Changing Workplaces in the Knowledge-Based Economy

Evidence from Micro Data

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

> "IT (...) amplifies brain power in the same way that the technologies of the industrial revolution amplified muscle power."
> Brad DeLong, University of California Berkeley
> The Economist (September 23, 2000).

In recent decades, there has been a major shift in production away from labor and capital towards knowledge-based activities.[1] While the traditional inputs, labor and capital, still play a role, knowledge has been gaining steadily in importance as a factor of production. These changes have been reflected by several broad trends: There has been a sectoral shift towards service industries. In West Germany, for example, the share of employees working in the service sector was about 40 percent in 1970 and about 65 percent in 2000. Similarly, the share in value added of the service sector increased from less than 50 percent in 1970 to about 70 percent in 2000.[2] Within the service sector, the increase in employment of business-related services such as tax and management consultancies, computer services and technical advisors has been the most pronounced.[3] In addition to these sectoral changes, there has been a major shift away from blue-collar occupations towards white-collar occupations. Blue-collar workers made up about 40 percent of the West German workforce in the 1970s and less than 30 percent in the late 1990s. The share of white-collar workers employed, by contrast, increased from 50 percent of the workforce in the 1970s to more than 60 percent in the late 1990s. Among white-collar occupations, the growth

[1] See, for example, OECD (1996a, 1996b).
[2] Statistisches Bundesamt (2001, 1980).
[3] Kaiser (2002).

in the number of managerial, professional, technical and administrative employees has been particularly marked.[4] Simultaneously, there has been a massive diffusion of information and communication technologies (ICT) such as computers and the Internet at the workplace. In the late 1970s only about 6 percent of the workforce used a computer on the job. In the 1980s and 1990s, the spread of computers increased on average by more than 40 percent per annum. In the late 1990s, more than 55 percent of employees used computers at the workplace. The adoption of computer capital has been particularly pronounced among employees with higher levels of education and in professional, technical, managerial, administrative and clerical occupations.

The rapid diffusion of ICT in the workplaces has been accompanied by vivid discussions in public and among economic scholars. There has always been a discussion on the impact of technological change in economics. The historical debate focused, however, on the labor-saving features of technological change. Discussions today acknowledge that labor is a heterogeneous factor and that the effects of technological change, in particular advances in ICT, may not be equally distributed among employees. This notion has been spurred by the diverging labor market success of employees with different levels of formal education. In West Germany in the late 1970s, for example, the incidence of unemployment among employees without a vocational training degree was only around 4 percentage points higher than that of employees with a degree from university. During the 1980s and 1990s the qualification-specific unemployment rates diverged sharply. The gap peaked in 1997 with a difference of more than 20 percentage points in unemployment rates between the two groups. It declined thereafter, but it was still around 15 percentage points in 2003.[5]

In the U.S. and U.K., by contrast, the discussion has been provoked by the differing trends in real wages of employees with different educational backgrounds. Employees with a low level of education have seen their real wages decrease since the mid-1980s, while the returns to education rose sharply. This development was particularly astonishing because the supply of employees with higher levels of education has also increased. These stylized facts – diverging qualification-specific unemployment rates and differing trends in real wages for employees with different educational backgrounds – brought about the notion that the recent developments in computer technologies have been skill-biased, shifting labor demand toward em-

[4]Spitz (2003).

[5]Reinberg and Schreyer (2003).

ployees with high levels of education. This feature has often been referred to as the skill-biased technological change (SBTC) hypothesis.

This thesis includes four essays on various aspects of how workplaces have been changing in recent decades, all being characterized by the shift towards knowledge-based activities in production and the extensive spread of ICT at the workplace. The content of Chapter 3 is twofold. It includes a descriptive analysis that establishes the stylized facts about trends in occupational skill requirements in West Germany since 1979. It then provides evidence on the role workplace computerization has had in this development. Chapter 4 investigates the relationship between computer usage at the workplace and wages. This analysis is extended by the aspect of organizational changes within companies in Chapter 5. Chapter 6, in contrast to the previous chapters, focuses on managers as a particular group of employees that has been gaining steadily in importance in terms of employment in recent decades. This chapter investigates the incentive effects of managerial ownership. The analyses in Chapters 3-5 are based on individual-level data, whereas the analysis in Chapter 6 is based on a company-level data set.

One of the implications of the continuing shift towards a knowledge-based economy for the labor market is that the demand for skills and capabilities changes steadily. This feature is at the center of the analysis of Chapter 3. It analyzes how changes in the task composition of occupations have altered occupational skill requirements in West Germany between 1979 and 1999. The analysis shows that skill requirements at the workplace have increased in recent decades, owing to a shift towards analytical and interactive activities and away from cognitive and manual routine activities. In addition, the analysis in Chapter 3 includes direct evidence on how workplace computerization has contributed to this development. The literature so far cites evidence on various aggregation levels supporting the SBTC hypothesis. However, up to now, direct evidence on *how* computer technologies have changed occupational skill requirements in recent decades is scarce. The analysis presented in Chapter 3 aims at closing this gap. It investigates the mechanisms that induce ICT to be complementary to employees with high levels of education and thus opens the "black box" that typically surrounds analyses on SBTC. The results suggest that ICT substitutes for workers in performing manual and cognitive routine tasks, whereas it complements workers in performing non-routine cognitive tasks. The skill-bias in recent technological change then arises because employees with high levels of education have a comparative advantage in performing analytical and interactive activities.

The widening wage structure in most industrialized countries has often been attributed to the impact of skill-biased technological change. Yet the empirical evidence with respect to the relationship between the use of ICT and wages on the individual level is at best mixed, with most studies favoring the argument that the observed positive correlations are spurious, that is, attributable to unobserved heterogeneity.

The analysis in Chapter 4 contributes to the discussion on the relationship between computer use at the workplace and wages. In contrast to previous studies in this body of literature, computer usage is interpreted as a treatment and methods of treatment evaluation are applied. The validity of these methods is backed by the informational richness of the data set. Results are presented for specifications that assume homogeneous treatment effects and for specifications that allow the treatment effects to be heterogeneous across individuals. The overall conclusion of the analysis is that computer users would be worse off had they not started to work with computers. The associated wage markup amounted to about 8 percent in West Germany in 1998/99.

Chapter 5 extends the analysis of Chapter 4 by the aspect of organizational changes within companies. It is a strongly revised version of Bertschek and Spitz (2003b), which has been published in German (Bertschek and Spitz, 2003a).

Over the past few years, there has emerged a growing awareness that in order to result in efficiency gains, the introduction of ICT in the workplace should be accompanied by appropriate organizational changes. The quantitative importance of these organizational changes has been documented in various studies on the company level. Typical features are: an increased role for teamwork and job rotation, a reduction in the number of management levels, an emphasis on continuous learning, a decentralization of responsibility within companies, and a direct involvement of employees in the decision-making process.

The contribution of this analysis to the literature is that it analyzes both organizational changes *and* computer usage in a common framework using individual-level data. The study investigates whether the use of ICT and organizational changes affect wage outcomes and, hence, whether or not employers share part of the productivity gains associated with ICT use and organizational changes with their employees. The analysis also contributes to the discussion about the complementarity relationship between ICT usage and organizational changes. The findings show that employees working in companies that have implemented organizational changes earn significantly higher wages. This wage markup accrues to all employees within these companies, independent of whether they had been directly affected by these changes. This finding suggests that companies that change their organizational structure pay efficiency wages or compensating wage differentials. By contrast, it is unlikely that the wage markup results from the increased productivity of employees owing to the organizational change.

The analyses of these first three chapters are based on the “Qualification and Career Survey,” a large, representative survey of employees 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). It includes four cross-sections launched over the period from 1979 to 1999, with each covering around 30,000 individuals. It is particularly suited for the analyses because it includes a large variety of variables that characterize the educational background of employees, the activities they perform at the workplace, the wages they earn and the technologies they use.

