Shifting employment patterns in business related services

Empirical evidence from German survey data

by

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Abstract: The impact of technology on the demand for heterogenous labor is controversely discussed throughout the literature. New technology which is said to favor high skilled labor and to substitute low skilled labor is often considered as the main reason for the decline in relative demand for low skilled labor. Although there is no consensus, most researchers believe that this skill–biased technological change is the main determinant for the decline in relative demand for low skilled labor. While most analyses focus on manufacturing industries, this paper presents empirical evidence that technologial skill bias is also present for business related services, an increasingly important sector in the German economy.

Cross–sectional data from an innovation survey in the service sector and panel data from a quarterly business survey in the service sector are used in the empirical investigation. The data allow to directly distinguish between five different skill groups. The micro-level data also allow to analyze shifting employment patterns for a single economic unit. Ordered probit models are utilized to study the determinants of skill shifts in business related services. It turns out that the share of investment in information and communication technologies relative to total investment is a complement of university graduates and a substitute of workers with completed vocational training. Total investment is substitutive to low skilled labor. The demand for technical skilled labor is unaffected by investment decisions. Other findings are that labor cost are not important for the demand for university graduates, technical skilled and unskilled labor but are highly significant for skilled labor.

Keywords: skill–biased technological change, capital–skill complementarity, panel data, service sector

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1 Introduction

Many developed economies have witnessed a steady decline in the demand for low skilled workers over the last few years. This decline was even steeper in Germany than in other OECD countries.[1] Changes in the demand for skills affect the distribution of incomes, the level of unemployment attributable to technological changes, and skill shortages may lead to a decreased international competitiveness (Capelli, 1993). The issue of shifting employment patterns is thus of high political interest.

The most challenging current problem in German economic policy is the high unemployment rate. Especially less qualified workers are affected by unemployment as becomes apparent from Figure 1.[2] In 1995, unemployment figures for unskilled workers were three times higher than for workers with completed vocational training (skilled workers, *Berufsschulabsolventen*) and workers who have completed a vocational and an additional technical training (technical skilled workers, *Fachschulabsolventen*) and roughly four times higher than for technical college (*Fachhochschule*) and university graduates. Further, the gap between unemployment levels of low and high skilled labor has steadily widened since the German unification.

Many politicians and economists hoped that the fast growing service sector could mitigate the unemployment problem of the less educated. Indeed, total employment in services has increased by 23.7 percent in West Germany between 1987 and 1995.[3] However, employment gains were unequally distributed across skill groups, even in services. An analysis of Mikrozensus data for the years 1991, 1993 and 1995 reveals that the share of university and technical college graduates in the sector "business related services" increased by roughly 1.5 percentage points while the share of unskilled workers decreased by 2.2 percentage points.[4]

insert Figure 1 about here

The decreasing demand for low–skilled workers is well documented in the existing literature, at least for manufacturing industries. While there is no consensus between labor economists, most researchers believe that *skill–*

[1] See OECD (1996) and Papaconstantinou (1997).

[2] Source: Mikrozensus and Institut für Arbeitsmarkt– und Berufsforschung (IAB), Nuremberg, various issues.

[3] Source: IAB and ZEW (Mannheim Regions Monitor).

[4] Source: ZEW–70 percent sample of the Mikrozensus.

biased technological change, (Bound and Johnson, 1992), is the main reason for the decline in the demand for unskilled labor. That skill–biased technological change is the main explanation for detoriation in the demand for low skilled workers has been shown for many developed countries.[5] Most of these studies are concerned with manufacturing industries. Some studies additionally investigate a very broadly defined service sector, often simply defined as "non–manufacturing". Such a broad definition of services clearly is inappropriate given the heterogeneity of this sector.

In this paper, I concentrate on business related services, an increasingly important and, due to very limited data availability, not well researched part of the service sector.[6] Business–related services proved to be a driving force behind the increase in employment in the service sector. Employment in business related services rose by 42.6 percentage points between 1987 and 1995 while employment figures for personal, social and distributive services increased by 9.4, 18.8 and 14.0 percentage points, respectively.[7] Employment in manufacturing decreased by 8.9 percentage points in the same period.

By using a German panel data set, this paper shows that a shift toward high skilled labor is also present for business related services. The effect is permanent rather than, due to cyclical fluctuations, transitory. Since the data set allows to explicitly distinguish between the different skill levels — (1) university and technical college graduates in the natural sciences, (2) university and technical college graduates in the social sciences,[8] (3) technical skilled labor, (4) skilled labor and (5) unskilled labor —, major criticisms related to the construction of human capital proxy variables put forward by Leamer (1994) can therefore be overcome.[9]

Another novel feature of this paper is that it uses micro–level data to uncover the determinants of employment shifts. A weakness of most existing studies which use aggregated data is that the distinction between "wi-

[5]See OECD (1996) and Papaconstantinou (1997).

[6]The inappropriate provision with data on the service sector in Germany has recently been criticized by the Council of Economic Advisors (Sachverständigenrat, 1997) and Hax (1998). Waller (1997) describes that a data lack for the service sector is also present for most European countries.

[7]Source: IAB and ZEW (Mannheim Regions Monitor). Both the IAB and the Mannheim Regions Monitor data use a broader definition of business related services than I do in the rest of this paper. Specifically, I use four–digit industry classifications while the IAB and the Mannheim Regions Monitor data use three–digit industry classifications. More disaggregated data are not available at the moment.

[8]These first two skill categories are grouped into one "academic" skill group in the subsequent econometric analysis.

[9]Leamer (1994) points out that separation of workers into 'production" and "non–production" is not an appropriate device for studying income inequality.

thin" and "between" industry shifts of employment patterns is not always clear–cut. The micro–level data used here allow to thoroughly investigate changes within a single firm. A central finding of this paper concerns the impact of investment in physical capital and in information and communication technology (IT) on the demand for heterogenous labor.
The microeconometric evidence presented here supports the skill–biased technological change hypothesis. It turns out that total investment per capita has a significantly negative effect on the demand for unskilled labor and a significantly positive impact on the demand for technical skilled labor. The share of IT–investment in total investment has a significantly positive impact on the demand for university graduates and a significantly negative impact on the demand for workers with completed vocational training. Griliches' (1969) capital–skill complementarity hypothesis is thus validated for high skilled labor.
Labor cost, differentiated by skill groups, do not affect the demand for high skilled labor but significantly negatively influence the demand for low skilled labor. Financial distress variables turn out to have a significant and negative effect only on the demand for unskilled labor giving evidence for labor hoarding effects for the better educated.

