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IT Capital, Job Content and Educational Attainment

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Non–technical Summary

The impact of technological change on the labor market has always been a major concern of economic research. The discussion even intensified in the last two decades due to the fast diffusion of personal computers at workplaces, and due to the empirical evidence that workers with high levels of education are more likely to use computer technology. This led to the hypothesis that information technologies are skill–biased, implying the labor demand to shift towards employees with higher educational attainment.

This study explores the link between information technologies and employees with higher educational levels by investigating how the introduction of computer technology alters the skill requirements of occupations. It is argued that computer technologies do not replace whole occupations, however, they rather substitute for repetitive and routinized tasks. Compared to previous technological developments that were mainly amenable to routinized manual tasks, computer technologies are additionally able to replace simple human cognition such as perceiving, choosing, and manipulating processes. Furthermore, computer technologies are complementary to analytical and interactive activities.

These technological features of computer technologies shifts the relative skill requirements of occupations towards analytical and interactive activities, for which employees with higher educational attainment have comparative advantages.

The analysis is based on a large data set of employees, covering four points in time, 1979, 1984/85, 1991/92, and 1998/99. The data set contains detailed information on the tasks that employees actually perform on–the–job, the technology they use, as well as on the educational attainment of employees.

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Abstract

Based on a large data set containing information on occupations between 1979 and 1999, this study explores the "black box" surrounding the skill–biased technological change hypothesis by analyzing the mechanisms that induce information technologies to be complementary to employees with higher skill levels. Using direct, multidimensional measures of occupational skill requirements, the analysis shows that IT capital substitutes repetitive manual and repetitive cognitive skills, whereas it complements analytical and interactive skills. These changes in the within occupational task mix result in an increased deployment of employees with high levels of education who have comparative advantages in performing non–repetitive cognitive tasks.

Keywords: skill–biased technological change, job task content, vocational education

JEL classification: O30, J23, J24, C30

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1 Introduction

In the last decades industrialized countries have witnessed a large increase in the supply of more educated workers and rising returns to education. This development favors the argument that technological change has been skill-biased, shifting labor demand towards employees with higher levels of skills. However, "...(skill–biased technological change) also tends to be something of a residual concept, whose operational meaning is often *labor demand shift with invisible cause*" (Bresnahan (1999), p. 340).

This study aims to open the "black box" of skill–biased technological change (SBTC) by investigating the mechanism that induces information technologies (IT) to be complementary to employees with higher levels of education. It is argued that the rapid diffusion of IT capital (which is mainly due to the exogenous price decline in IT devices) causes changes in the requirement for different kinds of skills at workplaces, which in turn shifts in the educational composition of employees.

The analysis is performed using direct measures of occupational skill requirements that are based on the activities that people perform on the job. These activities are classified in six skill categories: *analytical* tasks like research, planning or evaluation activities, *interactive* tasks like the coordination and delegation of work, *repetitive cognitive* tasks like double entry bookkeeping and calculating, *repetitive manual* tasks like machine feeding or running a machine, *non–repetitive manual* tasks like housekeeping or restoring houses, and *computing* tasks. These skill categories have been identified as being particularly important in modern work environments (e.g. Autor et al. (2001), Green et al. (2001), Howell and Wolff (1991), and Stasz (1997)).

The main focus in this study is on within occupational changes in skill requirements, which are assumed to be mainly technology–driven. However, as will be illustrated in the descriptive part of the paper, changes in the distribution of employment by occupational groups may also have important impacts on skill requirements.

The main hypotheses tested are, that (1) IT capital substitutes repetitive manual and repetitive cognitive activities, that (2) IT capital is complementary to analytic and interactive activities, and that (3) IT capital increases the requirement for computing skills. Thus, in contrast to widespread believes, IT capital does not substitute whole occupations. The scope for substitution is limited to certain tasks. This *limited substitution* relationship (Bresnahan (1999)) between IT capital and occupational tasks shifts the demand for labor towards employees with higher levels of educational attainment who are supposed to have a comparative advantage in performing non–repetitive cognitive tasks (Autor et al. (2001)).

The empirical analysis is based on occupation–by–industry groups. These groups are synthesized by aggregating individual level data. The data set contains four waves that were launched in 1979, 1985/86, 1991/92 and in 1998/99 with 26,000 observations on average. The data set is unique in the sense that it draws a clear picture of the task composition of occupations, that is, employees who participate in the survey indicate what they actually do on their jobs. The occupational classifications are constant over time, such that detailed analyses on the changing skill requirement patterns within occupations can be carried out on the basis of the task descriptions. In addition, the data set contains information on the equipment used by the workforce to perform the tasks (for example personal computers, pencils, or typewriters) and information on the human capital of employees.

Using weighted seemingly unrelated regression (SUR) techniques, the main findings are that highly computerizing occupation–by–industry groups are positively related to changes in the requirement for interactive, analytical and computing skills, whereas they are negatively related to changes in the requirement for repetitive cognitive and repetitive manual skills. Depending on the tasks, computerization accounts for between 8 and 137 per cent of the changes in skill requirements.

In addition, structural equations are set up based on temporal ordering of cause and effects. Using three–stage–least–square (3SLS) estimation techniques, the results indicate that the shifts in skill requirements are positively related to changes in the fraction of employees with high levels of educational attainment.

The paper is arranged in 6 sections. The next section discusses previous theoretical and empirical results concerning the relationship between IT capital, job skill requirements, and education. Section 3 describes the data set and the variables. Section 4 presents stylized facts on the occupational, educational, and technological trends in Germany since 1979. Section 5 investigates econometrically the relationship between IT capital, occupational skill requirements, and educational attainment on the basis of synthetic occupation–by–industry groups. Section 6 concludes.

2 Technology, Skills and Education in the Workplace

SBTC is one of the most prominent hypothesis explaining labor market trends across industrialized countries in the last three decades (for example Acemoglu (2002), Acemoglu (1998)). The extensive empirical research devoted to SBTC in recent years also reflects the attention that has been given to this question not only by researchers but also by policy makers. Chennells and van Reenen (1999) give a comprehensive overview of the literature on SBTC, covering the major empirical studies in this field of research. For Germany, empirical studies by Falk (2001), Falk and Koebel (2001), Fitzenberger (1999), and Kaiser (2000) support the view that technological change in the recent years has been skill–biased.

Human capital theory forms the basis of conceptual approaches to skills (Becker, 1964). In this view, skills are defined as the stock of human capital embodied in individuals. However, as this relatively vague definition might already suggest, there are a variety of empirical measurement strategies used to gauge the skill level of individuals.

Most studies use "traditional" skill measures to assess the skill level of employees such as broad categorizations (production workers/non–production workers (Berman et al., 1994) or blue–collar/white–collar workers (Berndt et al., 1992) or levels of formal educational attainment (Kaiser, 2000). These classifications are divisions according to occupational groups which are of limited usability in determining skill requirements. They document the structural shift towards increased deployment of white–collar work in all major sectors of industrialized countries and the increased employment of employees with higher levels of formal education. It is unlikely that they capture homogeneous groups of workers, and that they show what kinds of activities these workers are qualified for. In reality, some blue–collar jobs may for example require more skills than many white–collar jobs. Further, these skill classifications fail to capture the multidimensional nature of skills as set out by Spenner (1983).

In addition, these studies do not distinguish between the skills that people bring to jobs in the sense of individual possessions like knowledge, abilities or capacities and skills that jobs require, that is, skills that are required to perform certain tasks (Spenner, 1983, 1990). This distinction is, however, important since the possession of certain skills cannot be equated with their use. The massive increase in the share of employees with high educational attainment in industrial economies does not necessarily imply the existence of a higher number of skilled jobs (Borghans and de Grip, 2000). People with equal investment in their formal education may attain very different levels of skills. Moreover, the acquisition of skills continues after school, as does the depreciation of skills. In addition, the labor market might use the level of formal education as a signal of some underlying abilities rather than a source of skill supply (Borghans et al., 2001).

The skill measurement strategy in this analysis is in the tradition of studies that use direct measures of skills that rely implicitly on the assumption that the employees' occupational duties are an unbiased measure of employees' skills. Most of these studies use the *Dictionary of Occupational Titles* to analyze how skill requirements of jobs in the U.S. have changed in the last decades (see Autor et al., (2001), Rumberger (1981), Howell and Wolff (1991), and Wolff (2000)).[1] In a nutshell, they find that the changing occupational and industry employment patterns resulted in a upgrading of cognitive and interactive skills and a declining demand for manual skills.

Two of these studies investigate the relationship between changes in skill requirements and technological developments. Autor et al. (2001) use five measures of occupational skill requirements: non–repetitive cognitive/analytic, non–repetitive cognitive/interactive, repetitive cognitive, repetitive manual, and non–repetitive manual tasks. On various aggregation levels, they find that computer technology substitutes repetitive tasks, both manual and cognitive, and complements for non–repetitive cognitive tasks, both analytic and interactive. Wolff (2000) uses various measures of technological activity and three measures of occupational skills. They find that industry computerization is positively related to changes in interactive skills as well as to changes in substantive complexity. However, they do not find any significant relationship between computerization and changes in manual skills.