The last part of this thesis addresses the question of whether managerial ownership has a positive impact on company performance. The analysis thus focuses on one particular group of employees: managers. Managers are part of the “high-skilled white-collar” workers who have witnessed a sizeable increase in importance in terms of employment shares in the labor market during the emergence of the knowledge-based economy. The contribution of this paper to the literature is that it investigates this question for small and medium-sized companies with limited liability (GmbHs). Previous studies in this research area have predominantly focused on incentive effects in large, listed companies. GmbHs have always had an important role in West Germany. However, their overall importance increased steadily in recent decades, a process that is also related to the shift away from the traditional inputs in production, labor and capital, and towards knowledge-based activities. Small and medium-sized companies are at the heart of the emergence of the knowledge-based economy, which has forced companies to concentrate on their core competencies.[6] In addition, the analysis focuses on companies that operate in knowledge-intensive sectors such as computer services, tax consultancy and management consultancy.

This chapter largely corresponds to the paper “Managerial Ownership and Company Performance in German Small and Medium-Sized Private Enterprises”, jointly written with Elisabeth Müller, which will be published in the German Economic Review.

[6]See, for example, Audretsch and Thurik (2001) and Nooteboom (1994).

The analyses in this chapter are based on a business survey in the German business-related service sector carried out by the ZEW and Creditreform, Germany's largest credit rating agency. The data derived from the survey is merged with company information from the Creditreform database, which includes detailed information on the ownership structure of private companies. The data set is a panel that includes observations from 1997 to 2000.

Economic theory identifies two opposing effects of managerial ownership – the incentive and the entrenchment effect. On the one hand, managerial ownership aligns the objectives of owners and managers. From this incentive effect, a positive relationship between managerial ownership and company performance is expected. On the other hand, managers with large ownership shares have the ability to "entrench" themselves. Their large ownership share makes them immune to control by outside owners. If the entrenchment effect is larger than the incentive effect, performance decreases in managerial ownership.

The findings show that managerial ownership up to around 40 percent has a positive effect on company performance owing to the incentive effect. However, the results do not indicate a significant entrenchment effect.

Chapter 2

Einleitung

> "IT (...) amplifies brain power in the same way that the technologies of the industrial revolution amplified muscle power."
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> The Economist (September 23, 2000).

In den vergangenen drei Jahrzehnten hat sich die Produktionsstruktur in den Industrieländern stark verändert. Wissensintensive Tätigkeiten haben im Vergleich zu den traditionellen Produktionsfaktoren, Kapital und Arbeit, stark an Bedeutung gewonnen.[1] Diese Verschiebung zeigt sich empirisch an verschiedenen Trends: Es hat ein sektoraler Strukturwandel hin zu einem höheren Dienstleistungsanteil sowohl an der Bruttowertschöpfung als auch an der Beschäftigung stattgefunden. Als Folge waren 2000 bereits rund 65 Prozent der Arbeitnehmer im Dienstleistungssektor tätig (1970: rund 40 Prozent) und der Dienstleistungssektor erhöhte seinen Anteil an der Bruttowertschöpfung von weniger als 50 Prozent in 1970 auf rund 70 Prozent in 2000.[2]

Diese Zahlen unterschätzen jedoch den wahren Trend hin zur Dienstleistungsgesellschaft, da sie die zunehmende Bedeutung von Dienstleistungstätigkeiten innerhalb des verarbeitenden Gewerbes vernachlässigen. Dienstleistende Tätigkeiten gehen nicht nur jedem Produktionsprozess voraus, sondern sie sind auch zentraler Bestandteil von Produktion und Absatz. Darüber hinaus spiegeln diese Zahlen nicht wider, dass sich die Struktur der Dienstleistungsberufe ebenfalls verändert hat. Werden Dienstleistungsberufe traditionell mit Berufen gleichgesetzt, die ein relativ

[1] Siehe zum Beispiel OECD (1996a, 1996b).
[2] Statistisches Bundesamt (1980 and 2001).

geringes Qualifikationsniveau der Beschäftigten verlangen, und die mit einer relativ geringen Entlohnung verbunden sind (Verkaufspersonal, Gaststättenpersonal, Frisöre usw.), zählen heute sogenannte wissensintensive Berufsgruppen (Unternehmensberater, Steuerberater, Werbefachleute usw.) zu den wichtigsten Segmenten. Der unternehmensnahe Dienstleistungssektor (Unternehmensberatung, Marktforschung, EDV-Dienstleistung usw.) als einer der am schnellsten wachsenden Sektoren in Deutschland untermauert diese Entwicklung.

Im selben Zeitraum verbreiteten sich Informations- und Kommunikationstechnologien (IKT) am Arbeitsplatz. Während Ende der 70er Jahre nur rund 6 Prozent der Beschäftigten mit Computern arbeiteten, waren es Ende der 90er Jahre bereits mehr als 55 Prozent. Die Verbreitung von IKT war besonders rasant unter hochqualifizierten Beschäftigten und in bestimmten Berufsgruppen. So war die Verbreitung von Computern bei Angestellten deutlich stärker als bei Arbeitern. Innerhalb der Gruppe der Angestellten sind es die Büroangestellten, Manager und Verwaltungsangestellten, die den höchsten Verbreitungsgrad aufweisen.

Unter Wirtschaftswissenschaftlern und in der Bevölkerung wurde die rasante Verbreitung von IKT lebhaft diskutiert. Der Einfluss von technologischem Wandel wurde in den Wirtschaftswissenschaften schon immer thematisiert, wobei historisch die Auswirkungen eines arbeitssparenden technologischen Fortschritts im Mittelpunkt stand. Heute wird vielmehr die Heterogenität des Faktors Arbeit berücksichtigt und betont, dass der Einfluss von technologischen Veränderungen, insbesondere in IKT, nicht gleichmäßig auf die verschiedenen Gruppen der Arbeitnehmer verteilt ist. Hintergrund dieser Verschiebung des Schwerpunkts der Diskussion bildet der unterschiedliche Erfolg, den Beschäftigte unterschiedlicher Qualifikationsgruppen in den vergangenen drei Jahrzehnten am Arbeitsmarkt hatten. In Westdeutschland hatten beispielsweise Ende der 70er Jahre Erwerbspersonen ohne abgeschlossene Berufsausbildung eine nur um 4 Prozentpunkte höhere Arbeitslosigkeit als Erwerbspersonen mit Universitätsabschluss. Im Lauf der 80er und 90er Jahre hat sich diese qualifikationsspezifische Arbeitslosenquote stark auseinander entwickelt. Am deutlichsten war der Unterschied 1997, als Erwerbspersonen ohne formalen Berufsabschluss eine um 20 Prozentpunkte höhere Arbeitslosenquote aufwiesen als Erwerbspersonen mit Universitätsabschluss. Diese große Diskrepanz verringerte sich danach zwar wieder, 2003 lag sie aber trotzdem noch bei rund 15 Prozentpunkten.[3]

In den USA und in Großbritannien wurde die Diskussion dadurch aufgeworfen,

[3] Reinberg and Schreyer (2003).

dass sich die realen Löhne der Geringqualifizierten seit Mitte der 80er Jahre verringerten, wohingegen die Erträge auf Bildungsinvestitionen stark stiegen. Diese Entwicklung war auch deshalb überraschend, da im gleichen Zeitraum das Angebot an Hochqualifizierten stark zunahm. Diese stilisierten Fakten – Divergenz der qualifikationsspezifischen Arbeitslosenquoten und der realen Löhne – führten zur Hypothese, dass die Verbreitung von IKT am Arbeitsplatz in den vergangenen Jahren qualifikationsverzerrend war, das heißt, dass sich die Nachfrage nach Arbeit verschoben hat zugunsten von hochqualifizierten Beschäftigten. Diese Besonderheit wird in der Literatur als qualifikationsverzerrter technologischer Fortschritt (engl.: skill-biased technological change, SBTC) diskutiert.

Diese Dissertation enthält vier Studien über die tiefgreifenden Veränderungen, die in den vergangenen drei Jahrzehnten am Arbeitsplatz stattgefunden haben. Sie stehen alle im Zusammenhang mit der zunehmenden Bedeutung wissensintensiver Tätigkeiten und der Diffusion von IKT am Arbeitsplatz. Der Inhalt des dritten Kapitels ist zweigeteilt: Der erste Teil zeigt deskriptiv, wie sich seit 1979 die Qualifikationsanforderungen am Arbeitsplatz in Westdeutschland verändert haben. Der zweite Teil untersucht ökonometrisch die Bedeutung, die die Verbreitung von Computern am Arbeitsplatz an dieser Entwicklung hat. Kapitel 4 untersucht den Zusammenhang zwischen Computernutzung und der Lohnhöhe der Beschäftigten. Diese Analyse wird im Kapitel 5 um den Aspekt der organisatorischen Veränderungen erweitert. In Kapitel 6 wird die Analyse auf die Berufsgruppe der Manager eingegrenzt. Manager sind eine Berufsgruppe, in der in den vergangenen Jahren die Beschäftigung stark gestiegen ist. In diesem Kapitel wird untersucht, welche Anreizwirkungen davon ausgehen, dass Manager Unternehmensanteile halten. Die Analysen in Kapitel 3-5 werden mit Hilfe eines Individualdatensatzes durchgeführt, in Kapitel 6 werden Unternehmensdaten genutzt.

