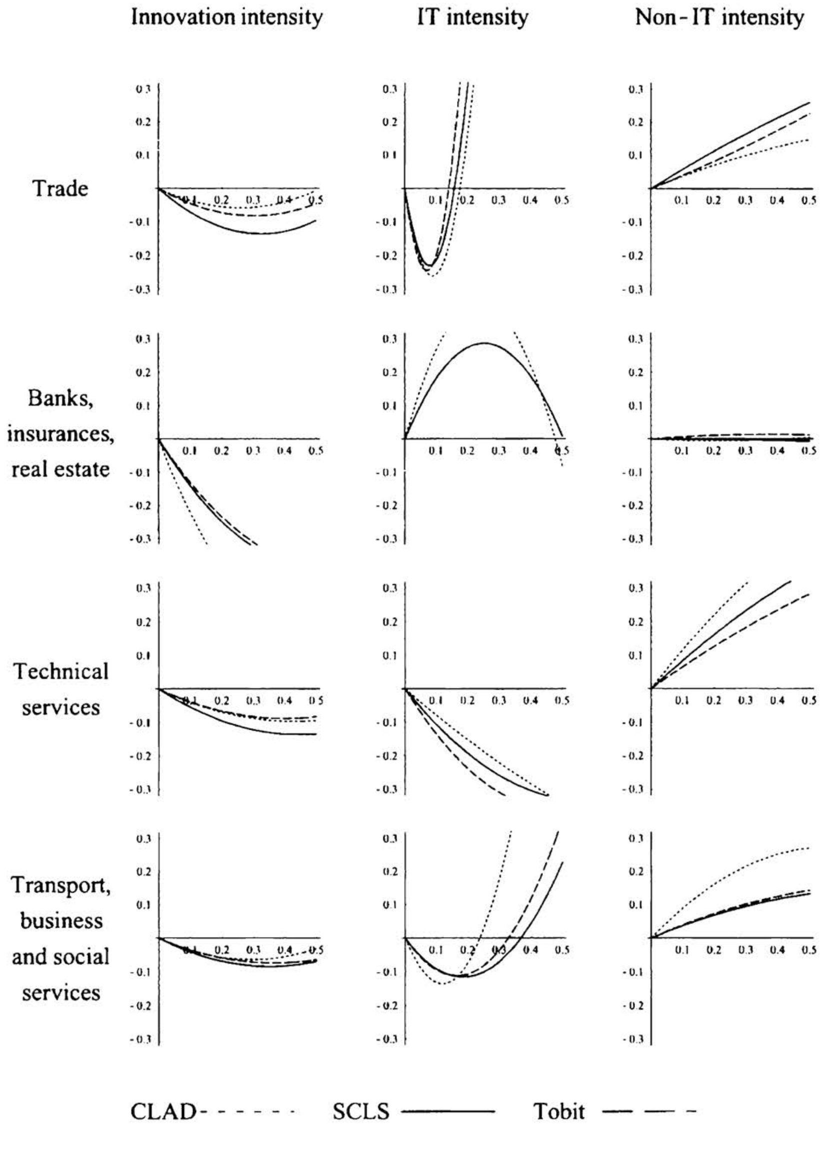

Figure 3: Nonlinear effects of innovation, IT and non-IT intensities

The effects displayed here have a straightforward interpretation. Ceteris paribus a trade firm with an IT intensity of 0.1 can be expected to have a medium skilled share that is 20 percentage points lower than the medium skilled share of a firm without innovation expenditures. Since the investment and innovation intensities are rarely above 20% (see Figure 2), the directions of the effects are unambiguous for relevant values but cannot be interpreted for larger values.