The skill categories used in these studies are those which case studies identified as the "key" skills required by modern workplaces of industrialized countries (for example Hirschhorn (1984), Stasz (1997, 2001). Their overall importance is mainly ascribed to the diffusion of IT capital at workplaces and stems from two arguments: First, the distinction between manual and cognitive tasks results from one technological feature unique to IT capital. Compared to previous technologies that were only amenable to repetitive manual tasks, IT capital is also amenable to repetitive cognitive tasks. This particular feature is due to the fact that IT capital, with the help of software programs, is able to store, retrieve, and act upon information. Second, although in principle computer technology is only amenable to repetitive and well–defined tasks, it also has the potential to complement non-repetitive cognitive tasks (analytical and interactive tasks). IT capital is in particular said to increase the requirement for interactive skills such as problem solving, teamwork, and communication skills as computer–based management techniques like

[1] One exception is the study by Green et al. (2001) who use the British Skill Survey to investigate various sources of workplace skills, in particular problem–solving, communication, social, and teamworking skills.

customer relationship management intensify the contacts with customers. Moreover, customer service has become an important dimension of competition. Cooperation of workers has become more important due to modern work organization. Collaborative work forms (also called 'high performance work practices') like self–managed teams, problem–solving groups or quality circles have been broadly adopted in the 90s (Osterman (2000)). Personal interaction increases as firms concentrate increasingly on the integration of all parts of the internal processes (planning, construction, sales, etc.), inter–firm relationships (for example strategic alliances), and high flexibility of technology (Altmann et al. (1986b)).

As Bresnahan (1999) pointed out, an examination of the history of IT applications reveals the importance of organizational computing such as corporate accounting, billing, or payroll systems since the late 50s. The examples show that organizational computing applications are designed for specific departments, typically information–intensive functional areas of companies, rather than for a person. This argument is also emphasized by industrial sociologists who stress the new type of rationalization which is associated with IT capital: *systemic rationalization*, which is characterized by a change in the major aims of rationalization purposes. Rationalization takes place increasingly in a perspective of reorganizing the whole production processes within firms. The aim is to integrate and reorganize the different parts of the production process to enhance the overall efficiency (Altmann et al. (1986a), Baethge and Baethge–Kinsky (1995)). Thus, IT capital does not take over whole occupations. It is able to substitute and complement certain tasks, however, the scope for substitution is limited, as Bresnahan (1999) argues. He focuses on white–collar work, since "computers are good at repetitive task, and bureaucracies are full of repetitive tasks that might be automated" (p. F403). Computers thus revolutionized a formerly mainly paper- and people–based organization. This development has had a large impact on white–collar work, in particular as the increased industrialization allowed this type of work to be separated into "front–office" and "back–office" components. Employees in the back–office mainly perform data processing tasks. This concerns mostly clerks with medium levels of education. Front–office workers, in contrast, foster customer contacts and relationships with entities outside the firm which increases the requirements for interactive skills for these kinds of workers.

In this study, the *limited substitution* relationship between IT capital and workplace tasks is investigated. It is viewed as the main mechanism on which SBTC is based since it increases the relative requirement for non–repetitive cognitive tasks (analytical and interactive) for which employees with higher levels of educational attainment have comparative advantages. However, the analysis not only concentrates on white–collar work. It is argued that IT as a general purpose technology has comparable effects on blue–collar work. IT capital substitutes routinized, repetitive manual tasks. Not literally by taking these tasks over. However, IT capital is embedded in various machineries such as CNC and CAD machines that are capable to perform these tasks. Thus, the *limited substitution* relationship between IT capital and workplace tasks is also present in blue–collar work.

The *limited substitution* mechanism changes the task composition of occupations. Autor et al. (2001) is the only study that investigates how IT capital shifts the occupational tasks composition. They find a positive relationship between IT capital and non–repetitive analytical and non–repetitive interactive tasks, and a negative relationship between IT capital and repetitive cognitive tasks.

3 Data Set and Definitions of Variables

The analysis is based on the so–called BIBB/IAB–data set which is a survey among employees. It contains four cross–sections that were launched in 1979, 1985/86, 1991/92 and in 1998/99. Based on these individual level data, occupation–by–industry groups are synthesized, where occupations are defined on the 2–digit–level.[2] This level of classification contains nearly 100 different occupations. Table A in Appendix B lists the 42 industries that are considered. The estimations are based on 2125 occupation–by–industry groups. 35 per cent of the groups are observed in each of the four waves, 52 per cent in three or four waves, whereas 31 per cent are only observed once.[3]

People are classified according to the occupation they actually perform (Erwerbsberuf), rather than according to the occupation they learned (Ausbildungsberuf). This allows to analyze how technology changes what people actually do on the job. By contrast, occupational training curricula remain fairly stable over time and reveal little about task changes within occupations. The focus on occupations that people actually perform has two implications: First, people are not necessarily classified within the occupational title they have learned. Second,

[2]The classification of occupational titles corresponds to that of the German Federal Employment Bureau, 1988.

[3]The data set has various advantages compared to the Dictionary of Occupational Titles (DOT), a data set that is often used by researchers in the U.S. for questions related to skills. The DOT is a survey in which experts examine the task content of occupations. The experts assign scores to different indicators characterizing the occupations. This proceeding encourage behavior of analysts that results in an underestimation of the true changes in job content. Moreover, occupational titles in the DOT are not consistent over time (for detailed criticism see Spenner (1983) and references cited there).

people classified within the same occupational title may have different educational background. This source of variation will be analyzed later.

Appendix A contains a detailed description of the data set as well as the definitions of variables. The working assumption is that the workers' job duties are an unbiased measure of their skills. Thus, skill requirements are measured by the task composition of occupations. Tasks are classified in six categories: *analytical* tasks (such as mathematical, logical reasoning, and problem–solving tasks), *interactive* tasks (such as interpersonal, organizational, and managerial tasks), *repetitive cognitive* tasks (such as bookkeeping, time–sheet accounting, and inventory control tasks), *repetitive manual*, *non–repetitive manual* tasks, and *computing tasks.* Table B in Appendix B illustrates the assignment of activities to the six categories. On the individual level, each of the six task intensities measures the share of the respective task, for example 20 percent of the tasks that employee x has to perform are analytical tasks. Thus, on the occupation–by–industry level, the task measures are the average task intensities of employees within occupation–by–industry groups.

Skill supply is measured by the level of educational attainment of employees. The employees are classified according to three levels of education: First, employees without formal vocational attainment (low level of education), these are people with no occupational training degree. Second, people who completed either an apprenticeship or have a degree from a vocational college (medium level of education). Third, people holding a university or technical college degree (high level of education).

4 Descriptive Evidence

4.1 Broad Occupational and Educational Trends

Table 1 displays the occupational composition of employment over the period 1979 to 1999.[4] Some of the changes have been quite pronounced: In 1979, operatives and crafts represented the largest occupational category, whereas in 1999 this position has been held by the occupational group of professionals, technical workers, administrators, and managers. Professional and technical workers etc. increased by around 7 percentage points as a proportion of the workforce. Clerical workers remained fairly stable as a proportion of the workforce, so did sales workers.

The proportion of the labor force employed as operatives or craftsman declined from 35 per

[4]Occupational groups are assorted on the basis of the 3–digit–level of occupational titles according to the German Federal Employment Bureau, 1988

Table 1: Distribution of Employment by Occupational Groups

Occupational Group	1979	1985/86	1991/92	1998/99
White–collar workers	53.7	53.2	54.4	60.4
Professional, Technical workers, Managers, Administrators	23.0	24.1	24.4	30.1
Clerical	22.7	21.2	21.6	21.8
Sales	8.0	7.9	8.4	8.5
Blue–collar workers	38.8	38.0	36.6	30.1
Operatives and Craft	35.4	35.1	33.7	27.5
Laborer	3.4	2.9	2.9	2.6
Personal service workers	6.6	7.6	7.9	8.5
Farm workers	1.0	1.2	1.1	1.0

The sample includes workers ages 15–65 with residence in West Germany and German nationality. Details on the construction of occupational groups can be found in the Data Appendix.

cent to around 28 per cent. Laborers always played a minor role as a proportion of the labor force.

Comparing these occupational trends in West Germany with comparable figures for the U.S. (for example Wolff, 2000), the occupational changes appear to be relatively modest. Contrary to the relatively stable occupational trends for clerical work and sales work in West Germany, clerical work in the U.S. witnessed a sizeable reduction as a proportion of the labor force and sales work witnessed a sizeable increase.

Table 1 documents that in addition to the structural shift towards service industries the importance of service occupations increased throughout the economy.[5] Traditionally, service work is categorized into three groups: personal service, clerks and administrative support, and sales. Face to face or voice to voice interactions are considered as fundamental aspects of work. However, there is considerable variation in the content of work of these occupational categories and, thus, in the substitutability of parts of the work tasks by IT capital. The work of clerks and administrative support, with a high fraction of work tasks being transactional in nature, is particularly amenable to the introduction of computer technology. The work of sales, however, with a high fraction of work being more relational in nature, is only in a limited scope amenable to IT capital (Committee on Techniques for the Enhancement of Human Performance, 1999).

[5] Bund-Länder-Kommission (2001), p. 37, Figure 1, displays changes in the sectoral structure of employment in West Germany between 1978 and 1999.

In addition, as Table 2 documents, clerical and sales occupations have also major differences in the educational structure of employees. Clerical occupations witnessed an educational upgrading within the last two decades, whereas the educational structure of sales occupations remained fairly stable.

Table 2: Distribution of Educational Attainment by Occupational Groups

Occupational Group	1979	1985/86	1991/92	1998/99
Professional, Technical etc.				
highly educated	30.47	31.47	41.93	42.22
medium educated	53.11	49.81	53.48	52.22
low educated	16.42	18.72	4.59	5.56
Clerical				
highly educated	2.37	3.34	9.00	10.07
medium educated	79.20	79.69	79.06	81.22
low educated	18.43	16.97	11.93	8.72
Sales				
highly educated	1.48	1.52	3.86	2.83
medium educated	83.81	82.26	82.95	82.78
low educated	14.71	16.21	13.19	14.39
Operatives and Craft				
highly educated	0.59	0.52	0.96	1.35
medium educated	78.04	77.65	81.37	81.56
low educated	21.37	21.84	17.67	17.09

The sample includes workers ages 15–65 with residence in West Germany and of German nationality. Details on the construction of occupational groups can be found in the Data Appendix.