Eine der Implikationen der Verschiebung der ökonomischen Aktivitäten hin zu wissensintensiven Tätigkeiten für den Arbeitsmarkt ist, dass sich die Anforderungen an die Fertigkeiten und Fähigkeiten der Beschäftigten stetig verändern. Dieses Merkmal der modernen Arbeitswelt liegt im Zentrum der Analyse des Kapitels 3. Zunächst wird untersucht, wie sich durch die Veränderung der Tätigkeitszusammensetzung der Arbeitsplätze die Qualifikationsanforderungen an die Beschäftigten in Westdeutschland zwischen 1979 und 1999 ausgewirkt hat. Die Untersuchung zeigt, dass die Qualifikationsanforderungen in den vergangenen drei Jahrzehnten gestiegen sind. Analytische und interaktive Fähigkeiten haben an Bedeutung gewonnen, wohingegen manuelle und kognitive Routinetätigkeiten an Bedeutung verloren haben. Darüber hinaus wird analysiert, welche Rolle Computertechnologien bei diesen Veränderungen spielen. Im Unterschied zu bisherigen Studien zum SBTC, die indirekte Evidenz zum Zusammenhang zwischen Computertechnologien und der Nachfrage nach Arbeit liefern, wird in diesem Kapitel direkt untersucht, wie Computertechnologien die Qualifikationsanforderungen am Arbeitsplatz verändern. Es werden die Mechanismen aufgezeigt, die dazu führen, dass Computertechnologien zu Beschäftigten mit höheren Bildungsabschlüssen komplementär sind. Die Analyse öffnet somit die "black box", die Studien in dieser Literatur typischerweise unberücksichtigt lassen. Die Ergebnisse zeigen, dass Computertechnologien Beschäftigte in der Ausübung manueller und kognitiver Routinetätigkeiten substituieren, wohingegen sie komplementär sind zu analytischen und interaktiven Tätigkeiten. Die qualifikationsverzerrende Eigenschaft des technologischen Fortschritts ist somit darauf zurückzuführen, dass er die relative Bedeutung analytischer und interaktiver Tätigkeiten erhöht, bei deren Ausübung Beschäftigte mit höheren Bildungsabschlüssen einen komparativen Vorteil haben.

Die zunehmende Spreizung der Lohnverteilung in den meisten industrialisierten Ländern wird häufig dem qualifikationsverzerrten technologischen Fortschritt zugeschrieben. Die empirischen Ergebnisse hierzu sind jedoch sehr unterschiedlich. Viele Studien kommen zu dem Ergebnis, dass die beobachtete positive Korrelation zwischen der Computernutzung und den Löhnen unbeobachtbarer Heterogenität zuzuschreiben sei.

Die Analyse in Kapitel 4 trägt zur Diskussion über die Lohneffekte der Computernutzung bei. Im Unterschied zu vorhergehenden Studien wird die Computernutzung als "treatment" interpretiert. Dieses Vorgehen erlaubt die Schätzung von Teilnahmeeffekten. Die Vielzahl an Variablen im Datensatz begründet die Angemessenheit dieser Methode in der vorliegenden Analyse. Es werden Ergebnisse für Spezifikationen ausgewiesen, die sowohl homogene als auch heterogene Teilnahmeeffekte zulassen. Insgesamt zeigt sich, dass Computernutzer sich in Bezug auf die Lohnhöhe besser stellen im Vergleich zur Situation, wenn sie nicht mit Computern arbeiten würden. Der Lohnaufschlag beträgt 1998/99 etwa 8 Prozent in Westdeutschland.

Das fünfte Kapitel erweitert die Untersuchung in Kapitel 4 um den Aspekt der organisatorischen Veränderungen. Dieses Kapitel ist eine stark überarbeitete Version von Bertschek and Spitz (2003b), das in einer deutschen Version veröffentlicht wurde (Bertschek and Spitz, 2003a).

In den vergangenen Jahren wurde deutlich, dass die Implementierung von Computertechnologien am Arbeitsplatz Hand in Hand mit entsprechenden organisatorischen Veränderungen gehen soll. Nur so können Effizienzgewinne erzielt werden. Zahlreiche Untersuchungen auf Unternehmensebene dokumentieren die Bedeutung, die organisatorische Veränderungen heute im Unternehmen haben. Folgende Maßnahmen werden dabei typischerweise aufgezählt: eine zunehmende Rolle von Gruppenarbeit und Job Rotation, eine Abflachung der Hierarchieebene im Unternehmen, die zunehmende Bedeutung des lebenslangen Lernens, eine Dezentralisierung der Verantwortlichkeiten im Unternehmen und eine direkte Beteiligung der Beschäftigten am Entscheidungsprozess.

Die Ergebnisse deuten darauf hin, dass Unternehmen, die organisatorische Änderungen durchgeführt haben, Effizienzlöhne oder kompensatorische Lohndifferenziale bezahlen. Hingegen deutet wenig darauf hin, dass die Beschäftigten deshalb besser entlohnt werden, weil ihre Produktivität durch die organisatorischen Veränderungen gestiegen ist.

Datengrundlage der Untersuchungen in diesen ersten drei Kapiteln bildet die Befragung des Bundesinstituts für berufliche Bildung (BIBB) und des Instituts für Arbeitsmarkt- und Berufsforschung (IAB). Der Datensatz besteht aus vier unabhängigen Querschnitten, die zwischen 1979 und 1999 erhoben wurden. Jeder Querschnitt enthält Beobachtungen über rund 30.000 Individuen. Der Datensatz eignet sich besonders zur Analyse der Fragestellungen, da er Informationen zum Bildungshintergrund der Beschäftigten, den Tätigkeiten am Arbeitsplatz, Löhnen, Nutzung von IKT und Informationen zum Arbeitgeber enthält.

Das letzte Kapitel der Dissertation untersucht, ob sich die Höhe des Eigentumanteils eines Managers positiv auf den Unternehmenserfolg auswirkt. Im Mittelpunkt dieser Analyse steht somit eine bestimmte Berufsgruppe: Manager. Manager gehören zur Gruppe der "hochqualifizierten Angestellten", die sich im Zuge der Verschiebung zur wissensintensiven Ökonomie durch besonders hohe Beschäftigungszuwächse ausgezeichnet haben. Der Beitrag dieses Kapitels zur Literatur ist, dass es die Fragestellung für kleine und mittlere Unternehmen in der Rechtsform der GmbH analysiert. Bisherige Studien haben hauptsächlich Anreizeffekte in großen Unternehmen, die am Aktienmarkt gelistet sind, analysiert. GmbHs haben in Deutschland aber immer eine große Rolle gespielt. Ihre Bedeutung hat in den vergangenen Jahren durch die Verschiebung hin zu wissensintensiven Aktivitäten jedoch nochmals stark zugenommen. Kleine und mittlere Unternehmen stehen im Zentrum der wissensintensiven Ökonomie, die die Unternehmen zwingt, sich auf ihre

Kernkompetenzen zu konzentrieren.[4] Darüber hinaus fokusiert die Analyse auf wissensintensive Sektoren wie zum Beispiel Steuerberater und Unternehmensberater.

Dieses Kapitel entspricht zu weiten Teilen der gemeinsamen Arbeit mit Elisabeth Müller, "Managerial Ownership and Company Performance in German Small and Medium-Sized Private Enterprises", die demnächst im German Economic Review veröffentlicht wird.

Die Datengrundlage bildet eine Umfrage bei unternehmensnahen Dienstleistern, die das ZEW in Zusammenarbeit mit dem Verband der Vereine Creditreform durchführt. Die Umfragedaten werden mit Informationen der Creditreform-Datenbank erweitert. Diese Datenbank enthält umfangreiche Informationen über die Eigentumsstruktur der Unternehmen. Der Datensatz ist als Panel aufgebaut und umfaßt die Jahre 1997 bis 2000.