The paper proceeds as follows: Section 2 briefly reviews existing studies on technological skill bias and capital–skill complementarities, section 3 describes the data sets, section 4 presents evidence for shifting employment patterns, section 5 introduces a simple theoretical model for the demand for heterogenous labor, section 6 discusses estimation results, and section 7 concludes with a summary and suggestions for further research.

2 A brief overview of previous studies

The decline in relative demand for low skilled labor has given rise to an increasing amount of literature. Four main explanations can be found: (1) skill–biased technological change, (2) Stolper–Samuelson effects of increased exposures from trade with developing countries, (3) decreasing demand for goods where a large amount of high skilled labor was needed (between–industry shifts) and (4) a relative increase in the supply of high skilled labor.

Berman et al. (1994) point out that skill–biased, or low skilled labor–saving, technological change is the driving force behind the decline in relative demand for low skilled workers in the US since 1979. Skill–biased technological change means that it is the increased use of new technology, such as information and communication technologies, which has caused wages and employment prospects of low skilled labor to detoriate.
Bound and Johnson (1992) find that skill–biased technological change is a main explanation for the phenomenon that during the 80's wages for the more educated workers increased while wages for the less educated decreased, leaving the average wage level constant. Also, Bound and Johnson (1992) give evidence for within rather than between industry shifts. Support for their finding comes from Berman et al. (1994), who show that the impact of technological–skill bias outweighs Stolper–Samuelson effects of increased exposures to trade from developing countries. Effects of increased defence expenditures in the 90s are also dominated by technological skill bias.[10]
For ten OECD countries, Berman et al. (1997) show that it is skill–biased technological change rather than increased trade with developing countries which has caused the decline in relative demand for low skilled labor. Wolff (1996), who uses data from the US dictionary of occupational titles, comes to the conclusion that due to technical change more complex and interactive skills were increasingly demanded between 1950 and 1990, pushing up the relative demand for more educated labor.
Conflicting evidence for skill–biased technological change comes from Goux (1996) for France and Robinson and Manacorda (1997) for Great Britain. Goux (1996) finds that the main reasons for the decline in relative demand for low skilled labor between 1970 and 1993 are the decreased demand for goods which require low skilled labor as input and the increased supply – and an associated decline of their relative earnings – of high skilled labor. Robinson and Manacorda (1997) also stress the impact of labor supply conditions on skill shifts for the period 1984–1994.[11]
While there exists no general agreement on the main reason of the decline of the relative demand for low skilled labor, the validity of Griliches' (1969) capital–skill–complementarity hypothesis is unchallenged. Using Swedish data, Bergström and Panas (1992) show that the capital–skill hypothesis

[10] The reason why Berman et al. suspected the increased defense expenditures to have a positive effect on the demand for high skilled labor is that the armaments industry is very R&D and hence skilled labor intensive.

[11] Acemoglu (1997) presents a theoretical framework which focuses on the impact of supply of different skills on the direction of technical change.

is valid for alternative specifications of the production function.
Specifically, the impact of modern IT technology has gained much attention in recent contributions. According to Autor et al. (1997), the industries which have upgraded their workforce are those with high computer usage. They conclude that 30–50 percent of the skill changes in the US since the 1970s are accounted for by computers. The estimations of Berndt et al. (1992) give evidence for complementarity of capital and both high tech capital and skill. Bartel and Lichtenberg (1987) show that with growing plant and equipment age the demand for educated workers declines. In a case study in the banking industry, Levy and Murnane (1996) conclude that computers have increased the demand for skilled labor but the reason for the increase is foremost the way PCs changed the scope of banking activities and to a lesser extent changing skill requirements.
Machin (1996), using British data, shows that within–industry and within–establishment shifts in labor demand are related to technological change indicators. In a comparison between Great Britain, Sweden, Denmark and the US, Machin et al. (1996) find evidence for high skilled labor and new technology complementarities.
Skill–biased technological change as well as capital–skill complementarities are also well documented for Germany. Fitzenberger et al. (1995), investigating the wage structure, give evidence consistent with the skill–biased technological change hypothesis. A recent contribution by Steiner and Mohr (1998) finds no evidence for effects of international trade on the demand for heterogenous labor but empirical results point at skill biased technological change. Falk and Koebel (1997) in a study for 28 sectors of the German economy find weak evidence for technological skill bias. FitzRoy and Funke (1995) show capital and white collar labor complementarities.

Almost all of the studies mentioned above use highly aggregated data which do not account for differences within a single sector. This paper adds to the existing literature in that it focuses on a rather homogeneous segment of the service sector. Utilization of micro–level data makes it possible to reveal the determinants of shifting labor demand within individual firms. Also, many studies use very broad categorizations of skill levels. Early studies simply differentiate between blue collar and white collar labor, more recent ones differentiate between occupations. Neither of both give precise information on whether an individual is skilled, semi–skilled or unskilled. The dataset used in the empirical investigation allows to directly distinguish between five different skill groups: university graduates from the natural and social sciences, technical skilled, skilled and unskilled workers.

3 Data

The lack of data on the service sector has recently been criticized by various authors [Bullinger (1997), Sachverständigenrat (1997), Waller (1997), Hax (1998)]. In reaction to this, the ZEW started to conduct a business survey in the ten business related service sectors in cooperation with Germany's largest credit rating agency, CREDITREFORM. This survey is called the Service Sector Business Survey (SSBS). The SSBS is a stratified random sample, stratified with respect to sector, three employment classes and region (East/West Germany). Data provided by CREDITREFORM served as the sampling frame.[12]

The panel information from the SSBS is useful for the analysis of the direction of changes in the demand for heterogenous labor. However, for an investigation of the determinants of skill shifts, it does not contain enough information. Therefore, the first — and up to now only available — wave of the Mannheim Innovation Survey in the Service Sector (MIP–S) is used in the second part of the empirical investigation.