The fourth category of service work analyzed in this study, containing professionals, technical workers, managers and administrators, is becoming more and more important. In 1998/99, their importance as a fraction of the workforce was equal to that of all blue–collar workers. Professionals and technical workers such as scientists, engineers, lawyers or technicians are often termed experts or knowledge workers, who are viewed as being critical to both economic growth in industrial countries and the structural change towards postindustrial economy. The growth in professional and technical work is mainly attributed to four related trends:[6] corporate

[6]Committee on Techniques for the Enhancement of Human Performance (1999), p.146ff., and references cited

growth, commercialization of scientific knowledge in particular physics and chemistry as well as advances in life sciences, demographic changes, and technological change.

This service category is often viewed as being comprised of 'high–skilled' occupations, resulting from the educational structure of employees. As Table 2 shows, the occupational category of professionals, technical workers, managers, and administrators always held the highest proportion of employees with university or technical college degree. This group of occupations witnessed a relatively sharp increase in the share of employees with high levels of education over the period 1979 to 1999. The proportion of employees with low levels of education correspondingly declined.

Many studies classify the skill level of employees using broad occupational classifications such as white–collar/blue–collar workers. As already noted, however, every occupational group is composed of employees with different educational background (Table 2). Employees with medium levels of education always represented the largest proportion within each occupational group, both for white–collar and blue–collar occupations.[7]

Table 3 documents, that the West German labor force as a whole witnessed a sizeable relative increase in the proportion of workers with high levels of education.

Table 3: Employment Shares of Different Educational Groups

Aggregate Trends in the Employment Share of Different Educational Groups				
	1979	1985/86	1991/92	1998/99
High Levels of Education	8.1	8.9	13.3	16.4
Medium Levels of Education	71.1	68.3	71.2	70.3
Low Levels of Education	21.8	22.8	15.4	13.3

The sample includes workers ages 15–65 with residence in West Germany and of German nationality.

The proportion of the workforce holding a university degree or a degree from a technical college increased from about 8 per cent in 1979 to 16 per cent in 1999, whereas the proportion of employees without formal educational attainment experienced a substantial decline. However, workers with medium level of education who either completed an apprenticeship or have a degree

there.

[7]The table does not contain the descriptive results for laborers, personal service workers, and farmers. Laborers and farm workers only represent a small proportion of the workforce. Personal service workers are not part of the main interest of this study. However, the results are available on request from the author.

from a vocational college still represent the largest proportion of the workforce. Compared to other figures that document the structure of qualification of employees in West Germany (see for example Bund-Länder-Kommission (2001), p. 35, Table 6), the figures in Table 3 seem to be representative. The small overrepresentation of employees with medium levels of education is attributable to the fact that the data set in this study excludes employees with foreign nationality whereas other statistical sources refer to all West German employees. West German employees with foreign nationality, however, tend to have lower levels of education compared to their German counterparts. Moreover, the data set contains part–time workers. Male part–time employees tend to have high educational levels.

Summarizing the descriptive results, in the last two decades of the twentieth century, West Germany witnessed a substantial increase in white–collar occupations and a corresponding reduction in blue–collar occupations. It also experienced a considerable increase in the proportion of employees with high levels of education. The occupational group of professionals, technical workers, managers, and administrators, who saw the highest increases as a fraction of the workforce, put the highest emphasis on employees with high levels of education. Formal degrees seem to have become more important in all occupational groups. However, the descriptive figures also demonstrate that each occupational category is compound by employees with all three levels of formal education.

4.2 Trends in Occupational Skill Requirements

In addition to these trends in the occupational composition of employment, it is also interesting to investigate trends in skill requirements. As already noted, the working assumption is that the respondents occupational duties are an unbiased measure of occupational skill requirements. The descriptive results displayed in Table 4 show that three out of the six skill measures witness quite clear aggregate trends over the period 1979 to 1999. The trend in interactive tasks is the most pronounced. In 1979, interactive tasks represented on average around 10 per cent of the activities on–the–job, whereas in 1999 they represented more than 60 per cents. Although still representing a small proportion of activities on–the–job, computing tasks also experienced an increase in importance between 1979 and 1999. In contrast, the proportion of repetitive cognitive tasks witnessed a sizeable reduction.

These trends in aggregate skill requirements may result from transformations along two tracks: First, from changes in the occupational structure of employment (see subsection 4.1), and second, from changes in skill requirements within occupations.

Table 4: Trends in Aggregate Skill Requirements

	analytic skills	interactive skills	repetitive cognitive	repetitive manual	non-repetitive manual skills	computer skills
1979	12.8	11.5	15.2	10.9	49.2	0.3
1985/86	10.0	23.8	16.7	18.8	27.9	2.8
1991/92	8.3	23.6	15.3	11.4	36.1	5.3
1998/99	15.2	63.7	3.0	2.1	11.0	5.0

The sample includes workers ages 15–65 with residence in West Germany and of German nationality. Details on the construction of task intensities can be found in the Data Appendix.

Table 5 displays descriptive figures on task intensities by major occupational groups since 1979. Professional and technical workers, administrators, and managers have always had the highest intensities in analytical skill and, together with sales personnel, in interactive skills.

The figures show, however, an increase in the average proportion of interactive activities in the work of all occupational categories. In 1998/99 interactive tasks represent the highest proportion of on–the–job activities for both blue– and white–collar occupational groups. Repetitive manual and repetitive cognitive task intensities, in contrast, sharply declined and in 1998/99 they play only a minor role in all occupational groups.

In the late 70s, computing skills started to play an important role at the workplace of all occupational groups. Since then, computer skills increased as a fraction of on–the–job activities within all occupational groups, but most pronounced for clerical workers.

Sales workers witnessed an increase in the proportion of analytical, interactive, and computing tasks in the period 1979 to 1999. In contrast, the proportion of repetitive cognitive tasks declined on average.

In 1979, the work of operatives and craftsmen was dominated by non–repetitive manual, repetitive manual and repetitive cognitive activities. Since then, they experienced a sharp increase in the requirements for analytical and interactive skills.

Table 5: Distribution of Skill Requirements by Occupational Groups

Occupational Group	1979	1985/86	1991/92	1998/99
Professional, Technical etc.				
analytic	25.24	20.80	17.04	18.46
interactive	24.60	38.85	38.27	61.08
repetitive cognitive	17.32	16.09	15.06	4.73
repetitive manual	5.30	5.34	4.13	0.62
non–repetitive manual	27.10	16.28	20.27	9.65
pc–skills	0.44	2.64	5.24	5.45
Clerical				
analytic	17.96	11.01	7.99	13.75
interactive	8.68	26.61	24.90	65.92
repetitive cognitive	25.60	44.73	39.80	4.42
repetitive manual	15.47	6.88	1.99	0.21
non–repetitive manual	31.38	2.23	10.45	5.46
pc–skills	0.91	8.54	14.86	10.24
Sales				
analytic	7.50	2.73	1.80	9.72
interactive	23.55	59.11	58.55	74.62
repetitive cognitive	18.64	17.92	13.84	1.67
repetitive manual	20.34	13.95	1.27	0.50
non–repetitive manual	29.87	4.31	21.88	10.74
pc–skills	0.10	1.98	2.67	2.75
Operatives and Craft				
analytic	3.03	4.80	4.65	16.81
interactive	3.85	7.08	6.97	58.20
repetitive cognitive	9.02	3.52	3.63	0.72
repetitive manual	9.24	35.27	25.02	5.72
non–repetitive manual	74.81	48.88	58.51	16.26
pc–skills	0.05	0.44	1.23	2.29

The sample includes workers ages 15–65 with residence in West Germany and of German nationality. Details on the construction of occupational groups and task intensities can be found in the Data Appendix.

Employees with higher levels of education are often viewed as having comparative advantages in performing non–repetitive cognitive task, in particular analytical but also interactive tasks. Table 6 displays the means of task intensities by educational groups. The descriptive evidence confirms this view. In addition, the higher the educational attainment the higher the requirements for computing skills. In contrast, the figures indicate that employees with low levels of education are more occupied with repetitive manual and with non–repetitive manual tasks.

Table 6: Distribution of Task Intensities by Educational Groups

	analytic skills	interactive skills	repetitive cognitive	repetitive manual	non-repetitive manual skills	computer skills
high levels of education	19.1	53.6	12.1	2.0	8.3	5.0
medium lev. of education	11.4	28.4	13.3	10.9	32.5	3.4
low levels of education	8.0	23.2	10.0	15.9	41.4	1.5

The sample includes workers ages 15–65 with residence in West Germany and of German nationality. Details on the construction of task intensities can be found in the Data Appendix.

4.3 Workplace Computerization in West Germany between 1979 and 1999

Whereas at the beginning of the IT revolution main–frame computers dominated the data–processing units of large firms, from the late 70s on personal computers began to diffuse to business users. Due to the steady price decline, this diffusion process has been pronounced. Table 7 displays the percentage share of computer users at work. The table shows that within twenty years, more than half of the workforce uses computers on–the–job. Between 1979 and 1999, computer diffusion increases on average by around 45 per cent per annum.