Aus theoretischer Sicht ist das Halten von Eigentumsanteilen durch das Management mit zwei gegenläufigen Effekten verbunden: einem Anreizeffekt und einem Entrenchmenteffekt. Auf der einen Seite bringt der Eigentumsanteil des Managers seine Interessen näher an die Interessen der anderen Anteilseigner, weshalb man einen positiven Zusammenhang erwarten könnte. Auf der anderen Seite führt ein hoher Eigentumsanteil des Managers dazu, dass er sich "verschanzen" kann und nur schlecht kontrolliert werden kann, was auf einen negativen Zusammenhang hindeutet. Falls der Entrenchmenteffekt den Anreizeffekt überwiegt, sinkt der Unternehmenserfolg mit steigendem Eigentumsanteil des Managers.

Die Ergebnisse deuten darauf hin, dass es einen positiven Zusammenhang bis zu einem Eigentumsanteil von 40 Prozent gibt. Es lässt sich aber keine empirische Evidenz für das Vorliegen eines Entrenchmenteffekts finden.

[4] Siehe, zum Beispiel, Audretsch and Thurik (2001) und Nooteboom (1994).

Chapter 3

Computer Use, Job Content and Educational Attainment

3.1 Introduction

In recent decades industrialized countries have witnessed both a major increase in the supply of more educated workers and rising returns to education. This development supports the argument that technological change has been skill-biased, shifting labor demand towards employees with high levels of education.[1] A conclusion, however, that is based on indirect evidence.[2] Up to now, there is little direct evidence on how skill requirements in the workplace have changed in recent decades.

A conclusive judgement of whether occupational skill requirements have changed in recent decades is only possible if measures of skill requirements in the workplace are available. Skill requirements in the workplace are difficult to measure. Most studies rely on measures of formal education or wages. Education, however, is an input factor. It is very likely that people with equal investment in their formal education attain different levels of skills. Each education group is therefore best characterized by a distribution of skills.[3] In addition, skills that people bring to

[1]See, for example, Acemoglu (1998), Berman, Bound and Griliches (1994), Berndt, Morrison and Rosenblum (1994), Autor, Katz and Krueger (1998) and Berman, Bound and Machin (1998). Comprehensive reviews of this literature can be found in Katz and Autor (1999) and Chennells and van Reenen (2002).

[2]See Card and DiNardo (2002) for a critique of the skill-biased technological change hypothesis.

[3]The evidence presented by Katz and Murphy (1992), Levy and Murnane (1992) and Juhn, Murphy and Pierce (1993) points to the importance of distinguishing between formal education and skills in the context of wage inequality. Murnane, Willett and Levy (1995) present evidence

jobs in the sense of individual attributes - such as knowledge, abilities or capacities - do not necessarily coincide with the skills that are required to perform certain tasks at the workplace.[4] Wages, on the other hand, may not reflect the "true" skill level of individuals either. This is a very likely scenario in countries with centralized wage bargaining institutions such as West Germany and France. It may likewise be the case in other countries owing, for example, to discrimination or segregation in the labor market.

The present study uses direct measures of occupational skill requirements based on the task-composition of occupations to assess whether there has been a skill upgrading in the workplace in recent decades. Labor market institutions or other factors that may distort the relationship between skills and wages (or formal education) are less likely to have an equally strong influence on the task-composition of occupations.

The empirical analysis is based on occupations at the 2-digit-level. The groups are synthesized by aggregating individual-level data for West Germany. The data set contains four waves, launched in 1979, 1985/86, 1991/92 and in 1998/99 with 26,000 individuals 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 participated in the survey indicated what they actually do in their jobs. The occupational classifications are constant over time, so that detailed analyses of the changing skill requirement patterns within occupations can be carried out on the basis of the task descriptions.

The main findings are that occupational skill requirements have increased in recent decades, even in occupations that were the least demanding in 1979. This skill upgrading has also occurred within detailed education and age groups. A numerical assessment shows that changing occupational skill requirements account for nearly 50 percent of the educational upgrading in recent decades. Given that the analysis focuses solely on the within-occupational changes in task inputs neglecting the large shifts in the occupational distribution in employment towards more skill demanding occupations such as professionals and managers, this figure is large. In addition, the paper includes direct evidence on the role workplace computerization has had in this development. The results suggest that computer technology substitutes for workers in performing manual and cognitive routine tasks, whereas it complements

of the growing importance of cognitive skills. The diversity of skills within demographic categories is also emphasized by Heckman and Sedlacek (1985).

[4]See Spenner (1983, 1990).

workers in performing non-routine cognitive tasks. This relationship is found within occupations, within occupation-education groups and within occupation-age groups.

The chapter is organized in 8 sections. The next section discusses the related literature and introduces the task framework used in this study. Section 3.3 describes the data set and the variables. Section 3.4 presents stylized facts on occupational skill requirements as well as educational and technological trends in West Germany since 1979. Section 3.5 econometrically investigates the relationship between computer use, occupational skill requirements and educational attainment on the basis of synthetic occupation groups. Section 3.6 tests the robustness of results to changes in the task measure. Section 3.7 includes a note on wage developments. Section 3.8 presents the conclusions.

3.2 Occupational Skill Requirements and Rising Educational Supplies

The effect of technological change on labor demand has always been a major concern of economic research. A central theme in this discussion is whether the restructuring and reorganization of workplaces owing to technological developments leads to skill upgrading or skill downgrading.[5] The discussion has intensified with the spread of computer technology at workplaces in recent decades. Based on the observed shifts in the earnings distribution in the U.S. in recent decades, non-neutral technological change, increasing the productivity of highly skilled employees more than that of less skilled workers, has been given particular attention. In addition, the "polarization" of the labor force has been discussed.[6]

Empirical research has provided evidence of robust correlations between computer-based technologies and the use of highly skilled employees on various aggregation levels, strengthening the hypothesis that recent technological change has been skill-biased. These studies emphasize the higher skills now required at the workplace owing to computerization. In addition, the stylized fact of rising returns to education in spite of the fact that the supply of more educated workers increased supports

[5] A classical study is Braverman (1974), others are Spenner (1983) and Diprete (1988). Goldin and Katz (1996, 1998) provide a historical perspective on the relationship between technology and skill demand.

[6] See, for example, Levy and Murnane (1992) and Goos and Manning (2003).

the skill-biased technological change (SBTC) hypothesis.[7] Katz and Autor (1999), Acemoglu (2002) and Chennells and van Reenen (2002) give comprehensive reviews of the literature on SBTC, covering the major studies in this field of research. Empirical studies by Machin and van Reenen (1998), Falk (2001), Falk and Koebel (2001), Fitzenberger (1999) and Kaiser (2000) investigate SBTC in West Germany. The picture they present is consistent with the view that recent technological change in West Germany has also been skill-biased.

The oppositional view has been taken by the over-education literature that states that skill requirements did not change considerably in recent decades and that the increased deployment of highly-educated employees resulted in them holding occupations that were previously performed by employees with lower education levels. Empirical studies are, for example, Rumberger (1987), Duncan and Hoffman (1981), Sicherman (1991), Alba-Ramirez (1993), Verdugo and Verdugo (1989) and Groot and Maassen van den Brink (2000). The empirical studies have been criticized for the way they operationalize over-education (see, among others, Halaby, 1994, Smith, 1986). In addition, results of recent studies that take unobserved heterogeneity into account or use instrumental variable techniques question the positive wage effects of over-education found in cross-section analyses (see, for example, Bauer, 2002). These results convincingly demonstrate that part of what is referred to over-education simply reflects the heterogeneity of individual abilities and skills within particular educational qualifications. In addition, the simultaneous increase in the returns to education and in the supply of more educated workers question that over-education could be a large scale phenomenon. Why should employers pay more to educated workers for jobs that have previously been performed by employees with lower levels of education? In the light of these arguments, over-education, similarly to polarization, will be discussed only marginally in the analysis that follows.