The Service Sector Business Survey

The definition of business related services is controversially dicussed in the literature.[13] To the author's knowledge, no clear-cut and broadly accepted definition exists. Some authors, e.g. Hass (1995) and Strambach (1995), define business related services by simple enumeration of sectors. Since it is probably not worthwhile to add to the definition discussion, I will follow this convention. The sectors defined as business related services are: software, chartered accountancy and accountancy, consulting, architecture, technical support and planning, advertisement, vehicle rental, machine rental, transport, and waste and waste water removal.

By and large, these are "knowledge–based services" [Alic (1997)]. The firms participating in the SSBS are interviewed quarterly since June 1994.

[12] Details on the SSBS can be found in Kaiser and Buscher (1998).

[13] See Homburg and Garbe (1996) for a survey.

The one page SSBS–questionnaire consists of two parts. In the first part, the participating enterprises are asked to indicate whether their prices, profits, turnover, employment and demand increased, stayed the same or decreased during the last quarter. While the first part of the questionnaire does not change quarterly, the second does. The second part is used to cover topics of current economic interest.

Throughout this paper the 6th (1995), 10th (1996) and 14th (1997) wave of the SSBS are taken, all corresponding to the first quarter. These waves included in the second part of the questionnaire a question on expected and realized changes – depicted on an ordinal scale – in the number of employees differentiated by skill levels. The original question in the SSBS questionnaire is: "In what direction did your number of employees change in the last twelve month within the following skill groups?". Answers could be given on a three–point scale (increase, no change or in employment figures). It is not known from the SSBS how many employees of the different skill levels are actually employed by an individual firm. Only qualitative information on the direction of change is observed.

The SSBS is an unbalanced panel. On average, 1000 firms participate quarterly. 314 firms participated in all of the three waves in consideration, 278 two times and 866 just once.

The ZEW Innovation Survey in the Service Sector (MIP–S)

This data set was originally collected in order to analyze the innovation behaviour of the German service sector. It is thoroughougly described in Licht et al. (1997).

The MIP–S is a mail survey which was designed and carried out in 1995. The survey's population refers to all firms with more than four employees found in the records of CREDITREFORM.[14] The CREDITREFORM data were used to stratify the sample by sector and firm size classes as well as by region (East/West Germany). The survey is restricted to marketed services and, therefore, only comprises firms from wholesale and retail trade, transportation, banking, insurance, transport, software, technical consultancy. Since the industry affiliation is not as disaggregated as in the SSBS, in the second part of the empirical investigation only transport, software, consulting and other business services — among these the other seven sectors covered by the SSBS — are considered.

[14] Due to the inadequacy of official registers, this source seems to be the most accurate available sampling frame.

Overall, about 2,900 firms participated in this voluntary survey. 1,750 belong to transport, consultancy, software and other business services.
The survey design extends the traditional concept of innovation surveys in manufacturing as summarized in the OECD Oslo-Manual (1997) to the service sector. Information collected in the questionnaire include (1) general information about the firm (size, industry, sales, number of employees, labor costs, exports, strategic management objectives, customers and product characteristics), (2) workforce of the firm and (3) investment in new physical assets and investment in information technologies.

4 Evidence for shifting employment patterns

In this section it will be shown that employment patterns are also shifting in business related services and that this effect is persistent, rather than transitory.
Before proceeding, a few words should be devoted to the dimensions of the different skill groups relative to total employment in business–related services. Table 1 displays mean, median and standard deviation of the shares each skill group in total employment. The data are taken from the MIP–S and are expanded.[15]

Table 1 shows that workers with completed vocational training make the largest share of total employment in business–related services. The two academic skill groups taken together are as important as unskilled labor.

The figures in Table 1 have been calculated from the MIP–S since a drawback of the SSBS data is that they do not contain information about the actual employment figures for the different skill levels. Therefore, for a first view on employment patterns in business related services, the balance between the share of enterprises answering that employment in a certain skill level has increased minus the share of enterprises reporting a decrease is considered. A positive balance means that the share of enterprises

[15]The MIP–S is a stratified random sample, stratified with respect to sectors, regions and employment classes. The sample was drawn proportionally. The expansion factors are calculated from a sampling frame provided to the ZEW by CREDITREFORM as the inverse of the drawing probability corrected by non–response.

Table 1: Share of each skill group in total employment in business related services

	mean	median	std. dev.
univ. grad. Nat. sc.	0.14	0	0.24
univ. grad. Soc. Sc.	0.08	0	0.14
techn. Skilled	0.13	0.06	0.17
skilled	0.43	0.40	0.30
unskilled	0.22	0.08	0.29

Table 1 displays mean, median and standard deviation of each skill groups share in total employment. Source: MIP–S.

reporting an increase is larger than the share of enterprises reporting a decrease. Figure 2 shows the balances for the different skill categories for 1995, 1996 and 1997. As in Table 1, employment weights are attached to each enterprise.[16]

insert Figure 2 about here

Figure 2 shows that the relative demand for skilled and unskilled labor has declined between 1995 and 1997. Unskilled labor has undergone a decrease in employment for the entire period. Employment opportunities did not change much for technical skilled workers. University graduates did even have relatively good employment chances in 1996, when a majority of enterprises reported decreased total employment figures. The employment situation for skilled and unskilled workers worsened considerably in 1996. It thus seems that cyclical fluctuations merely affected the amplitude and not the direction of employment patterns in business related services.
One problem with figure 2 is that information on what happens to an individual firm over time is not taken into account: these balances only reflect an average across the participating firms rather than skill level changes of an individual enterprise.
Whether if these skill shifts are transitory rather than persistent is central to the discussion about shifting employment patterns. It could be argued that cyclical fluctuations drive the decreased relative demand for low skilled labor. Due to lower hiring and firing costs for low skilled labor, labor hoarding is more likely to occur for the more qualified in times of a sluggish economy.
A standard device in analyzing panel data is to calculate transition probabilities. Transition probabilities give the probability that a firm or an individual switches from one category to another (or stays in one catego-

[16] The SSBS data are expanded in a similar way as the MIP–S data.