Table 7 also demonstrates that the adoption of computer technologies increases in educational attainment of employees. In 1979, already more than ten per cent of employees with high levels of education used a computer at the workplace. In 1999 this fraction has increased to more than 80 per cent.

The computer diffusion process was not uniform with respect to different economic sectors.

Table 7: Trends in Aggregate Computer Use and Within Different Educational Groups

Diffusion of Computer, Terminals, Portables, electronic data processing devices				
	Overall	Low Educated	Medium Educated	Highly Educated
1979	6.0	3.7	6.0	12.4
1985/86	18.1	10.1	19.8	25.5
1991/92	34.5	16.1	33.6	60.7
1998/99	55.4	27.2	54.4	82.7

The sample includes workers ages 15–65 with residence in West Germany and of German nationality.

Table 8 demonstrates that the key adopters of computer capital are service industries in which information is the most important good. Whereas major previous technologies were used firstly in manufacturing, computer use was relatively low in manufacturing in 1979 and is still below average in 1999. The table also demonstrates the vanguard function of financial services (Barras, 1990). In 1979, financial services already had the highest penetration rates of computer capital. In 1999, nearly every employee within these sectors uses a computer at work. Although the public and quasi public sectors had relatively low computer penetration rates in 1979, they catched up in the twenty years thereafter. From the mid–80s on, these sectors had the second highest fractions of computer users.

However, this differentiation according to sectors plays down that IT capital not only had major influence on service industries but also on the service functional areas of manufacturing industries. As Table 9 shows, computer adoption was quite different for different occupational groups.

Table 8: Diffusion of Computer Capital by Sectors

	1979	1985/86	1991/92	1998/99
Manufacturing Sectors	4.8	15.2	31.1	46.1
Financial Sectors	24.3	63.0	83.3	96.9
Services Sectors	6.0	16.7	33.2	58.5
Public Sector	4.4	17.8	40.9	60.5

The sample includes workers ages 15–65 with residence in West Germany and of German nationality.

It was particularly pronounced in professional, technical, managerial, administrative, and clerical occupations. The diffusion of computer capital was much broader among clerical occupations than among sales occupations. This may indicate the division of office work in back– and front–office functions as for example Bresnahan (1999) pointed out, with employees in the back–office being occupied with data–entry and data–processing tasks (clerks), and employees in the front–office spending most of their time serving customers and clients (sales personnel).

In contrast to the widespread diffusion of computers in most white–collar bureaucracies, operatives and crafts occupations witnessed a much slower penetration rate of computer capital at the workplace. Because of the relatively narrow definition of IT capital in this study, these figures miss the high importance of IT capital "embedded" in machine devices such as computer numerical controlled (CNC) machines employed by blue–collar workers. Thus, these figures are rather conservative measures of the adaption of IT capital by blue–collar occupations.

Table 9: Diffusion of Computer Capital by Occupational Groups

Occupational Group	1979	1985/86	1991/92	1998/99
White–collar workers				
Professional, Technical workers, Managers, Administrators	8.5	23.4	47.3	71.8
Clerical	13.4	43.7	70.7	90.9
Sales	3.7	15.1	23.5	44.5
Blue–collar workers				
Operatives and Craft	1.4	4.2	12.3	24.9
Laborer	0.6	1.8	11.2	21.4
Personal service workers	3.0	6.6	15.2	31.9

The sample includes workers ages 15–65 with residence in West Germany and of German nationality. Details on the construction of occupational groups can be found in the Data Appendix.

5 Empirical Findings on Skills, Education and Technology in the Workplace

5.1 Technology and Skill Requirements

In order to determine the relationship between technology and skill requirements the following regression equations are estimated. It is assumed that changes in job skill requirements are related to both technological as well as educational inputs:

$$
\begin{aligned}
\Delta S_{jct} &= \beta_{0j} + \Delta PC_{ct}\beta_{1j} + \sum_{h,m} ED_{c(t-1)}\beta_{2j} + \sum PED_{c(t-1)}\beta_{3j} + \sum_{i=1}^{6} OC_{ic(t-1)}\beta_{4j} \\
&+ Z_{c(t-1)}\beta_{5j} + X_{c(t-1)}\beta_{6j} + \Delta\epsilon_{jct}
\end{aligned}
\tag{1}
$$

j = 1,...,6

$$
j = \begin{cases}
1 & : \text{analytic tasks} \\
2 & : \text{interactive tasks} \\
3 & : \text{repetitive cognitive tasks} \\
4 & : \text{repetitive manual tasks} \\
5 & : \text{computing tasks} \\
6 & : \text{non–repetitive manual tasks}
\end{cases}
$$

$$
i = \begin{cases}
1 & : \text{professionals, technical workers, managers, administrators} \\
2 & : \text{clerical workers} \\
3 & : \text{sales personnel} \\
4 & : \text{operatives and crafts} \\
5 & : \text{laborers} \\
6 & : \text{personal service workers} \\
7 & : \text{farm workers}
\end{cases}
$$

where S_{jct} represents the intensity of task j in occupation–by–industry group c at time t, $t = 1979, 1984/85, 1991/92, 1998/99$. PC_{ct} is a vector containing the proportion of employees using a computer within occupation–by–industry group c at time t and ED_{ct} is a vector containing the proportion of employees in the particular educational group (h = high levels of education, m = medium levels of education). PED_{ct} is a vector containing information on knowledge obtained through work–based learning, that is the mean years of work experience within occupation–by–industry groups and the mean years of tenure with the current employer within occupation–by–industry groups. OC_{ict} represents employment shares in different occupational groups i. Z_{ct} contains various interaction terms. Interacted variables are all defined as deviations from their means. Further control variables such as the share of part–time employees, share of female workers, income classes, time–, and sector dummies are included in X_{ct}. Δ denotes annualized changes (in percentage points) between t and $t-1$ in the respective variable. The $\beta's$ are allowed to vary across the task equations, however, they are assumed to be constant over time. Table C in Appendix B summarizes the definitions of variables and Table D displays summary statistics.

The literature suggests that there is a correlation between changes in skill requirements and the pace of technological change. Thus, in the first specification changes in task intensities are regressed on contemporaneous changes in computer use. In addition, it is assumed that the initial stock of educational attainment $ED_{c(t-1)}$ within occupation–by–industry group also matters for changes in skill requirements by enabling occupations with higher levels of educational attainment to adopt technology faster. As skill requirements at workplaces have a high practical component, the stock of work experience and tenure with the current employer within occupation–by–industry group are also considered as important factors influencing the restructuring of the occupational task composition.

The occupation–by–industry groups are defined on the 2–digit–level of occupational classification. This aggregation level contains employees in various occupational groups, such as managers, clericals or sales personnel (defined on the 3–digit–level). The pace of changes in skill requirements caused by technological developments may also be related to the occupational structure of employees within occupation–by–industry groups. For example, technical change may have different effects on occupation–by–industry groups whose employees are mainly clerical workers compared to occupation–by–industry groups whose employees are mainly operatives and crafts.

The notion that the effect of technical change on skill requirements depends on the educational and occupational structure of occupation–by–industry groups is captured by including various interaction terms in the regression equation (Z_{ct}).

Equations (1) are estimated simultaneously as a system of seemingly unrelated regressions (SUR). The system estimation technique allows the consideration of cross–equation constraints. By construction, for each observation the task intensities S_j sum up to 100 over all equations ($\sum_{j=1}^{6} S_{jct} = 100$), which leads the ΔS_j to sum to zero. This implies that out of the six task equations only five are linearly independent and that for each observation the disturbances across equations must always sum to zero. In addition, this also leads the parameters estimated by equation–by–equation OLS to obey following conditions: $\sum_{j=1}^{6} \beta_{0j} = \sum_{j=1}^{6} \beta_{1j} = \sum_{j=1}^{6} \beta_{2j} = \sum_{j=1}^{6} \beta_{3j} = \sum_{j=1}^{6} \beta_{4j} = \sum_{j=1}^{6} \beta_{5j} = \sum_{j=1}^{6} \beta_{6j} = 0$. One procedure is to estimate five out of the six equations simultaneously and to obtain parameter estimates of the "left–out" equation indirectly by using the above conditions. From an econometric perspective, the parameter estimates of the above specifications are invariant to the choice of the "left–out" equation.[8] However, since the hypothesis concerning the relationship between non–repetitive manual tasks and IT is that IT is neither a complement nor a substitute for these tasks, it seems straightforward to drop this equation since the results for the other equations are more interesting from an economic point of view. Weighted SUR–estimations are performed, with the number of individuals within occupation–by–industry group as weights.

However, before presenting the results for the rich specification that controls for numerous effects, Table 10 displays the first–order relationship between technological change and changes in occupational skill requirements detected by a bivariate regression.

Table 10: Basic Bivariate Regression: Changes in Within–Occupational Skill Requirements

Dep. Variables: 10 x (Annualized Changes in Task Intensities)					
	Δ analytic	Δ interactive	Δ repetitive cognitive	Δ repetitive manual	Δ computing
Δ computer use * 10	-0.02**	0.02	0.04***	-0.12***	0.10***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)
Intercept	2.52***	27.63***	-8.23***	0.15	-0.17
	(0.44)	(0.89)	(0.53)	(0.89)	(0.18)
$Pseudo-R^2$	0.00	0.00	0.00	0.01	0.16
χ^2 (3001 dof)	4.33	1.21	8.98	37.60	579.14
Number of observations:			3002		

Standard errors are in parentheses; regressions are weighted by the number of individuals in occupation–by–industry groups; ***,**,*–indicate significance on the 1, 5, 10 per cent level.