Most studies in the SBTC literature use "traditional" skill measures to assess the skill level of employees, such as production workers/non-production workers or blue-collar/white-collar workers.[8] These classifications use divisions according to

[7]The analysis in the present study focuses on technological change (as opposed to de-industrialization and globalization as alternative explanations for the skill upgrading in recent decades), measured by workplace computerization, because it is the only explanation that generates predictions about within-occupational task changes. De-industrialization and globalization, on the other hand, emphasize between-industry or between-occupation developments. In addition, SBTC is the only factor that explains why the large increase in the supply of more educated workers has not been accompanied by a decrease in the education premium in recent decades.

[8]For example Berman, Bound and Griliches, (1994), Berndt, Morrison and Rosenblum, (1994).

occupational groups that are of limited usability in determining skill requirements. They document, for example, the structural shift towards increased deployment of white-collar work in all major sectors of industrialized countries.

The recent study by Autor, Levy and Murnane (2003), however, now offers a framework that makes it possible to analyze occupational skill requirements directly.[9] The major feature of their framework is that they conceptualize work as a series of tasks, and therefore, the changing task composition of occupations in recent decades can be analyzed.

Following this framework, I use direct measures of occupational skill requirements that are based on the activities people perform on the job. These activities are classified in five skill categories: *non-routine analytical* tasks such as research, planning or evaluation activities; *non-routine interactive* tasks such as the coordination and delegation of work; *routine cognitive* tasks such as double-entry bookkeeping and calculating; *routine manual* tasks such as machine feeding or running a machine and *non-routine manual* tasks such as housekeeping or restoring houses.

The terms *routine* and *non-routine* characterize the relationship between the respective task measure and IT.[10] Both manual and cognitive routine tasks are well-defined in the sense that they are expressible in rules, which makes them easily programmable, therefore computers can perform them at economically feasible costs (Levy and Murnane, 1996). Hence, routine tasks are subject to substitution by computer capital.[11] *Non-routine* tasks are not well-defined and programmable, often because they require optical recognition so that they are not expressible in rules. Therefore, at present, they cannot be accomplished by computers. However, computer capital is complementary to non-routine cognitive tasks, both analytical and interactive, in the sense that computer technology increases the productivity of employees performing those tasks. The term *analytical* refers to the ability of workers to think, reason and solve problems encountered at the workplace. The term *inter-*

[9]This framework sheds light on the "black box" that typically encloses studies on SBTC, as was, for example, expressed by Bresnahan (1999, p. 340): "...(skill-biased technological change) also tends to be something of a residual concept, whose operational meaning is often *labor demand shift with invisible cause*".

[10]Following Autor, Levy and Murnane (2003), the occupational production function is assumed to have a constant returns to scale Cobb-Douglas form: $Q = (L_R + C)^{1-\beta} L_N^{\beta}$, $\beta \in (0, 1)$, where L_R and L_N are routine and non-routine task inputs and C is computer capital, all measured in efficiency units. The exogenously declining price of computer capital is the causal force in this model.

[11]See Rule and Attewell (1989) for a description about the role of computing in organizations.

active refers not only to communication skills - that is, the ability to communicate effectively with others through speech and writing - but also to the ability to work with others, including co-workers and customers.[12]

The scope for substitution is thus limited to certain tasks. This *limited substitution* relationship (Bresnahan, 1999) between IT and occupational tasks shifts the demand for labor towards employees with higher levels of educational attainment who are presumed to have a comparative advantage in performing non-routine cognitive tasks.[13] Autor, Levy and Murnane (2003) present a general equilibrium model that is the foundation of this informal reasoning showing how computerization (owing to the exogenous declining price of computer capital) alters the allocation of labor across different task inputs.

Although the empirical evidence suggests that technological change in West Germany has also been skill-biased in recent decades, wage trends are often considered different from developments in other countries.[14] Fitzenberger (1999) and Fitzenberger et al. (2001), however, provide evidence that the wage structure in West Germany is less stable than commonly believed, even though the changes are small by international standards. Wages of employees with a medium level of education deteriorated after 1980 relative to both employees with high and low levels of education, and the relative wage position of the bottom part of the wage distribution of employees with high levels of education has slightly deteriorated over time. In addition, the wage dispersion among medium- and high-educated employees increased over time. The main difference to developments in other countries is in the group of employees with low levels of education. In contrast to the wage decreases in most other countries, their wages slightly increased and the wage dispersion within this group of workers remained stable over time. However, this group of workers experienced a sharp increase in unemployment since the 1980s. The lack of adjustment of wages of employees with low levels of education is often explained by union wages that are binding floors for low-wage earners.[15]

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[12] Case studies identified analytical and interactive skills as the "key" skills required by modern workplaces in industrialized countries (for example, Hirschhorn, 1984, Stasz, 1997, 2001).

[13] Maurin and Thesmar (2004) follow the same line of arguments.

[14] The most comprehensive analyses of wage trends exists for the U.S., for example by Bound and Johnson (1992), Katz and Murphy (1992), Levy and Murnane (1992) and Juhn, Murphy and Pierce (1993). Gottschalk and Smeeding (1997) provide an international comparison of earnings and income developments since the early 1980s.

[15] The European unemployment problem and the U.S. inequality problem are often referred to

The present study is most closely related to the study by Autor, Levy and Murnane (2003), which provides the theoretical and conceptional framework for this analysis. It extends their work by focusing on within-occupational task changes. In addition, the data set used in the present study has several advantages over the Dictionary of Occupational Titles, the data set used by Autor, Levy and Murnane (2003). I provide evidence on SBTC in West Germany where previous findings are less clear than in other countries. The findings in both analyses support the argument that IT increases the demand for highly educated labor through shifting the task composition towards analytical and interactive activities for which these employees have comparative advantages.

3.3 Data Set and Definition of Variables

The analysis is based on the "Qualification and Career Survey" which is a survey of employees 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). It includes four cross-sections launched in 1979, 1985/86, 1991/92 and 1998/99 each covering around 30,000 individuals (men and women).[16]

The level of analysis is defined by the occupational affiliation of employees. The employees are classified according to their occupation. The classification of occupational titles corresponds to that of the German Federal Employment Bureau, 1988. In the present study the 2-digit level of classification is used, which includes around 80 different occupations.[17] Based on the 2-digit level occupations, the micro level

as two sides of the same coin (Krugman, 1994, Freeman, 1995). Criticism of this hypothesis can be found, for example, in Nickell and Bell (1996) and Krueger and Pischke (1997). Card, Kramarz and Lemieux (1999) provide evidence for France (often considered to be similar to West Germany with respect to its labor market institutions) that is inconsistent with the "two-sides-of-the-same-coin" hypothesis.

[16]The target population is not uniform within the four waves. Due to this changing sample design the sample used in the present study had to be restricted to West-German residents with German nationality, in other words East-German residents and non-German employees are excluded from the sample since these groups of employees were not interviewed in every wave. Moreover, the sample does not include self-employed and unemployed persons, employees with agricultural occupations and employees working in the agricultural sector. In addition, persons younger than 18 and older than 65 are excluded from the sample.

[17]The 2-digit level of occupational classification is used rather than the 3rd or 4th level, since it is well known that in survey data occupational affiliations are subject to measurement error issues.

data of the 4 cross-sections are aggregated into occupation cells and the group means are used for the analysis. The firms employing these employees cover a wide range of industries, both services and manufacturing. Table A in the appendix lists the 42 industries considered.

The data set is particularly suited to analyze changes in within occupational skill requirements since occupations in all four waves are categorized according to the 1988 classification. The constant occupational titles thus provide the reference point for the analysis. In addition, survey respondents indicated what kind of activities they perform on the job. It is very unlikely that this causes an underestimation of true changes in job content as in the Dictionary of Occupational Titles (DOT), the description of occupations often used by researchers in the U.S. for questions related to skills.[18] The credibility of the analysis in the present study would be impaired if the answers of survey participants with high levels of education were systematically biased towards analytical and interactive activities. I do not think, however, that this is particularly likely because survey participants only indicate whether they perform certain activities or not. They do not assign scores to the different measures. In addition, most of the analysis is performed in "first-differences". The reporting bias therefore would only pose a problem if it changed over time. As will be presented later on, the empirical results even hold within-occupation-education groups.

The most important variables for the present analysis are the measures of occupational skill requirements, the measure of technology, and the level of employees' formal education. Table 3.2 shows the summary statistics.