ry) given the initial decision. Such transition probabilities are depicted in Table 2. The probability to either switch from "up" to the other categories "unchanged" and "down" or to stay in "up" is shown in columns two to three of Table 2. The probability to stay in the "up" category is largest for high skilled labor. While 47 (37) percent of the firms which initially reported increased employment for university graduates from the social sciences (natural sciences) stay in this category, this is true for only roughly 24 percent for skilled and unskilled workers. 15 percent of those firms which initially indicated "up" for technical skilled workers end up indicating "up".
The strongest persistency effect is present for the "unchanged" category. A majority of enterprises which initially indicated unchanged employment figures keep reporting "unchanged" employment figures. The effect is present across all skill groups. However, the probability to switch from "unchanged" to "up" is higher for the high skilled while just the reverse is true for the low skilled. Likewise, the probability to switch from "unchanged" to "down" is considerably higher for the low skill groups.
Transition probabilities for the "down" category do not differ much across skill groups. Firms tend to switch, if at all, from "down" to "unchanged". A similar share of enterprises switches from "down" to "unchanged" as stays in "down".
It is quite striking that the probability to switch from "down" to "up" or from "up" to "down" – except for the unskilled group – is relatively low. This indicates that firms only gradually make adjustments to their labor force.

The inspection of transition probabilities shows three things: (1) persistency is quite large especially for the "unchanged" category and for the probability to stay in "up" for the high skilled worlers, (2) the probability to stay in "unchanged" and the probability to switch from "unchanged" to "up" is larger for high skilled labor than for low skilled labor and (3) firms rarely switch from "up" to "down" – with the exeption of the demand for unskilled labor – or from "down" to "up".
The descriptive analysis of the SSBS dataset gives thus evidence that shifting employment patterns are present for business related services and that the effect is persistent rather than transitory. The rest of this paper is devoted to uncover the determinants of these skill shifts.

Table 2: Transition probabilities

	from "up" to...			from "unchanged" to...			from "down" to...		
	"up"	"unch."	"down"	"up"	"unch."	"down"	"up"	"unch."	"down"
univ. grad. Nat. Sc.	36.9 (45)	50.8 (62)	12.3 (15)	13.7 (39)	75.8 (216)	10.5 (30)	3.7 (3)	48.2 (39)	48.2 (39)
univ. grad. Soc. Sc.	47.3 (35)	46.0 (34)	6.8 (5)	11.1 (33)	76.5 (228)	12.4 (37)	14.6 (7)	41.7 (20)	43.8 (21)
techn. Skilled	14.6 (7)	77.1 (37)	8.3 (4)	5.8 (21)	83.4 (301)	10.8 (39)	1.5 (1)	47.0 (31)	51.5 (34)
skilled	24.3 (26)	65.4 (70)	10.3 (11)	7.9 (35)	74.0 (327)	18.1 (80)	3.3 (4)	49.2 (59)	47.5 (57)
unskilled	24.6 (14)	49.1 (28)	26.3 (15)	9.1 (33)	71.7 (261)	19.2 (70)	4.6 (5)	52.8 (57)	42.6 (46)

Table 2 shows that, e.g., the probability that an enterprise switches from indicating increased employment figures to unchanged employment figures for technical skilled workers is 77.1 percent. The value in brackets give the actual frequencies. Source: SSBS.

5 Theoretical framework

In this section a simple theoretical model for the dynamic demand for heterogenous labor is outlined.

The theoretical framework stems from the classical paper by Nadiri and Rosen (1969) which basically is an extension of the partial adjustment model widely used in economics. These standard dynamic labor demand models [Hamermesh (1993)] are derived from a quadratic adjustment cost function of the form

$$C(\dot{L}) = a\dot{L} + b\dot{L}^2, \quad a,\ b > 0, \tag{1}$$

where $\dot{L}$ is the change of employment figures between periods t and $t-1$. Equation (1) implies that it is costly for a firm to rapidly alter employment levels since adjustment cost rise with the square of changes.

If perfectly competitive markets and constant interest rates are assumed, firms wish to maximize their discounted present value, $\Pi(t_0)$ at period t_0:

$$\max_{L_t} \quad \Pi(t_0) = \int_0^\infty \{F(L_t) \ - \ wL_t \ - \ C(\dot{L}_t)\}\ e^{-rt}\ dt, \tag{2}$$

where w denotes the wage rate and r the discount rate. The production function, only dependent on labor input, is denoted by $F(L_t)$ and a and b are parameters. The Euler equation which describes the optimal path of equation (2) is given by

$$2b\ddot{L}_t \; - \; 2br\dot{L}_t \; + \; F'(L_t) \; - \; w \; - \; ra \; = \; 0. \tag{3}$$

In the steady state, $\ddot{L}_t \; = \; \dot{L}_t \; = \; 0$ and the equilibrium labor demand is given by $F'(L^*) \; = \; w \; + \; ra$, where L^* denotes the equilibrium or optimal level of employment. The latter differs from the standard result from static optimization only by the adjustment cost component ra.
If static expectations about wages and prices are assumed, the optimal path of employment written in discrete time is then given by

$$\Delta L_t = \gamma \; [\; L^* \; - \; L_{t-1} \;], \; \gamma > 0, \tag{4}$$

where L^* is the equilililibrium or optimal employment level. The parameter γ denotes the size of adjustment.
If, e.g., four factors of heterogenous labor $(L_{1t}, \ldots, L_{4t})$ are used in the production, and output is assumed to be exogenous, equation (4) can be generalized to [Nadiri and Rosen (1969)]

$$\begin{bmatrix} \Delta L_{1t} \\ \Delta L_{2t} \\ \Delta L_{3t} \\ \Delta L_{4t} \end{bmatrix} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix} \begin{bmatrix} L^*_{1t} - L_{1t-1} \\ L^*_{2t} - L_{2t-1} \\ L^*_{3t} - L_{3t-1} \\ L^*_{4t} - L_{4t-1} \end{bmatrix}. \tag{5}$$

In the Nadiri and Rosen (1969) paper, variables influencing L^*_{jt} $(j = 1, 2, 3, 4)$ are output and factor price ratios. Due to measurement problems, capital stock was not included.