Only two of the coefficients are in line with the hypotheses. The bivariate regressions detect

[8]See Berndt (1991), p.473 ff. for a discussion of the choice of which equation is deleted.

that technological change is significantly negative related to repetitive manual tasks, and that it is significant positively related to changes in computing tasks. However, the results for the analytical task equation and for the repetitive cognitive task equation contradict the hypotheses. These findings are interpreted as indicating that changes in workplace skill requirements not only depend on changes in technology, but are also influenced by the educational and occupational conditions that prevail within occupation–by–industry group.

Table 11 displays the results of specification 1. The results indicate a complementary relationship between IT and analytical, interactive and computing tasks, and a substitutive relationship between IT and repetitive manual tasks. However, it is found that rapid technological change is significantly positive associated with changes in repetitive cognitive tasks, which contradicts the hypothesis.

Changes in analytical task intensities: Changes in analytical skill requirements are significantly related to changes in computer use. The size of the coefficient indicates that nearly 20 per cent of the changes in task intensities may be accounted for by changes in IT usage within occupation–by–industry groups.[9] The results also show that besides of technological changes other factors are significantly related to changes in analytical skill requirements. As the performance of analytical tasks requires foundation skills and knowledge in natural science, occupation–by–industry groups with both high levels of shares of employees with medium education and high levels of shares of highly educated employees are positively related to changes in analytical skill requirements. In addition, having a highly experienced workforce, that for example has a lot of expertise concerning the production processes or concerning the organizational structure of the firm, facilitates changes in analytical skill requirements. The results for the interaction terms indicate that technological change has different effects depending on the occupational structure within occupation–by–industry groups. For rapidly computerizing blue–collar and personal service occupations the changes in analytical skill requirements was particularly pronounced. In contrast, rapidly computerizing occupations with employees with mainly medium levels of education witnessed smaller increases in analytical skills.

Changes in interactive task intensities: The estimation results indicate that nearly ten per cent of changes in interactive task intensities are directly associated with changes in computer utilization. The educational background within occupation–by–industry group as well as the

[9]The figures on the bottom of Table 11 show an average annual increase in analytical task intensities of 0.25 percentage points. Using the coefficient of 0.04 and the mean value of changes of computer utilization of 2.36 percentage points, this implies that around 20 per cent of changes in analytical tasks may be accounted for by changes in IT usage.

level of work experience are important factors related to changes in the requirement of interactive skills. However, high tenure with the current employer seems to hamper changes in interactive skills. The coefficients for the interaction terms reveal, that significant effects are only found for clerical occupations. Rapidly computerizing clerical occupations are negatively associated with changes in interactive task intensities. This may plead for the hypothesis that the introduction of IT separated white–collar work into front– and back–office components. Those working with IT are in the back–office and do not have much customer contact.

Changes in repetitive cognitive task intensities: In contradiction to the hypothesis, the results indicate that changes in computer use are positively associated with changes in repetitive cognitive tasks. However, it is found that educational background as well as the stock of work–related knowledge is negatively related to changes in repetitive cognitive tasks. Moreover, in professional occupations a substitutive relationship between IT and repetitive cognitive tasks is found. This holds analogously for occupations with high shares of operatives and crafts as well as for occupations with high shares of personal service workers.

Table 11: Changes in Within–Occupational Skill Requirements

Dep. Variables: 10 x (Annualized Changes in Task Intensities)					
	Δ analytic	Δ interactive	Δ repetitive cognitive	Δ repetitive manual	Δ computing
Δ computer use * 10	0.04***	0.10***	0.06***	-0.18***	0.09***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)
Vocational Education					
Share highly educated	0.07***	0.16***	-0.17***	0.01	-0.03***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.01)
Share medium educated	0.07***	0.13***	-0.08***	0.01	-0.01
	(0.02)	(0.04)	(0.02)	(0.04)	(0.01)
Work-based Learning					
work experience	0.32***	1.33***	-0.21**	-0.50***	-0.04
	(0.08)	(0.16)	(0.10)	(0.17)	(0.03)
tenure	0.03	-0.61***	-0.48***	0.46**	-0.07*
	(0.10)	(0.20)	(0.12)	(0.21)	(0.04)
Interaction Terms					
highly educ. * Δ comp. use * (1/100)	-0.06	-0.05	0.04	0.23**	-0.01
	(0.06)	(0.11)	(0.07)	(0.12)	(0.02)
medium educ. * Δ comp. use * (1/100)	-0.08**	0.04	-0.02	0.19**	-0.02
	(0.04)	(0.09)	(0.05)	(0.09)	(0.02)
professionals * Δ comp. use * (1/100)	0.10	-0.03	-0.20**	-0.00	-0.01
	(0.09)	(0.18)	(0.10)	(0.18)	(0.04)
clericals * Δ comp. use * (1/100)	0.02	-0.29*	0.04	-0.00	0.16***
	(0.09)	(0.18)	(0.10)	(0.18)	(0.04)
sales * Δ comp. use * (1/100)	0.14	-0.05	-0.09	0.06	-0.00
	(0.09)	(0.19)	(0.11)	(0.20)	(0.04)
operatives/crafts * Δ comp. use * (1/100)	0.19**	0.17	-0.20**	-0.18	-0.02
	(0.09)	(0.17)	(0.10)	(0.18)	(0.04)
laborers * Δ comp. use * (1/100)	0.20*	-0.28	-0.06	-0.29	0.11**
	(0.12)	(0.24)	(0.14)	(0.24)	(0.05)
(personal) service * Δ comp. use * (1/100)	0.22***	0.13	-0.23**	0.02	-0.00
	(0.09)	(0.19)	(0.11)	(0.19)	(0.04)
(unconditional) mean of depend. variable	2.52	28.22	-6.90	-3.10	2.21
$Pseudo-R^2$	0.09	0.08	0.08	0.04	0.23
χ^2 (2954 dof)	291.16	267.53	250.45	111.87	892.13
Number of observations:			2981		

Control variables are: share of part–time employees, share of female employees, occupational structure of employees, time–, and sector dummies. The share of farm workers and employees with low levels of education are the base category. Standard errors are in parentheses; regressions are weighted by the number of individuals in occupation–by–industry groups; ***,**,*–indicate significance on the 1, 5, 10 per cent level.

Changes in repetitive manual task intensities: The results indicate that IT substitutes for repetitive manual tasks. Nearly 140 per cent of the changes in repetitive manual task intensities can be accounted for by increases in computerization, or said differently, without computerization the within occupation–by–industry intensities in repetitive manual task ceteris paribus would have had increased by around 40 per cent. Interestingly, computerization increases the requirement for repetitive manual tasks in occupations with high shares of both highly educated and medium educated employees.

Changes in computing task intensities: Nearly 100 per cent of changes in the requirement of computing skills may be attributed to the pace of computer diffusion within occupation–by–industry group. A high educational background as well as long tenure with the current employer, however, seems to reduce the potential for changes in computing skill requirements. Rapid computerization in clerical occupations as well as in occupations with mainly laborers is positively associated with changes in computing skills.

Empirical research is usually concerned with the question whether associations found in regression analysis are causal relationships. In this study, a strategy of temporal ordering is used to infer to this question. Two specifications are tested: First, changes in task intensities are regressed on lagged changes in computer use. Second, changes in task intensities are regressed on lagged levels of computerization within occupation–by–industry groups. In addition to pointing to causal effects, the strategy of temporal ordering may also reveal that for some of the skill categories the adaption process to IT needs time. This may for example result from organizational changes that have to be made or from the fact that employees have to be trained to meet the new requirements.

Table 12 displays the estimation results. Panel A contains the results of the regression in which lagged changes in computer usage are the main explanatory variable, Panel B contains the results of the regression in which lagged shares of computer utilization are the main explanatory variable. Although not reported, the regression specifications contain all the variables that were used in the regressions depicted in Table 11, "adjusted" to the new computer variable. In order to clarify the presentation of results, the analysis focuses on the IT variable. However, appendix B, Table E and Table F, contain the complete regression results. As in the above regressions weighted SUR–estimations are performed, with the number of individuals within occupation–by–industry group c as weights.

The results displayed in panel A show that using lagged annualized changes in computer use gives insignificant results for the coefficients concerning analytical and repetitive manual task intensities. The coefficient for the interactive task equation only changes slightly compared to the results in Table 11 both with respect to the size as well as with respect to the precision. However, two coefficients change their sign. Both changes in repetitive cognitive skill requirements and changes in computing skill requirements are significant and negatively related to lagged changes in computerization. In the case of repetitive cognitive tasks which was found to be positively related to contemporaneous changes in computerization, the result may indicate that the substitution process is associated with considerable adjustment costs resulting for example from the necessity to reorganize the production process.

Surprisingly, it is found that occupation–by–industry groups that computerized rapidly in the previous period are negatively related to changes in computing skills in the actual period. However, the previous results indicated that the contemporaneous pace of technological change accounts for around 100 per cent of the changes in the requirement for computing skills. Assuming that the pace of IT diffusion declines over time, it seems plausible that occupation–by–industry groups that had high pace of computerization in the previous period and thus high increases in the requirement for computing skills, witness smaller increases in the successional period.

As two of the computer coefficients are insignificant, lagged annualized changes in computer utilization are suspected to be a weak signal for technological change that induces changes in occupational skill requirements. There are six years between two successive waves which means that the computer change variable is a six–year average of computerization. This fact may lead the variable to pick up only a limited fraction of relevant information. Thus, regressions on lagged shares of computer use are performed. It is assumed that this variable contains more information concerning the technological condition prevailing within occupation–by–industry groups. In addition, this also serves as a test of robustness.