Occupational Skill Requirements: Occupational skill requirements are measured by the workers' job duties, depicted in the survey by the activities that employees have to perform at the workplace.[19] In light of the hypotheses, the variety of activities asked for in the survey questionnaire are pooled to five task categories. These tasks categories are: *analytical* tasks (such as mathematical, logical reasoning and problem-solving tasks), *interactive* tasks (such as interpersonal, organizational and managerial tasks), *routine cognitive* tasks (such as bookkeeping, time-sheet ac-

The potential measurement error, however, decreases the higher the level of aggregation.

[18]In the DOT, experts assign scores to different indicators characterizing the occupations. It is well known that this process encourages analysts to underestimate 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).

[19]I use the terms "skill requirements" and "skill/task inputs" interchangeably throughout the paper, although the term "skill/task inputs" is strictly speaking only correct. In order to being able to speak of "skill requirements", I would need information about task prices.

counting and inventory control tasks), *routine manual* tasks and *non-routine manual* tasks. Table 3.1 illustrates the assignment of activities to the five categories. On the individual level i, the task measures ($Task_{ijt}$) are defined as:

$$Task_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in cross-section } t}{\text{total number of activities in category } j \text{ at time } t} * 100 \tag{3.1}$$

where
$t = 1979, 1984/85, 1991/92 \;\text{ and }\; 1998/99, \;\text{ and}$

$$j = \begin{cases} 1 & : \text{ non-routine analytic tasks} \\ 2 & : \text{ non-routine interactive tasks} \\ 3 & : \text{ routine cognitive tasks} \\ 4 & : \text{ routine manual tasks} \\ 5 & : \text{ non-routine manual tasks.} \end{cases}$$

For example, if the analytical task category includes 4 activities and employee i indicates that she performs 2 of them, her analytical task measure is 50.

The data set does not include information about the time spent on different activities. The most important drawback of the data set is, however, that questions concerning the activities that employees perform at the workplace changed over time. I dealt with this difficulty by reducing the activities in each category j to those that are comparable over time.

Computer use: The data set includes detailed information on the tools and machines used by employees at the workplace. The focus in the present study is on the use of computers, terminals and electronic data processing machines. Based on these variables a dummy variable for computer use is generated indicating whether or not the employee uses one of the above devices on-the-job.

Table 3.1: Assignment of Activities

Classification	Tasks
non-routine analytic	researching, evaluating and planning,
	making plans, constructing, designing, sketching
	working out rules/regulations
	using and interpreting rules
non-routine interactive	negotiating, lobbying, coordinating, organizing
	teaching or training
	selling, buying, advising customers, advertising
	entertaining or presenting
	employing or managing personnel
routine cognitive	calculating, bookkeeping
	correcting of texts/data
	measuring of length/weight/temperature
routine manual	operating or controlling machines
	setting up machines
non-routine manual	repairing or renovation houses/apartments/machines/vehicles
	restoring art/monuments
	serving or accomodating

Table 3.2: Summary Statistics on the Occupation Level (weighted by the number of individuals within occupation group)

Variable	Mean	Std. Dev.	Minimum	Maximum
average value of...				
analytic task measure	9.419	8.416	0.000	50.000
interactive task measure	16.257	13.434	0.000	66.667
routine cognitive task measure	29.317	22.974	0.000	100.000
routine manual task measure	24.542	20.919	0.000	100.000
non-routine manual task measure	19.643	19.176	0.000	100.000
proportion of ...				
computer users	28.348	29.921	0.000	100.000
employees with high education	11.126	23.333	0.000	100.000
employees with medium education	70.633	23.595	0.000	100.000
employees with low education	18.242	16.375	0.000	100.000
female employees	38.710	29.417	0.000	100.000
annualized changes in...				
analytic task measure	0.425	0.760	-5.556	4.218
interactive task measure	0.980	1.019	-4.167	6.111
routine cognitive task measure	-0.849	3.238	-12.245	14.286
routine manual task measure	-0.504	3.301	-10.030	10.829
non-routine manual task measure	0.607	2.429	-8.477	11.136
computer use	2.465	1.834	-8.333	12.500
the prop. of empl. w/ high educ.	0.266	1.258	-10.417	16.667
the prop. of empl. w/ medium educ.	-0.049	1.409	-11.310	8.333
the prop. of empl. w/ low educ.	-0.363	1.326	-11.111	11.012
the prop. of female empl.	0.264	0.725	-11.111	9.028

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 qualifications are not considered):[20] People with lower levels of education, that is, people with no occupational training. People with medium level of education, that is, people with a vocational qualification who might have either completed an apprenticeship or graduated from a vocational college. People with high level of education, that is, people holding a degree from a university or technical college. These variables are dummy variables, taking on the value 1 if the employee falls within the particular education level.

Theoretically there should be 332 observations in the stacked data set (83 occupations observed in four waves). It turns out that 94.5 percent of the occupations are observed in all waves, whereas 1.5 percent of the occupations are observed only once, 1.2 percent twice and 2.8 percent are observed three times. One might wonder whether there are occupations that disappear over time and others that are newly created, in particular, as there were a number of "information technology" occupations created by the German Federal Institute for Vocational Training beginning in 1996. The disappearance of one occupation is most arguably attributable to structural change, namely the occupation in which workers prepared minerals ("Mineralaufbereiter"). None of the occupations that appeared over time was one of the newly-founded "information technology" occupations. Overall, the occupations that were observed less than 4 times seem to be a random draw. In particular, the pattern of their appearance is clearly not driven by the question of interest.

3.4 Overall Trends in Educational Supplies, Occupational Skill Requirements and the Evolution of IT at the Workplace

As in most industrialized countries, in West Germany the labor force has witnessed a sizeable relative increase in the proportion of workers with high levels of education (see Table 3.3).[21] The proportion of the workforce holding a university degree or

[20] Most studies on West Germany use this classification rather than years of schooling because it is more appropriate to the system of vocational training. See Card (1999) for different measures of education in different institutional settings.

[21] The descriptive evidence is based on the individual level data.

a qualification from a technical college increased from about 8 percent in 1979 to more than 16 percent in 1999, whereas the proportion of employees without formal educational attainment experienced a substantial decline. However, workers with a medium level of education who either completed an apprenticeship or have a qualification from a vocational college still represent the largest proportion of the workforce.[22]

Table 3.3: Proportion of Different Educational Groups in Employment

	1979	1985/86	1991/92	1998/99
high level of education	8.18	8.85	13.30	16.48
medium level of education	72.38	68.33	71.28	70.57
low level of education	21.84	22.81	15.42	12.95

The sample includes workers aged 18-65 with residence in West Germany and of German nationality.

Contemporaneously to this educational upgrading of the labor force, there was a considerable change in aggregate skill requirements. Table 3.4 shows the trends in aggregate skill inputs. The analytical task measure grew on average by 0.5 percentage points between 1979 and 1999, and the interactive task measure by 1.3 percentage points. In contrast, the requirements for routine cognitive and routine manual skills has decreased during that period with an average annual decline of 0.7 percentage points each.

The trend in the requirements for non-routine manual skills was less clear. The overall period, however, suggests an increase of around 0.6 percentage points annually. This increase in the non-routine manual task measure over time bears the potential for work polarization as, for example, expressed by Goos and Manning

[22]Spitz (2003) provides more descriptive details based on this data set. The descriptive findings are comparable to developments in other industrialized countries. For example, West Germany witnessed a substantial increase in white-collar occupations and a corresponding reduction in blue-collar occupations in the last two decades of the twentieth century. The occupational group of professionals, technical workers, managers and administrators saw the highest increase as a fraction of the workforce. This group places 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 includes employees with all levels of formal education.

(2003). Non-routine manual activities are typically associated with low paying service occupations. By contrast, cognitive and manual routine activities are associated with middling occupations such as clerical or skilled manual jobs. The argument then is that the decrease in manual and cognitive routine tasks reduces the employment opportunities in those “middle class jobs”, typically referring to occupations with earnings in the “middle” of the earnings distribution, whereas the positive trend in non-routine manual activities increases employment in occupations with earnings in the lower tail of the earnings distribution.