In the empirical specification of equation (5) used in this paper, output is approximated by turnover per capita. Difficulties in measuring capital endowment of individual firms also arise in the MIP–S data. Therefore, I assume that the capital stock K_t is proportional to investment I_t, $K_t = \alpha \, I_t$. This assumption is probably not so misleading since the main input factor in the production of services — despite labor, of course —is capital in the form of IT technologies [Maleri (1997, ch. 2)] which is depreciated quickly. In the estimation equations, both investment per capita and investment in IT as the share of total investment, are included.[17] The share of the jth skill group in total employment can be directly calculated from the MIP–S. More difficulties arise from the calculation of prices for labor and capital.

[17] I have chosen different denominators in order to avoid potential collinearity problems.

I assume that differences in interest rates only arise from different credit standings. Therefore, in the empirical analysis a potential credit rationing variable is constructed as an approximation for the interest rate. It is coded one if an enterprise reported in the MIP–S questionnaire that either debt or equity shortages hampered innovative activity. I hereby follow Winker (1996).
From the MIP–S dataset neither labor cost nor wages for the different skill groups can be directly observed. Fortunately, the dataset gives information on total labor cost and the share of the different skill groups per firm. From these two pieces of information a labor cost decomposition is derived in appendix A so that labor cost for each skill group j can be calculated.

In order to elaborate more on the dynamics of demand for heterogenous labor, the *expected* rather than the actual change of labor demand is considered here. Specifically, in the MIP–S questionnaire firms indicated on a five point scale the expected change in the demand for heterogenous labor, $E[\Delta L_{t+1j}]$. As in the derivation of equation (5), I assume static expectations. However, for turnover the MIP–S gives more precise information. Firms are also asked to indicate on a five point scale what direction the change of turnover will take in the next period. Thus, as an approximation of expected turnover in period $t+1$ I use turnover in period t and the information from expected turnover changes, included in the estimation equation as dummy variables.
The estimation equation thus includes the following variables (j denotes the corresponing skill level and $i = 1, 2, 3, 4$):

(1) labor cost by skill j group, LC_j

(2) total investment per capita, INV^{pc}

(3) IT–investment as share of total investment, IT

(4) number of employees in each skill group, $LEVEL_i$

(5) turnover and turnover expectation (as dummy variables), $TEXP$

(6) potential credit rationing dummy variable, RAT.

The total investment and turnover variables are transformed by taking the natural logarithms.

I further assume that firms reach their decision on employment changes in skill group j conditional on an information set Ω_j which includes the variables noted above and an iid gaussian distributed error term ϵ_j which is known to the firm but not to the econometrician. Thus, the following equation is estimated

$$\begin{aligned} E[\Delta L_{jt} \mid \Omega_j] = \gamma_1 LC_j + \gamma_2 INV^{pc} + \gamma_3 IT + \gamma_4 TEXP \\ + \gamma_5 RAT - \sum_i^4 \beta_{ji} LEVEL_i + \epsilon_j, \end{aligned} \tag{6}$$

where ϵ_j is an iid gaussian distributed error term.
In order to control for observable firm heterogeneity, various other variables are included in the estimation equation. These are export activity, firm size, sector affiliation and regional affiliation (East/West Germany). Also, two dummy variables which (a) indicate that a firm either already has or expects foreign competitors in the home market and (b) indicate that it expects foreign competition but does not yet have to compete with foreign firms are constructed. Exporting activity and expected or present foreign competition may force an enterprise to upgrade the skill level of its workforce in order to be more competitive. The impact of international competition is incorporated by an export dummy variable. Size effects are captured by the logarithm of the total number of employees and its square.

The dependent variable of equation (6) can be directly adopted from the questionnaire. The participating firms are asked: "Please give your opinion on the expected development of employment in your enterprise by skill levels for the period 1995 until 1997". Five answering categories were allowed: (1) "strong increase", (2) "increase", (3) "unchanged", (4) "decrease" and (5) "strong decrease". It is thus not known explicitely how large the expected change in labor demand is, the direction of change and and indicator of the maginitude of change is available. Table (3) shows how the answers were distributed across the categories and skill groups. As it can be seen, the extreme categories are very thinly occupied so that the decrease/strong decrease and the increase/strong increase are summarized for the empirical analysis.

Since there should be (and actually are) only marginal difference between the demands for university graduates from the natural and social sciences,

Table 3: Distribution of answering categories across skill groups

	univ. grad. nat. sc.	univ. grad. soc. sc.	techn. skilled	skilled	unskilled
strong decrease	3.00	2.53	1.83	3.30	8.10
decrease	4.53	3.94	6.56	11.61	13.36
no change	72.88	72.56	67.26	52.09	61.23
increase	16.71	17.80	21.81	27.87	13.83
strong increase	2.88	3.17	2.54	5.13	3.49

both skill groups are aggregated into to an "academic" skill group. I proceeded as follows: if a firm expected decreased (increased) employment figures in both skill groups or if it expected decreased (increased) employment figures for one skill group and unchanged figures for the other, I coded the new "academic" skill group variable as "decreased" ("increased"). If a firm reported unchanged figures for both groups, the new variable was also coded as "unchanged". By proceeding this way, 37 observations were lost because firms indictated increasing employment figures for one group and decreasing figures for the other.

If technical change is actually substitutive to less skilled labor and complementary to more skilled labor, investment per capita and IT–investment relative to total investment should have a significantly negative impact on the demand for unskilled labor and a significantly positive impact on the demand for high skilled labor. If this is actually the case, this is evidence in favor of skill–biased technological change. Capital then replaces low skilled labor and favors high skilled labor.
Labor cost should exhibit a negative effect on labor demand at least for the skilled and unskilled.
The capital shortage variable should turn out to be significantly negative for low skilled labor while having no impact on high skilled labor due to labor hoarding effects. As Bartel and Sicherman (1995) show, firms invest more in the human capital of high skilled labor which implies that low skilled labor is more likely to be released in times of economic trouble.
In order to account for the discreteness of the expected change of employment figures across different skill groups, separate ordered probit models are estimated for each of the skill groups.[18] Simultaneous estimation of the ordered probit models where correlation among the error terms is allowed

[18]See Greene (1997, ch. 19.8) for details on the ordered probit model. The software package STATA5.0 was used for the estimation.

(multivariate probit models) clearly is a topic for furter research. Albert and Chib (1993) propose a Bayesian estimation approch which is advantegeous over classical estimation in that it does not require calculation of multivariate normal integrals and provides the basis for exact inference, as opposed to inference relying ond asymptotive approximations.