Panel B displays the estimation results. Except for the repetitive manual equation, all of the coefficients are significant at the one percent level. The signs of the coefficients support the hypotheses of a substitutive relationship between IT and repetitive cognitive tasks and a complementary relationship between IT and analytical as well as interactive tasks.

Table 12: Changes in Within–Occupational Skill Requirements

Dep. Variables: 10 x (Annualized Changes in Task Intensities)					
	Δ analytic	Δ interactive	Δ repetitive cognitive	Δ repetitive manual	Δ computing
A					
Lagged Δ computer use * 10	0.01	0.12***	-0.09***	0.02	-0.04***
	(0.02)	(0.04)	(0.02)	(0.03)	(0.01)
$Pseudo-R^2$	0.23	0.11	0.30	0.14	0.04
χ^2 (1682 dof)	223.91	208.74	716.92	275.03	77.92
Number of observations:			1707		
B					
Lagged share of computer usage	0.12***	0.19***	-0.46***	0.03	-0.12***
	(0.02)	(0.04)	(0.02)	(0.05)	(0.01)
$Pseudo-R^2$	0.10	0.11	0.25	0.04	0.15
χ^2 (2956 dof)	340.90	372.15	991.32	119.13	512.17
Number of observations:			2981		

In Panel A all interaction terms are interacted with lagged Δ computer use, in panel B they are interacted with the lagged share of computer users within occupation–by–industry groups. Control variables are: share of part–time employees, share of female employees, share of employees within occupational groups, time–, and sector dummies. The share of farm workers and employees with low levels of education are the base category. Standard errors are in parentheses; regressions are weighted by the number of individuals in occupation–by–industry groups; ***,**,*–indicate significance on the 1, 5, 10 per cent level.

5.2 Skill Requirements and Educational Upgrading

The aim of this paper is to contribute to the discussion on SBTC by analyzing the following chain of economic arguments: It is argued that the steady price decline of IT capital is the causal force underlying the rapid diffusion of IT capital at workplaces. This computerization of occupations changes the skill requirements at workplaces which forces the firms to adjust the qualification structure of their employees. As computer prices do not vary individually, they do not provide any useful information for the analysis at hand. However, the analyses reported in section 5.1 already investigated the relationship between IT and changing skill requirements at workplaces. In this section, the analysis integrates the question, how changes in occupational skill requirements are associated with changes in the demand for employees with different educational attainment in the above analysis. The empirical approach is to estimate two structural specifications simultaneously:

$$\Delta ED_{ct}^{h,m} = \alpha_{0j} + \sum_{j=1}^{5} \Delta S_{jct}\alpha_{1j} + X_{c(t-1)}\alpha_{2j} + \upsilon_{jct} \quad (1)$$

$$\Delta S_{jct} = f(PC, ED, PED, Z, X) \quad (2)$$

h = share of employees with high educational attainment.
m = share of employees with medium educational attainment.
For the definition of the other variables and parameters see equation 1.
j = 1,...,6.

$$j = \begin{cases} 1 & : \text{ analytic tasks} \\ 2 & : \text{ interactive tasks} \\ 3 & : \text{ repetitive cognitive tasks} \\ 4 & : \text{ repetitive manual tasks} \\ 5 & : \text{ computing tasks} \\ 6 & : \text{ non–repetitive manual tasks} \end{cases}$$

The first equation explains changes in educational attainment (ED) within occupation–by–industry group c by changes in occupational skill requirements (ΔS_{jct}). Further control variables such as the occupational structure of employees, the share of female employees, share of part–time employees, 8 income classes, sector and time dummies are also considered. The second equation explains changes in skill requirements within occupation–by–industry groups based on the results reported in section 5.1. The equations are estimated using three–stage–least square (3SLS) estimation techniques, thus the ΔS_{jct} in equation (1) are instrumented by equations (2).

Under the light of the results of section 5.1, two specifications are used to generate the instruments in equation (2). First, the specification with contemporaneous changes in computerization within occupation–by–industry groups, second, the specification with lagged shares of computer use. Table 13 displays the estimation results of the relationship between changes in task intensities and changes in the demand for employees with different educational attainment.

In panel A, the instruments for the changes in occupational skill requirements are generated using the specification with contemporaneous changes in computerization within occupation–by–industry groups whereas in panel B, the specification with lagged levels of shares of computer utilization is used.

The results indicate that occupation–by–industry groups with rapid increases in interactive and computing skill requirements witness rapid increases in the share of employees with high educational attainment. In contrast, increases in repetitive cognitive tasks as well as repetitive manual tasks are negatively related to changes in the share of employees with high education. Thus, as IT capital substitutes for repetitive cognitive and manual tasks, this results in an increasing deployment of employees with high levels of education. With respect to analytical tasks, only the coefficient in panel B is significant.

Concerning the development of the employment share of employees with medium levels of education, there are two unambiguous results. First, a negative relationship between changes in analytical skill requirements and changes in the share of employees with medium levels of education. Second, occupation–by–industry groups that witnessed a reduction in the intensities of repetitive manual tasks are associated with increases in the employment shares of employees with medium levels of education. However, the remaining coefficients do not allow any clear interpretation since they are only weakly significant or insignificant. In addition, they switch their sign depending on the specification of the instruments.

Table 13: Three–Stage Least Square Regressions

Dep. Variables: 10 x (Annualized Changes in the Share of...)				
	A: main instrument Δ computer use		B: main instrument computer use (lagged)	
	Highly Educated Employees	Medium Educated Employees	Highly Educated Employees	Medium Educated Employees
Δ analytic	-0.85	-7.82***	1.38**	-3.55***
	(0.63)	(1.62)	(0.69)	(0.86)
Δ interactive	1.59***	-0.06	0.57***	0.39*
	(0.22)	(0.57)	(0.18)	(0.22)
Δ repetitive cognitive	-1.98***	-2.44*	-1.92***	0.34
	(0.59)	(1.51)	(0.66)	(0.82)
Δ repetitive manual	-0.66**	-4.50***	-0.85***	-0.84**
	(0.34)	(0.88)	(0.28)	(0.35)
Δ computer skills	1.71***	-0.33	6.90***	-3.96
	(0.60)	(0.23)	(2.15)	(2.66)
Wald χ^2–Test (2897dof)	840.25	1419.21	854.72	157.58
No. of observations:	2923		2923	

Control variables in both equations are: share of part–time employees, share of female employees, share of employees of different occupational categories, 8 income classes, time–, and sector dummies. Standard errors are in parentheses; regressions are weighted by the number of individuals in occupation–by–industry groups; ***,**,*–indicate significance on the 1, 5, 10 per cent level.

6 Conclusion

The effect of technological change on the labor market has always been a major concern of economic research. The interest intensified in the last two decades with the diffusion process of personal computers at workplaces, and with the observation that workers with high levels of education are more likely to use computer technology. This observation suggests that computer technology is complementary with human capital, resulting in the skill–biased technological change hypothesis (e.g. Acemoglu (2002), Chennells and van Reenen (1999), Krueger (1993), Autor et al. (1998)).

The analyses in this study contributes to the widespread discussion on skill–biased technological change by using direct, multidimensional measures of occupational skill requirements. It is argued that because of *limited substitution* (Bresnahan (1999)) between IT capital and tasks that are required at workplaces, IT capital shifts the employment structure of employees towards employees with higher levels of formal education.

The empirical findings support the hypotheses that IT capital substitutes for repetitive activities, both cognitive and manual, and that IT capital complements analytical, interactive, and computing skills. The analysis also demonstrates that changes in analytical and interactive skills are positively related to changes in the share of employees with high levels of educational attainment. In contrast, changes in the requirement for repetitive manual and repetitive cognitive skills are negatively related to changes in the share of employees with high levels of educational attainment.

These findings support the argument that IT capital increases the demand for higher educated labor through shifting the task composition of occupations towards analytical and interactive activities for which higher educated employees have comparative advantages. The results are in line with the findings of Autor et al. (2001) who investigate how IT capital changes the task composition on various aggregation levels. However, the analysis in this study puts stronger emphasis on task changes within occupations. In particular, it is shown that the impact of technological change on changes in skill requirements depends on the educational structure within occupational groups.

References

Acemoglu, D. (1998). Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality, *The Quarterly Journal of Economics* pp. 1055–1089.

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

Altmann, N., Deiß, M., Döhl, V. and Sauer, D. (1986a). Ein "Neuer Rationalisierungstyp" - neue Anforderung an die Industriesoziologie, *Soziale Welt* **37**: 191–207.

Altmann, N., Deiß, M., Döhl, V. and Sauer, D. (1986b). Ein"Neuer Rationalisierungstyp"–neue Anforderungen an die Industriesoziologie, *Soziale Welt* **37**: 191–207.

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

Autor, D., Levy, F. and Murnane, R. (2001). The Skill Demand of Recent Technological Change: An Empirical Exploration, *Working Paper 8337*, NBER.

Baethge, M. and Baethge–Kinsky, V. (1995). Ökonomie, Technik, Organisation: Zur Entwicklung von Qualifikationsstruktur und qualitativem Arbeitsvermögen, *in* Arnold and Lipsmeier (eds), *Handbuch der Berufsbildung*, Opladen, pp. 142–156.

Barras, R. (1990). Interactive innovation in financial and business services: The vanguard of the service revolution, *Research Policy* **19**: 215–237.

Becker, G. (1964). *Human Capital*, National Bureau of Economic Research, New York.

Berman, E., Bound, J. and Griliches, Z. (1994). Changes In The Demand For Skilled Labor Within U.S. Manufacturing: Evidence From The Annual Survey Of Manufactures, *The Quarterly Journal of Economics* **109**: 367–397.