The dominant measure of job quality in the “polarization” literature is earnings. However, an alternative dimension could be the educational level of employees. Going back to the activities that underly the different task categories (Table 3.1) shows that routine cognitive tasks such as calculating and bookkeeping are in general performed by employees with a medium level of education. Thus, the negative trend in this task category reduces the employment opportunities for this group of employees, conforming to the previous result that classified occupations according to their earnings level. A difference in conclusion accrues, however, for the manual task categories. Routine manual tasks such as setting up machines are the kind of activities typically performed by employees without occupational training, although these occupations traditionally payed relatively high wages in Germany. By contrast, non-routine manual activities such as repairing or renovating houses are performed by employees with a vocational qualification (for example, masons, carpenters or painters).

Table 3.5 shows the aggregate trends in skill inputs for each education group separately. For each education group the analytic and interactive task measure increased over time, whereas the cognitive and manual routine task inputs declined.

Figures 3.1-3.4 illustrate this development by showing the absolute changes in aggregate skill inputs between 1979 and 1998/99. Figure 3.1 shows the overall trends, and Figures 3.2-3.4 show the development for each education group. One difference between groups is that the decline of routine cognitive task inputs and the increase in interactive and analytical task inputs was more pronounced for employees with high levels of education than for the other two groups. Employees with medium levels of education witnessed the greatest decline in routine manual activities.

Table 3.4: Trends in Aggregate Skill Inputs

	non-routine analytic	non-routine interactive	routine cognitive	routine manual	non-routine manual
1979	4.42	8.47	36.86	30.88	14.19
1985/86	9.71	10.47	31.81	26.18	19.90
1991/92	10.98	16.55	26.97	23.48	19.78
1998/99	13.93	33.81	22.11	17.19	26.04

The sample includes workers aged 18-65 with residence in West Germany and of German nationality.

Table 3.5: Trends in Aggregate Skill Inputs by Education

	non-routine analytic	non-routine interactive	routine cognitive	routine manual	non-routine manual
	Employees with High Level of Education				
1979	15.45	20.10	42.51	15.59	4.10
1985/86	21.40	18.76	45.74	9.30	4.46
1991/92	26.29	35.23	34.33	8.70	5.75
1998/99	24.62	48.40	11.44	7.77	2.41
	Employees with Medium Level of Education				
1979	4.16	8.63	39.15	33.40	16.18
1985/86	9.29	10.41	33.31	28.85	24.18
1991/92	9.39	14.99	28.22	26.27	23.73
1998/99	11.88	28.34	24.08	19.44	26.80
	Employees with Low Level of Education				
1979	2.78	4.80	27.47	26.50	10.11
1985/86	6.29	7.34	21.58	24.74	13.27
1991/92	4.94	7.47	20.42	23.37	13.73
1998/99	6.92	14.44	14.74	18.19	18.77

The sample includes workers aged 18-65 with residence in West Germany and of German nationality.

This overall pattern does not suggest that, at the late 1990s, high-educated employees perform more of the tasks that used to be done by medium-educated employees as postulated by the "over-education" literature. In contrast, the more pronounced development towards analytic and interactive activities and away from routine cognitive activities suggests that overall skill requirements were rising faster for high-educated employees than for the other qualification groups.

The argument could be made that these overall developments reflect cohort effects, that is, unobserved heterogeneity owing to, say, younger entry cohorts having better educational opportunities and therefore higher levels of analytical activities. To evaluate this possibility, Table 3.6 shows the trends in occupational task inputs for cohorts, defined by year of birth. The first birth cohort are individuals born before 1940, the second those born between 1940 and 1949, the third those born between 1950 and 1955 and so on. One follows one birth cohort over time by moving horizontally within the same row. One follows the same age group by moving diagonally upwards (employees born between 1956 and 1961 were between 18 and 23 years old in 1979, employees born between 1962 and 1968 were between 18 and 23 years old in 1985/86). Within cohorts, changes in task inputs are attributable to age and time effects. The age effect describes how the task inputs of a given cohort changes as the cohort ages. The time effect describes how task inputs for a given cohort shift due to, for example, macroeconomic shocks. Changes in task inputs within an age group, on the other hand, are due to cohort or time effects. Cohort effects describe differences between cohorts that may, for example, be due to changes in educational opportunities.[23]

[23]It is well known that the three components – time, cohort and age effect – are not separately identifiable without additional prior assumptions. This results from the identity that links birth year c, age a and calender year t: $t = c + a$.

Figure 3.1: Trends in Aggregate Skill Inputs

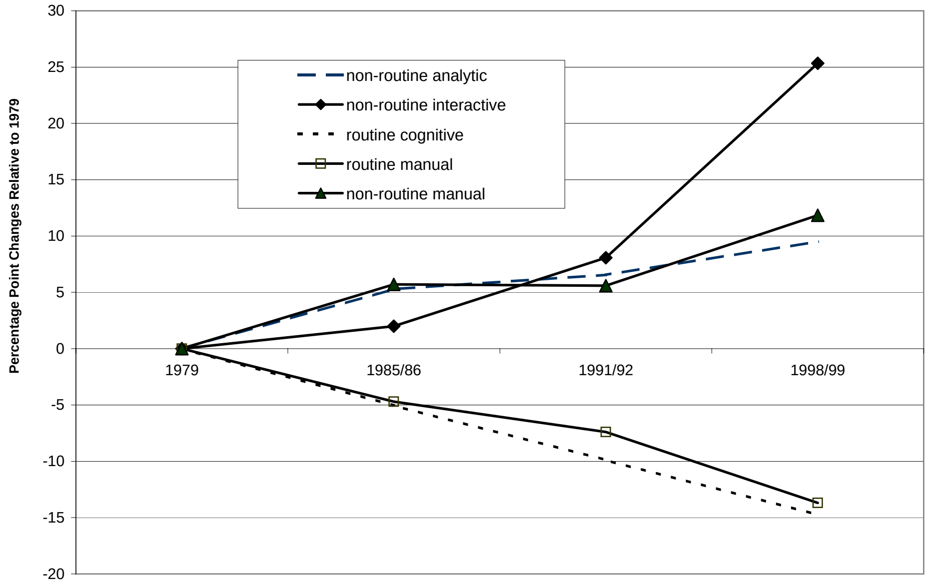


Figure 3.2: Employees with High Levels of Education: Trends in Aggregate Skill Inputs

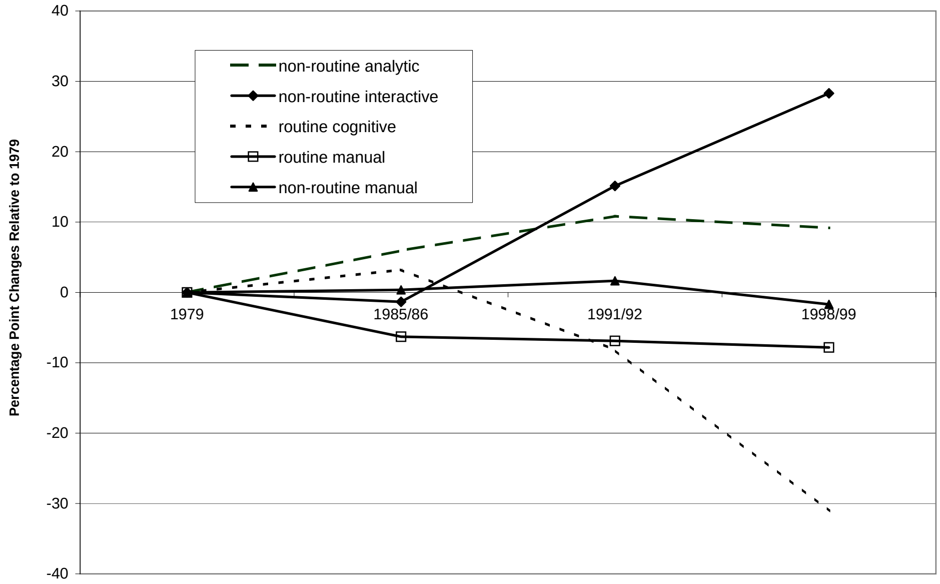


Figure 3.3: Employees with Medium Levels of Education: Trends in Aggregate Skill Inputs