6 Estimation results

Estimation results are presented in Table 4. The share of IT–investment in total investment influences expected labor demand quite differently across skill groups. It has a significantly positive impact on university graduates and is negatively significant for skilled labor. Total investment is significantly negative in the demand for unskilled labor. Neither total nor IT investment has a significant effect on the expected demand for technical skilled labor.[19]

The positive impact of IT–investment on the demand for high skilled labor is consistent with the findings by Autor et al. (1997) and Wolff (1996). Both papers show that the number of PCs per employee positively affects the demand for high skilled labor. High skilled labor is needed to implement new IT–technologies in a firm. IT–technology then is used to replace skilled labor. A little surprisingly, IT investment does not seem to influence the demand for unskilled labor at all. However, total investment has a negative and significant impact on the demand for unskilled labor pointing at a substitutive relation between unskilled labor and capital. For unskilled labor only the total amount of investment and not the distribution of investment across types of investment matters.

In Acemoglu's (1997) interpretation, IT–investment is "directed" at replacing skilled labor while investment generally is directed at replacing unskilled labor.

IT–investment favors university graduates and substitutes skilled labor. Likewise, total investment complements technical skilled labor and substitutes unskilled labor. Thus, evidence for both skill–biased technological change and capital–skill complementarities is found.

[19]Note that no comparison of the coefficients is possible across equations due to the scaling problem in ordered probit and ordered logit models.

insert table 4 about here

Labor costs only have a significant impact on the expected demand for skilled labor. This implies that decreased labor costs could improve employment prospects at least for skilled labor. This reasoning does not apply to the unskilled. Even lower labor cost would not improve employment prospect indicating that the abilities of this group simply do not match the current demand for skills.
Potential credit rationing only influences the demand for unskilled labor significantly. The effect is negative. This implies that firms lay off low skilled workers if getting into economic trouble. A reason for this may be that firms invest more in human capital accumulation for high skill labor than for low skill labor, as shown by Bartel and Sicherman (1995) for young workers in the US, so that the opportunity costs to fire low skilled workers are lower than for high skilled workers.
While the dummy variables for expected turnover are jointly significant for all skill groups, where favorable turnover expectations increase the probability to hire additional labor and vice versa, the level of turnover is significant (and positive) for academics and technical skilled labor only. This suggests that for employing the relatively expensive academics and technical skilled workers good business prospects are not sufficient. A good performance in the recent year is also needed. Good business prospects increase c.p. the expected demand for labor across all skill levels, the absolute level plays a role only for the demand for the higher skill groups.
The parameters of $LEVEL_j$ cannot really be interpreted as own and cross adjustment cost terms due to the ordinal nature of the dependent variable. However, it turns out that the number of university graduates and technical skilled workers increases the probability to expect increasing employment figures in these two categories. This implies that workers from these two categories are preferably hired if there already is a considerable number of workers of this skill level.
The control variable for East German firms turns out to be significantly negative for all but the unskilled and academics groups, indicating worse general business conditions for East Germany. Exporting firms do not differ from non–exporting firms in their demand for heterogenous labor. Except for the expected demand for university graduates, the same is true for firms which expect or already face foreign competition in the home market. Both expected and present foreign competition increase the probability to hire university graduates.

7 Conclusions and suggestions for further research

The empirical investigation gives evidence that shifting employment patterns are present for business related services. While the absolute effect remains unclear due to the lack of quantitative data, descriptive panel data analysis shows that a shift towards high skill labor is occurring and that this effect is persistent.
By further analyzing the reasons for these skill shifts I find that technological change and capital–skill complementarities are important determinants. Technological skill bias is a controversely discussed topic in public policy. If technology decreases employment chances of low skilled workers, policy has to put much effort into an upskilling of the less qualified. Low skilled workers are said to have more difficulties to adapt to new technologies than high skilled workers. Technological change favors the skilled and educated workers. The effect may be especially severe for services where IT investment makes up a large share of total investment.
By estimating separate ordered probit models for four different skill groups, I find that the larger the share of IT investment in total investment the higher is the probability to expect increased employment figures for university graduates and the lower is the probability to expect increased employment figures for skilled labor. Total investment turns out to be complementary for technical skilled labor and substitutive for unskilled labor.

A weakness of this approach is that the demand equations are estimated separately for the five skill groups. Simultaneous estimation allowing for correlation among the error terms appears to be more adaequate here. Also, simultaneous estimation where the expected changes in the jth ($j = 1, 2, 3, 4$) skill groups serve as explanatory variables in the determination of changes in the ith skill group ($i \neq j$). The appropriate microeconometric tool would be a nonlinear conditional method of moments estimator proposed by Newey (1990 and 1993).
Further, the impact of innovative activity on the demand for heterogenous labor should be of great interest. However, since innovative activity in services is often associated with organizational changes which in turn affect investment in information and communication technologies, the innovation variables have to be instrumented. Instrumentation will be faciliated as soon as the second wave of the MIP–S will be available.