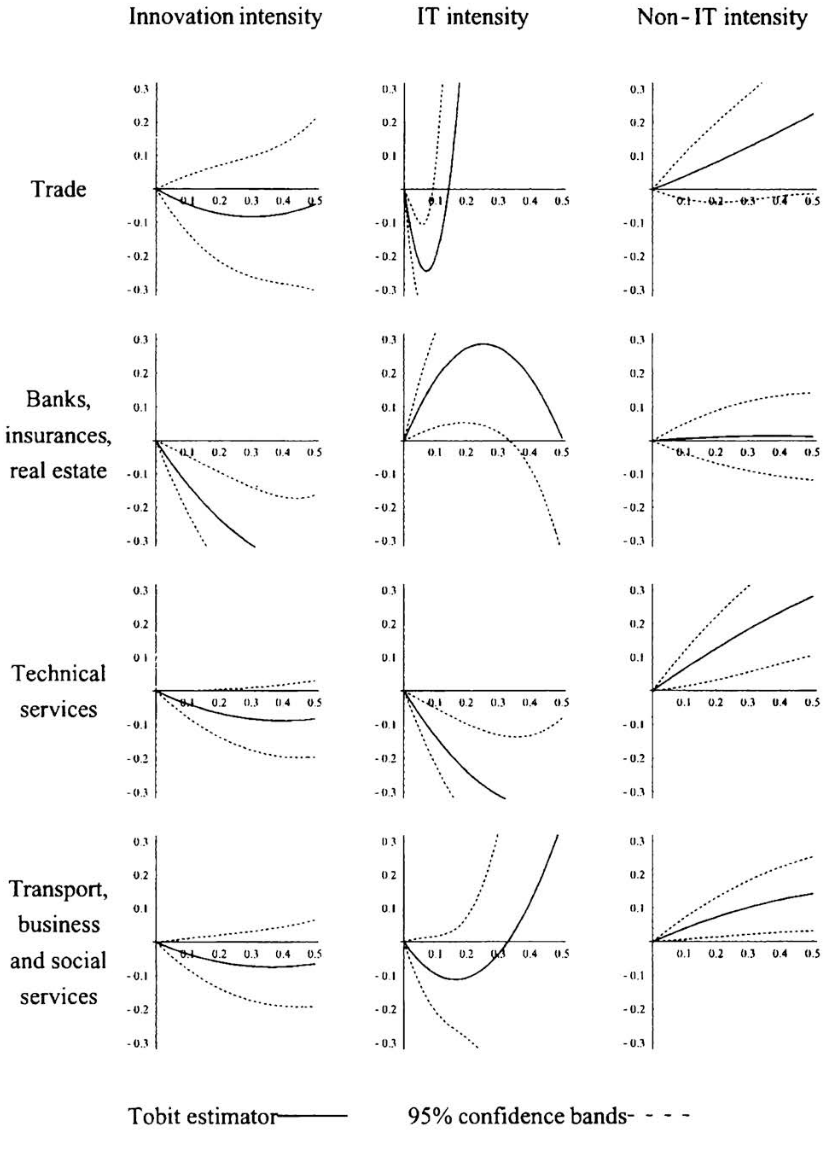

Figure 4: Confidence intervals around the nonlinear effects of innovation, IT and non-IT intensities

Table 5

Descriptive statistics: Means of variables before and after selection

	Before selection	After selection
Share of medium skilled employees	46.0	44.8
Innovation intensity	5.7	5.6
IT intensity	1.9	1.7
Non-IT intensity	7.3	5.5
Share employees in R&D departments	3.0	3.4
Own R&D projects	25.3	25.8
Firms with 5-10 employees	11.1	10.1
Firms with 10-49 employees	34.3	36.7
Firms with 50-249 employees	29.9	31.3
Firms with more than 250 employees	24.7	21.8
Sector 1: Wholesale trade	12.4	13.1
Sector 2: Retail trade	10.1	10.9
Sector 3: Transport	13.5	13.3
Sector 4: Banking and insurance	20.3	16.1
Sector 5: Real Estate and renting	4.4	4.1
Sector 6: Electronic data processing	10.5	11.7
Sector 7: Technical services	6.5	7.6
Sector 8: Business services	17.9	18.6
Sector 9: Social and personal services	4.4	4.6
Number of observations	3765	1864

Remarks: Means before selection concern firms with five or more employees who stated to have innovated or to have started an unfinished or unsuccessful innovation project. We dropped firms with missing values on at least one of the variables above. 118 exclusions were made for plausibility reasons. Those are observations with an innovation intensity greater than one, with IT investments greater than total investments and with a non-IT intensity greater than 2.

Source: Mannheim Innovation Panel for Services (MIP-S), Waves 1995, 1997, and 1999, own calculations.

Table 6

Descriptive statistics: Means by sectors (in %, 1994-1996)

	Share medium skilled employees	Innovation intensity	IT intensity	Non-IT intensity	Share employees in R&D departments	Own R&D projects (yes / no)
Wholesale trade	48.4	3.3	0.8	2.9	3.0	28.2
Retail trade	60.5	2.9	0.7	3.4	0.7	15.2
Transport	47.9	6.4	0.7	10.3	1.1	22.3
Banking and insurance	53.7	2.4	1.4	1.8	0.7	13.3
Real Estate and renting	54.7	4.2	1.8	21.6	1.2	15.6
Electronic data processing	29.0	12.3	3.7	2.6	9.7	47.2
Technical services	31.8	10.9	3.3	5.0	12.6	49.6
Business services	36.8	4.5	2.0	3.3	2.7	25.1
Social and personal services	42.5	8.5	1.2	20.8	0.5	20.8

Remark: The means were calculated for the estimation sample.

Source: Mannheim Innovation Panel for Services (MIP-S), Waves 1995, 1997, and 1999, own calculations.