Berndt, E. (1991). *The Classics of Econometrics*, Addison Wesley Publishing Company, Reading, Massachusetts.

Berndt, E. R., Morrison, C. J. and Rosenblum, L. S. (1992). High-Tech Capital Formation and Labor Composition in U.S. Manufacturing Industries: An Exploratory Analysis, *Working Paper 4010*, NBER Working paper series.

Borghans, L. and de Grip, A. (2000). *The Overeducated Worker? The Economics of Skill Utilization*, Edward Elgar Publishing Limited, Cheltenham and Northampton.

Bresnahan, T. (1999). Computerisation and Wage Dispersion: An Analytical Reinterpretation, *The Economic Journal* **109**: F390–F415.

Bund-Länder-Kommission (2001). *Zukunft von Bildung und Arbeit: Perspektiven von Arbeitskräftebedarf und -Angebot bis 2015*, Bund–Länder–Kommission, Bonn.

Chennells, L. and van Reenen, J. (1999). Has Technology Hurt Less Skilled Workers?, *Working paper*, IFS.

Committee on Techniques for the Enhancement of Human Performance (1999). *The Changing Nature of Work*, National Academy Press, Washington, D.C.

Falk, M. (2001). Diffusion of Information Technology, Internet Use and the Demand for Heterogenous Labor, *Discussion Paper No. 01-48 01-48*, ZEW.

Falk, M. and Koebel, B. (2001). A Dynamic Heterogeneous Labor Demand Model for German Manufacturing, *Applied Economics* **33**(3): 330–348.

Fitzenberger, B. (1999). *Wages and Employment Across Skill Groups*, Vol. 6 of *ZEW economic studies*, Physica–Verlag, Heidelberg and New York.

Green, F., Ashton, D. and Felstead, A. (2001). Estimating the determinants of supply of computing, problem-solving, communication, social, and teamworking skills, *Oxford Economic Papers* **3**: 406–433.

Hirschhorn, L. (1984). *Beyond Mechanization: Work and Technology in a Postindustrial Age*, MIT Press, Cambridge, Massachusetts.

Howell, D. and Wolff, E. (1991). Trends in the Growth and Distribution of Skills in the U.S. Workplace, 1960-1965, *Industrial and Labor Relations Review* **44**: 486–502.

Kaiser, U. (2000). New Technologies and the Demand for Heterogeneoous Labor: Firm–Level Evidence for the German Business–Related Service Sector, *Economics of Innovation and New Technology* **9**(5): 465–484.

Krueger, A. (1993). How computer have changed the wage structure: Evidence from microdata, 1984-1989, *Quarterly Journal of Economics* **108**: 33–60.

Lex Borghans, F. G. and Mayhew, K. (2001). Skills measurement and economic analysis: an introduction, *Oxford Economic Papers* **53**(3): 375–384.

Osterman, P. (2000). Work Reorganization in an Era of Restructuring: Trends in Diffusion and Effects on Employee Welfare, *Industrial and Labour Relations Review* **53**: 179–196.

Rumberger, R. (1981). The Changing Skill Requirements of Jobs in the U.S. Economy, *Industrial and Labor Relations Review* **34**(4): 578–590.

Spenner, K. (1983). Deciphering Prometheus: Temporal Change in the Skill Level of Work, *American Sociological Review* **48**(6): 824–837.

Spenner, K. (1990). Skill: Meaning, Methods, and Measures, *Work and Occupations* **17**(4): 399–421.

Stasz, C. (1997). Do Employers Need the Skills They Want? Evidence from Technical Work, *Journal of Education and Work* **10**(3): 205–223.

Stasz, C. (2001). Assessing skills for work: two perspectives, *Oxford Economic Papers* **3**: 385–405.

Wolff, E. (2000). Technology and the Demand for Skills, *in* L. Borghans and A. de Grip (eds), *The Overeducated Worker? The Economics of Skill Utilization*, Edward Elgar Publishing Limited, Cheltenham, UK, pp. 27–55.

A The BIBB/IAB–Data Set and Definitions of Variables

The analysis is based on the so–called BIBB/IAB–data set which is a survey among employees. This data set contains four cross–sections of the *Qualification and Career Survey* carried out by the German Federal Institute for Vocational Training ("Bundesinstitut für Berufsbildung (BIBB)") and the Research Institute of the Federal Employment Service ("Institut für Arbeitsmarkt- und Berufsforschung (IAB)"). The cross–sections were launched in 1979, 1985/86, 1991/92 and in 1998/99. The survey is designed to give detailed information on the qualifications and occupational career trends of German employees. It is unique in the fact that it contains detailed descriptions of the tasks performed on the job. Moreover, it contains information on computer use. Each survey covers around 30,000 observations. The sample of interviewed persons was drawn in a random route process.[10]

The target population is not uniform within the four waves. Due to this changing sample design the sample used in this study has to be restricted to West–German residents with German nationality, that is East–German residents and non–German employees are excluded from the sample since these groups of employees were not interviewed in every wave.[11] Moreover, the sample does not contain self–employed and unemployed persons.

This reduces the selected sample for the estimation purposes of this study to 28,784 observations in 1979, 26,361 observations in 1985/86, 23,210 observations in 1991/92, and 26,246 observations in 1998/99. It contains German employees with residence in West–Germany. They are between 15 and 65 years old. The firms employing these individuals cover a wide range of industries, both services and manufacturing. Table A in appendix B displays the industries that are contained in the sample.

Since the main interest of this study is the relationship between technology, job content, and educational attainment, this data set on the individual level is aggregated to observation on the occupational level. The individuals are classified according to the occupation they actually work in. In order to aggregate individuals with as homogeneous tasks as possible, occupations are furthermore distinct by their industry affiliation.

[10]The data sets as well as code books are publicly available through the Central Archive for Empirical Social Research at the University of Cologne. The code books document the sample design and expansion factors in detail.

[11]The exclusion of East-German employees is due to the existence of the German Democratic Republic up to 1989. The exclusion of employees with foreign nationalities is less clear. But since the questionnaire is only in German the results for Non–German employees is likely to be positively biased because knowing German is the main prerequisite for answering it.

The resulting data set then contains observations based on the occupation–by–industry means.

A.1 Skills Required by Occupations

As already set out in the main text, the demand side of skills is determined by the tasks occupations require. In order to make the analysis feasible, the variety of activities that is asked for in the survey questionnaire are pooled to 6 task categories: analytic, interactive, repetitive cognitive, non–repetitive manual, repetitive manual, and computing tasks. Table B in appendix B contains examples of tasks that are asked for in the survey questionnaire, and shows how they are pooled to the 6 task categories.

On the level of employees, each task category represents the fraction of tasks an employee has to perform within the particular category.

$$Task_j = \frac{\#Task_j}{\sum_{j=1}^{6} \#Task_j} * 100 \tag{3}$$

where

$$j = \begin{cases} 1 & : \text{analytic tasks} \\ 2 & : \text{interactive tasks} \\ 3 & : \text{repetitive cognitive tasks} \\ 4 & : \text{repetitive manual tasks} \\ 5 & : \text{non–repetitive manual tasks} \\ 6 & : \text{computing tasks} \end{cases}$$

For the purpose of this analysis, the task intensities at the individual level are aggregated to the occupation–by–industry level by taking group means.

A.2 Formal Educational Attainment

The data set contains detailed information on the vocational attainment of employees. The employees are classified into three qualification groups according to their vocational education (school degrees are not considered):

- People with lower levels of education, that is people with no occupational training.

- People with medium level of education, that is people with an vocational qualification who might have either completed an apprenticeship or have graduated from a vocational college.
- People with high level of education, that is, people holding a degree from a university or from a technical college.

These variables are dummy variables, taking on the value 1 if the employee falls within the particular group of educational level.

The information on the individual level is aggregated to the occupation–by–industry level by taking group means indicating the share of employees falling within the particular educational level.

A.3 Measurement of Technology

The data set contains information on the tools and machines the employees work with, which allows the researcher to get a detailed picture on the working realities and conditions at the respective point in time.

The focus in this study is on computers, terminals, and electronic data processing (edp) machines. "Computer use" is a dummy variable indicating whether the employee uses one of the above devices or not.

As with the previous variables, the information on the individual level is aggregated to the occupation–by–industry level by taking group means, thus indicating the share of computer user within the group.

A.4 Broad Occupational Classifications

The classification of occupations to professionals, technical workers, managers, administrators, clerical workers, sales, operatives, crafts, laborers and personal service workers are based on the classification of occupational titles on the 3–digit–level according to the Federal Employment Bureau, in the version of 1988.

Table C in Table Appendix gives an overview of the construction of the main variables on the individual level and Table D displays summary statistics.