Figure 1: Unemployment levels by skill group

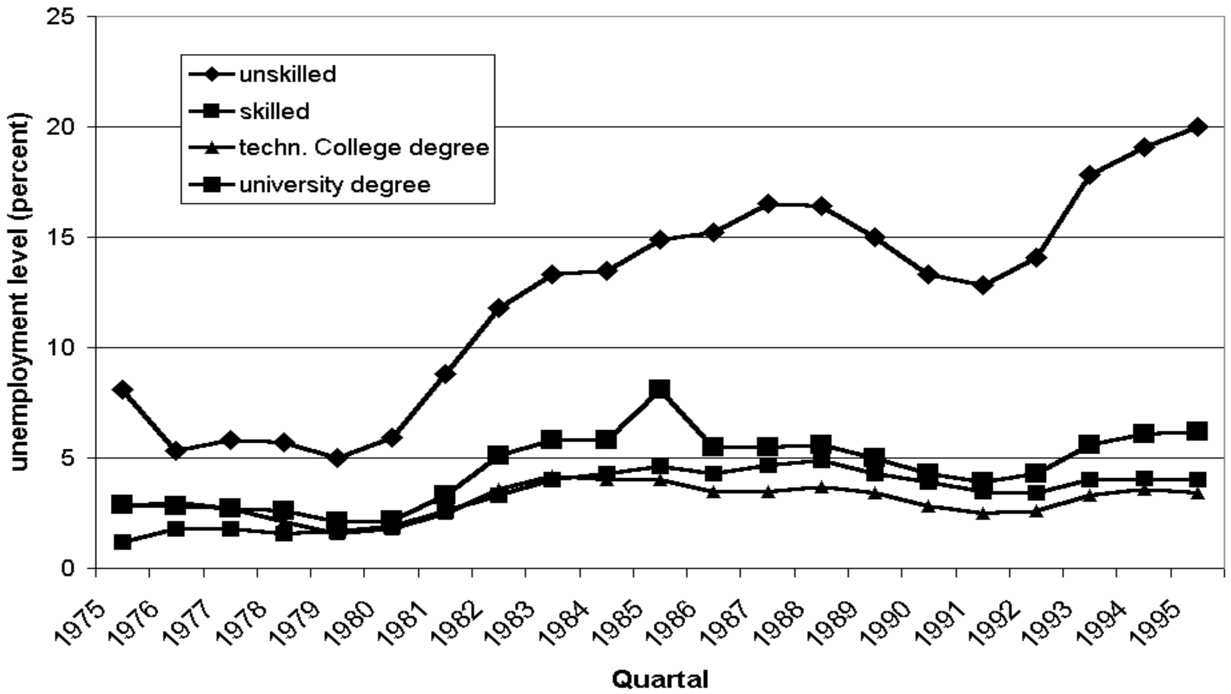

Figure 1 displays unemployment levels by skill groups for the period 1975 – 1995 (West Germany). Source: IAB and Mikrozensus, various issues.

Figure 2: Balance of employment judgements

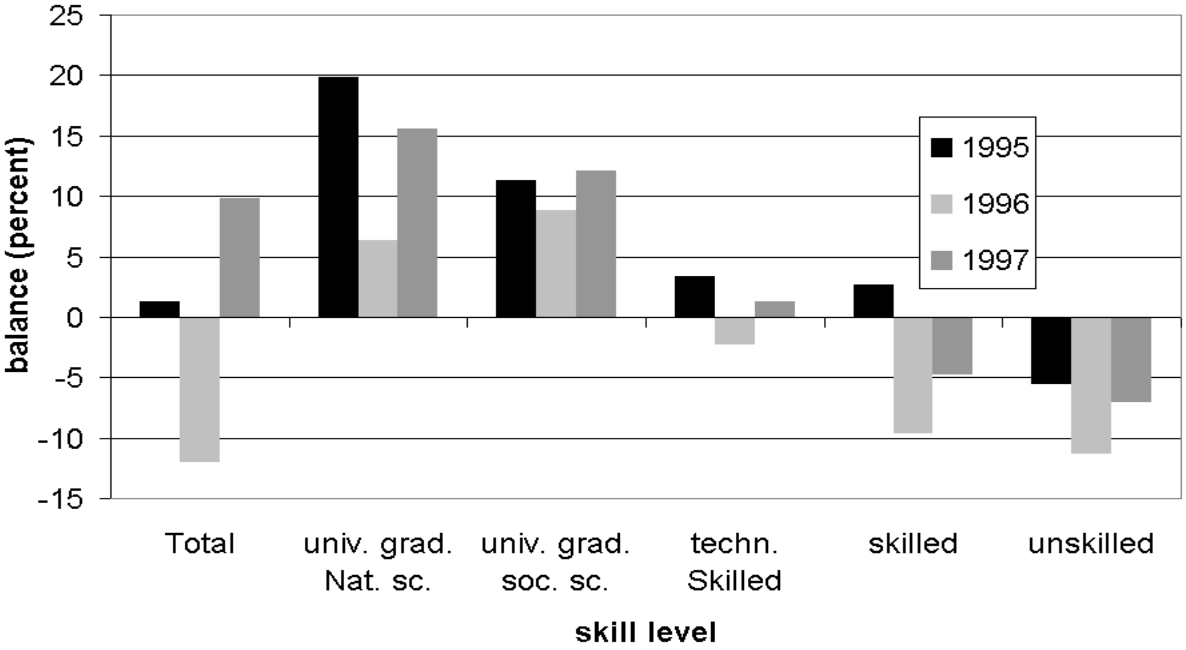

Figure 2 shows the share of firms reporting increased employment figures minus the share of firms reporting decreased employment figures for 1995, 1996, 1997. Source: SSBS.

Table 4: Ordered probit results results of labor demand equations by skill group

	univ. grad.			techn. skilled			skilled			unskilled		
	Coeff.	t-stat.	p-value	Coeff.	t-stat.	p-value	Coeff.	t-stat.	p-value	Coeff.	t-stat.	p-value
LC_I	0,001	0,492	0,623	0,000	-0,277	0,782	-0,004	-2,712	0,007	-0,001	-0,765	0,444
IT	0,004	2,581	0,010	-0,001	-0,732	0,464	-0,003	-1,998	0,046	0,000	0,270	0,787
log(INV^{PC})	0,020	0,931	0,352	0,022	0,980	0,327	0,006	0,277	0,781	-0,038	-1,779	0,075
log(univ. grad.)	0,035	3,092	0,002	-0,008	-0,669	0,504	-0,033	-3,027	0,002	-0,048	-4,347	0,000
log(techn. skilled)	0,013	1,282	0,200	0,034	3,434	0,001	-0,021	-2,259	0,024	-0,011	-1,112	0,266
log(skilled)	-0,001	-0,071	0,944	-0,015	-0,988	0,323	0,000	-0,021	0,983	-0,046	-3,112	0,002
log(unskilled)	0,016	1,772	0,076	0,019	2,048	0,041	0,020	2,231	0,026	0,009	1,035	0,301
log(turnover)	0,079	1,695	0,090	0,095	2,081	0,037	-0,012	-0,280	0,779	-0,038	-0,875	0,382
turnover exp. --	-0,754	-4,144	0,000	-0,854	-4,651	0,000	-0,956	-5,385	0,000	-0,666	-3,707	0,000
turnover exp. -	-0,477	-3,731	0,000	-0,320	-2,506	0,012	-0,410	-3,378	0,001	-0,083	-0,676	0,499
turnover exp. +	0,228	2,561	0,010	0,018	0,205	0,837	0,142	1,673	0,094	0,236	2,748	0,006
turnover exp. ++	0,690	3,886	0,000	0,378	2,254	0,024	0,487	2,959	0,003	0,511	3,192	0,001
pot. credit rationing	0,022	0,273	0,785	-0,017	-0,214	0,831	-0,067	-0,892	0,372	-0,199	-2,622	0,009
East Germany	-0,159	-1,766	0,077	-0,351	-3,913	0,000	-0,197	-2,304	0,021	0,105	1,227	0,220
transportation	-0,580	-3,381	0,001	0,024	0,146	0,884	0,333	2,107	0,035	0,170	1,069	0,285
consulting	-0,553	-3,501	0,000	-0,075	-0,501	0,616	0,101	0,702	0,483	0,140	0,963	0,335
other	-0,427	-2,889	0,004	0,089	0,637	0,524	0,314	2,360	0,018	0,198	1,467	0,142
foreign comp. expected	0,167	1,619	0,105	0,094	0,912	0,362	0,078	0,796	0,426	0,175	1,768	0,077
foreign comp. present	0,230	2,509	0,012	-0,022	-0,246	0,806	0,031	0,358	0,720	0,111	1,270	0,204
exoprting firm	-0,012	-0,114	0,909	-0,122	-1,219	0,223	-0,037	-0,389	0,697	0,133	1,371	0,170
threshold1	-1,220			-1,222			-1,282			-0,867		
threshold2	0,821			0,936			0,279			0,938		
no. of obs.:	1037			1059			1059			1059		
log-likelihood	-828,797			-834			-993			-949,982		

Table 4 displays ordered probit estimation results for each of the four skill groups.

A Labor cost decomposition

The average labor costs per employee for firm k are given by

$$\frac{\sum_{j=1}^{5} LC_{jk}}{EMP_k} = \sum_{j=1}^{5} w(j)\ \frac{Q_{jk}}{EMP_k} + \epsilon_k, \tag{7}$$

where j denotes the skill level, LC_{jk} the labor costs for skill group j and firm k, Q_{jk} denotes the number of employees in skill group j, EMP_k the total number of employees and ϵ_k is an error term. Then, $w(j)$ are the annual average labor cost for a worker with skill level j. Since Q_{jk}, EMP_k and $\sum_{j=1}^{5} LC_{jk}/EMP_k$ are known, the coefficients $w(k)$ can be estimated by ordinary least squares (OLS). OLS regression results of equation (7) are shown in table A1. Descriptive statistics of the variables used in this and the following estimations are displayed in appendix B. In order to control for observable firm specific effects, various control variables K are also included in the estimation.[20] Returns to education (Mincer, 1991) are reflected by the larger wage coefficients for higher skill levels.
The estimated residuals $\hat{\epsilon}_k$ from the estimated equation can, given correct specification, be interpreted as an unobserved firm specific wage effect. Therefore, total average payroll costs $w_k(j)$ for individual skill levels j and firm k can be decomposed as

$$w_k(j) = \hat{w}(j) + \hat{\gamma}\ K_k + \hat{\epsilon}_k, \tag{8}$$

where $\hat{\gamma}$ is the estimated coefficient of the matrix of control variables K and $\hat{w}(j)$ is the estimated coefficient from equation (7).

Table A1: OLS regression results of wage decomposition equation

	Coeff.	Std. err.
share of univ. grad.	46.0895	2.9436
share of techn. Skilled	33.1552	4.4531
share of skilled	11.9892	2.7328
east	-19.2411	1.4776
export	9.0406	1.8263
caps	-1.7798	0.4620
size2049	3.4135	1.8735
size50249	3.7972	1.7458
size250+	5.0301	2.0937
constant	48.5264	2.6798

[20] Steiner and Wagner (1997) give motivation for the inclusion of firm–specific variables in wage equations.

B Descriptive statistics

Variable	No. of obs.	Mean/Share	Std. Dev.	Median	Type
Labor cost					
LC(univ. grad.)	1420	84.5368	28.7204	81.2716	continuous
LC (skilled)	1420	71.6368	28.7204	68.3716	continuous
LC (skilled)	1420	50.4368	28.7204	47.1716	continuous
LC (unskilled)	1420	38.4368	28.7204	35.1716	continuous
Investment					
IT	1352	30.5806	32.4256	16.6667	continuous
log(INVpc)	1584	0.8348	3.4861	1.8612	continuous
Employment figures					
log(univ. grad.)	1668	0.2118	4.0714	1.3863	continuous
log(techn. skilled)	1648	-0.9138	4.1927	0.6931	continuous
log(skilled)	1651	2.0729	2.9834	2.4849	continuous
log(unskilled)	1651	-0.5850	4.8190	1.0986	continuous
Turnover					
log(turnover)	1659	5.1173	1.1600	5.0239	continuous
turnover exp. –	1677	0.0471	-	-	dummy
turnover exp. -	1677	0.1193	-	-	dummy
turnover exp. +	1677	0.4890	-	-	dummy
turnover exp. ++	1677	0.0811	-	-	dummy
Credit rationing					
RAT	1745	0.3794	-	-	dummy
Control variables					
East Germany	1745	0.3897	-	-	dummy
foreign comp. exp.	1733	0.1852	-	-	dummy
foreign comp. present	1733	0.2949	-	-	dummy
exporting firm	1738	0.1830	-	-	dummy
Labor cost decomposition					
total labor cost	1610	65.8574	108.5058	56.7361	continuous
share(univ. grad.)	1668	0.2223	0.2704	0.0913	continuous
share(techn. skilled)	1668	0.1150	0.1582	0.0556	continuous
share(skilled)	1668	0.4235	0.2937	0.1667	continuous
20-49 employees	1741	0.1953	-	-	dummy
50-249 employees	1741	0.2740	-	-	dummy
geq 250 employees	1741	0.1815	-	-	dummy
transport	1745	0.2264	-	-	dummy
consulting	1745	0.1662	-	-	dummy
other	1745	0.5255	-	-	dummy

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