B Table Appendix

Table A: Industry Classification

Agriculture	
Manufacturing incl. construction and mining	
10	Mining
11	Chemical Industry, Rubber and Synthetic Material
12	Stone and Clay, Glas and Ceramics
13	Iron and Steel Production
14	Steel and Light Metal, Tracked Vehicles
15	Machine Construction
16	Car Industry
17	Shipbuilding, Aircraft and Aerospace Industry
18	Office and Data–Processing Machines
19	Electrical Engineering
20	Precision and Optical Instruments
21	Musical Instruments, Toys, and Jewellery
22	Construction
23	Wood Processing
24	Cellulose and Paper Industry
25	Printing
26	Leather and Shoe Industry
27	Textile Industry
28	Food, Beverages and Tobacco
Services	
29	Laundry and Dry Cleaning
30	Hairdresser
40	Trade
52	Transport Services (including Carriage, Travel Agency, Warehouse)
53	Credit Institutions
54	Insurance Companies
55	Catering and Hotels
57	Health and Veterinary
61	Radio, TV, Publishing House, Art, Theater, Museum
62	Other Private Services
Public and Quasi–Public Institutions	
50	Postal Services
51	Railway Services

Table B: Assignment of Activities

Classification	Tasks
non–repetitive analytic	research, evaluation, and planning,
	making plans, constructions, designing, sketching
	working out laws/prescriptions
	using and interpreting laws
non–repetitive interactive	negotiating, lobbying coordinating,
	organizing, caring, and supplying
	to sell, to buy, to advise customers, advertise
repetitive cognitive	calculate, bookkeeping
	testing and controlling of goods and information
	correcting of texts/data
	calibration, weighting
	measuring of length/weight/temperatur
	chemical-physical analysis
	medical-biological analysis
repetitive manual	run a machine, machine set up
	mining minerals, extracting, recovering and collecting
	preparing, sorting, crushing of raw materials and plants
	centrifuge, cracking melting, founding
non–repetitive manual	repair houses, apartments, grow plants
	construction of buildings
	installing and connecting up cables
	painting, sewing, cutting out
	restoring of buildings/art/monuments
	repairing of machines/vehicles
	repairing of textiles, leather goods,
	synthetic materials, or household goods
computing tasks	programming, computer engineering,
	using applications software

Table C: Definition of Variables on the Individual Level

Variable	Definition
$Task_j$	$\frac{\#Task_j}{\sum_{j=1}^{5} \#Task_j} * 100$, where
	j = 1 : analytic
	= 2 : interactive
	= 3 : repetitive cognitive
	= 4 : repetitive manual
	= 5 : non–repetitive manual
	= 6 : computing
computer use	1: use of computer technology on the job, 0: otherwise
high education	1: university or technical college degree, 0: otherwise
medium education	1: apprenticeship or degree from vocational school, 0: otherwise
low education	1: no further occupational training, 0: otherwise
work experience	survey year-first year of employment
tenure	survey year-first year with current employer

Table D: Summary Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
annualized (percentage point) changes in...				
analytic task intensities	0.25	2.50	-16.67	16.67
interactive task intensities	2.82	4.59	-16.67	16.67
repetitive cognitive task intensities	-0.69	2.58	-16.67	16.67
repetitive manual task intensities	-0.31	4.54	-16.67	16.67
non–repetitive manual task intensities	-2.13	5.07	-16.67	16.67
computing task intensities	0.22	1.09	-8.33	8.33
computer use	2.36	4.75	-16.67	16.67
share of ...				
computer users	20.20	30.57	0.00	100.00
employees with high education	10.31	24.68	0.00	100.00
employees with medium education	67.38	32.65	0.00	100.00
female employees	28.41	34.86	0.00	100.00
part–time employees	11.11	21.52	0.00	100.00
farm workers, farm managers	1.67	12.75	0.00	100.00
personal service workers	9.03	28.60	0.00	100.00
laborers	3.95	18.92	0.00	100.00
operatives/crafts	44.68	49.51	0.00	100.00
sales personnel	3.49	18.35	0.00	100.00
clerical workers	11.64	32.08	0.00	100.00
administrators, managers etc.	25.52	43.53	0.00	100.00
average years of...				
work experience	20.40	7.66	1.00	49.00
tenure	11.21	6.34	0.00	44.00

Table E: Changes in Within–Occupational Skill Requirements, Lagged Δ Computer Use

Dep. Variables: 10 x (Annualized Changes in Task Intensities)					
	Δ analytic	Δ interactive	Δ repetitive cognitive	Δ repetitive manual	Δ computing
Lagged Δ computer use * 10	0.01	0.12***	-0.09***	0.02	-0.04***
	(0.01)	(0.04)	(0.01)	(0.02)	(0.01)
Vocational Education (lagged)					
Share highly educated	0.12	-2.41***	-0.15	1.62***	-0.08
	(0.33)	(0.80)	(0.36)	(0.54)	(0.01)
Share medium educated	0.57***	-0.87	-0.61***	1.53***	-0.00
	(0.23)	(0.55)	(0.25)	(0.37)	(0.11)
Work-based Learning (lagged)					
work experience	0.27***	0.81***	-0.44**	-0.40***	-0.14***
	(0.11)	(0.26)	(0.12)	(0.17)	(0.05)
tenure	-0.41***	-1.58***	0.51***	0.52***	0.19***
	(0.14)	(0.34)	(0.15)	(0.22)	(0.07)
Interaction Terms (lagged)					
highly educ. * Δ comp. use * (1/100)	0.02	0.00	0.03	-0.22**	0.01
	(0.07)	(0.17)	(0.08)	(0.11)	(0.04)
medium educ. * Δ comp. use * (1/100)	-0.04	0.02	0.06	-0.24***	0.05*
	(0.06)	(0.14)	(0.06)	(0.09)	(0.03)
professionals * Δ comp. use * (1/100)	-0.38***	0.15	0.18	-0.03	0.08
	(0.11)	(0.26)	(0.12)	(0.18)	(0.05)
clericals * Δ comp. use * (1/100)	-0.41***	0.16	0.24**	-0.03	0.10*
	(0.11)	(0.27)	(0.12)	(0.18)	(0.05)
sales * Δ comp. use * (1/100)	-0.39***	0.11	0.18	-0.00	0.09
	(0.12)	(0.28)	(0.13)	(0.19)	(0.06)
operatives/crafts * Δ comp. use * (1/100)	-0.25**	0.11	0.15	-0.09	0.08
	(0.11)	(0.26)	(0.12)	(0.18)	(0.05)
laborers * Δ comp. use * (1/100)	-0.32*	0.99	0.11	0.00	-0.07
	(0.18)	(0.43)	(0.19)	(0.29)	(0.09)
(personal) service * Δ comp. use * (1/100)	-0.35***	0.11	0.08	-0.03	-0.05
	(0.12)	(0.29)	(0.13)	(0.19)	(0.06)
$Pseudo - R^2$	0.23	0.11	0.30	0.14	0.04
χ^2	223.91	208.74	716.92	275.03	77.92
Number of observations:			1707		

Control variables are: share of part–time employees, share of female employees, occupational structure of employees, time–, and sector dummies. The share of farm workers and employees with low levels of education are the base category. Standard errors are in parentheses; regressions are weighted by the number of individuals in occupation–by–industry groups; ***,**,*–indicate significance on the 1, 5, 10 per cent level.

Table F: Changes in Within–Occupational Skill Requirements, Computer Use (lagged)

Dep. Variables: 10 x (Annualized Changes in Task Intensities)					
	Δ analytic	Δ interactive	Δ repetitive cognitive	Δ repetitive manual	Δ computing
Lagged share of computer use	0.12***	0.19***	-0.46***	0.03	-0.12***
	(0.02)	(0.04)	(0.02)	(0.04)	(0.01)
Vocational Education (lagged)					
Share highly educated	0.04	-2.41***	-0.04	0.03	0.01
	(0.03)	(0.80)	(0.06)	(0.06)	(0.01)
Share medium educated	0.06***	-0.87	0.01	-0.05	0.02**
	(0.02)	(0.55)	(0.02)	(0.04)	(0.01)
Work-based Learning (lagged)					
work experience	0.26***	1.12***	-0.14*	-0.38***	-0.04
	(0.08)	(0.16)	(0.09)	(0.17)	(0.04)
tenure	0.04	-0.42**	-0.41***	0.42**	-0.04
	(0.10)	(0.20)	(0.11)	(0.21)	(0.04)
Interaction Terms (lagged)					
highly educ. * Δ comp. use * (1/100)	0.03	0.54***	0.54***	-0.36*	0.10***
	(0.09)	(0.18)	(0.10)	(0.19)	(0.01)
medium educ. * Δ comp. use * (1/100)	0.02	0.21	0.31***	-0.40***	0.10***
	(0.08)	(0.15)	(0.08)	(0.16)	(0.03)
professionals * Δ comp. use * (1/100)	-0.37***	0.17	0.18	0.33	0.08
	(0.14)	(0.29)	(0.15)	(0.30)	(0.06)
clericals * Δ comp. use * (1/100)	-0.13	0.39	-0.32**	0.54*	-0.08
	(0.14)	(0.29)	(0.16)	(0.30)	(0.06)
sales * Δ comp. use * (1/100)	-0.38***	0.54*	0.05	0.37	0.07
	(0.16)	(0.32)	(0.17)	(0.33)	(0.07)
operatives/crafts * Δ comp. use * (1/100)	-0.27**	-0.06	-0.01	0.72***	0.05
	(0.14)	(0.29)	(0.15)	(0.30)	(0.06)
laborers * Δ comp. use * (1/100)	-0.25	0.19	-0.06	2.32***	0.16
	(0.23)	(0.46)	(0.25)	(0.47)	(0.10)
(personal) service * Δ comp. use * (1/100)	-0.37***	-0.34	0.22	-0.04	0.08
	(0.15)	(0.31)	(0.17)	(0.32)	(0.07)
$Pseudo - R^2$	0.10	0.11	0.25	0.04	0.15
χ^2	340.90	372.15	991.32	119.13	512.17
Number of observations:			2981		

Control variables are: share of part–time employees, share of female employees, occupational structure of employees, time–, and sector dummies. The share of farm workers and employees with low levels of education are the base category. Standard errors are in parentheses; regressions are weighted by the number of individuals in occupation–by–industry groups; ***,**,*–indicate significance on the 1, 5, 10 per cent level.