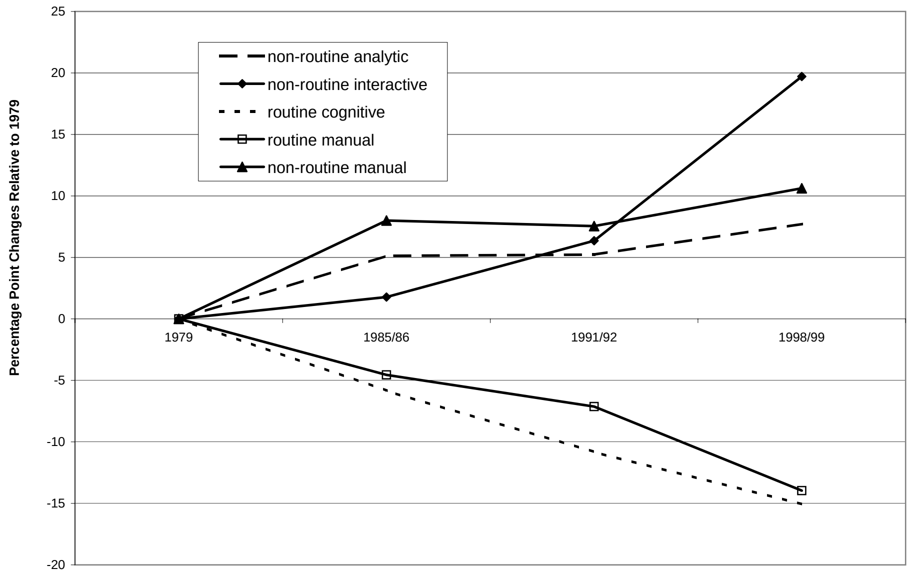


Figure 3.4: Employees with Low Levels of Education: Trends in Aggregate Skill Inputs

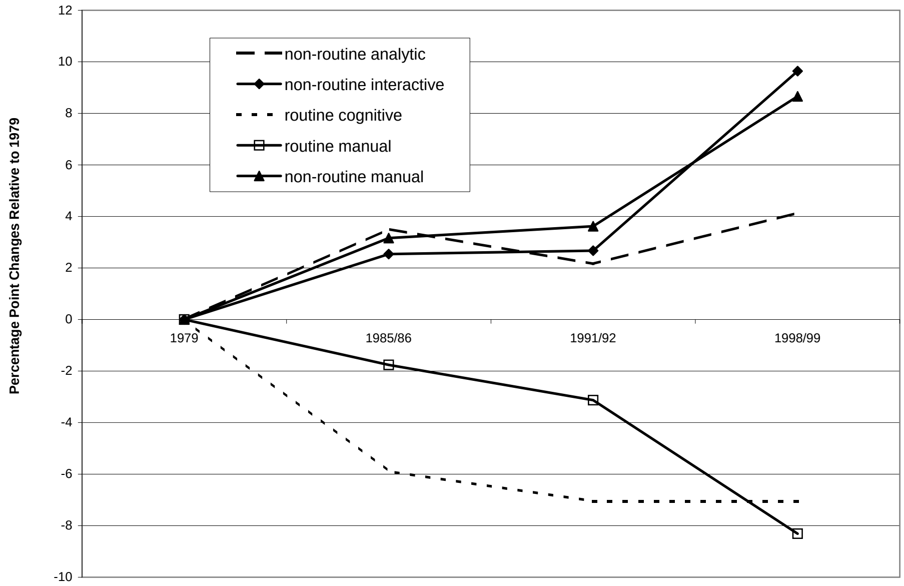


Table 3.6: Trends in Aggregate Skill Inputs by Birth Cohorts

Analytical Task Inputs				
Year of Birth	1979	1985/86	1991/92	1998/99
1975-1981				7.41
1969-1974			7.71	11.54
1962-1968		5.58	10.16	14.63
1956-1961	2.39	9.72	13.35	15.09
1950-1955	5.15	11.16	12.69	13.95
1940-1949	5.49	11.23	11.22	15.32
before 1940	4.23	9.47	8.76	16.56
10 x Average Annualized Changes 1979-1998/99				
Within Cohorts:	5.90			
Within Age Levels:	4.89			

Interactive Task Inputs				
Year of Birth	1979	1985/86	1991/92	1998/99
1975-1981				23.17
1969-1974			9.52	30.35
1962-1968		6.25	15.05	33.61
1956-1961	5.72	10.13	18.36	34.37
1950-1955	8.77	11.96	20.14	36.68
1940-1949	9.90	11.95	17.81	37.26
before 1940	8.48	10.65	14.15	36.98
10 x Average Annualized Changes 1979-1998/99				
Within Cohorts:	18.33			
Within Age Levels:	16.61			

Routine Cognitive Task Inputs				
Year of Birth	1979	1985/86	1991/92	1998/99
1975-1981				22.44
1969-1974			22.21	21.41
1962-1968		25.06	28.86	24.01
1956-1961	38.04	33.08	29.04	23.54
1950-1955	42.08	35.72	29.69	20.57
1940-1949	39.87	33.99	27.73	19.22
before 1940	32.36	29.43	21.45	23.05
10 x Average Annualized Changes 1979-1998/99				
Within Cohorts:	-6.11			
Within Age Levels:	-7.01			

<*Table continues on next page*>

<Table 3.6 continued>

Routine Manual Task Inputs				
Year of Birth	1979	1985/86	1991/92	1998/99
1975-1981				18.97
1969-1974			29.80	17.23
1962-1968		31.51	25.23	19.15
1956-1961	41.53	27.21	24.99	17.68
1950-1955	35.13	26.05	21.80	15.19
1940-1949	30.52	23.91	20.87	14.71
before 1940	25.21	24.80	22.91	17.61
10 x Average Annualized Changes 1979-1998/99				
Within Cohorts:	-10.47			
Within Age Levels:	-8.39			

Non-Routine Manual Task Inputs				
Year of Birth	1979	1985/86	1991/92	1998/99
1975-1981				30.28
1969-1974			25.23	27.78
1962-1968		22.83	22.36	25.94
1956-1961	15.42	20.78	20.18	25.69
1950-1955	14.18	18.05	18.35	25.68
1940-1949	13.39	18.91	17.31	24.45
before 1940	14.25	19.74	19.37	23.30
10 x Average Annualized Changes 1979-1998/99				
Within Cohorts:	4.68			
Within Age Levels:	6.57			

The sample includes workers aged 18-65 with residence in West Germany and of German nationality.

As the figures in Table 3.6 show, the trend towards analytical and interactive task inputs, and away from cognitive and manual routine activities occurred both within cohorts and within age groups. The overall trends are therefore not only a reflection of cohort effects. Older cohorts experienced the same trends. For analytical and interactive as well as routine manual task inputs, changes within cohorts were even more pronounced than changes within age levels. Within cohorts, analytical task inputs, for example, increased by around 0.6 percentage points annually on average, whereas the annual increase within age groups was 0.5 percentage points on average.

These trends in aggregate skill requirements may result from transformations along two margins: First, changes in the occupational structure of employment, and second, changes in skill requirements within occupations.[24] As the results of the shift-share analysis in Table 3.7 shows, most of the aggregate changes in skill requirements result from within occupational changes in task measures.[25] The last row, which shows the results for the entire period, clearly illustrates this point. For example, between occupational shifts represent around 15 percent of aggregate changes in the analytical task measure whereas within occupational task changes account for around 85 percent. In the case of changes in interactive (routine manual) skill requirements the values are quite similar with around 13 (14) percent attributable to the between shift and around 87 (86) percent to the within shift. The results for the routine cognitive task measure are even more pronounced, indicating that between-occupation shifts account for less than one percent of aggregate changes in routine cognitive skill requirements. For this task measure, it is also informative to have a look at the two subperiods 1985/86-1991/92 and 1991/92-1998/99 because between occupational results there point to slight increases in the requirements for routine cognitive skills, a pattern that has been counteracted by the within occupational task shifts. The overall result of this table of predominantly within occupational task shifts is largely in favor of technological developments rather than changes in final demand as the potential cause for changing skill requirements.

One important argument in this study is that the changes in the task composition of occupations towards analytical and interactive activities induced labor demand shifts towards employees with high levels of education who are viewed as having comparative advantages in performing non-routine cognitive tasks. Table 3.5 shows that the analytical and interactive task inputs are the highest for employees with high levels of education in each wave. Table 3.8 summarizes this result, by showing task means by education group over time. The descriptive evidence thus confirms

[24]Autor, Levy and Murnane (2003) provide a comprehensive analysis of the first source of variation for measuring changes in aggregate skill requirements, that is, changes in the occupational structure of employees.

[25]The shift-share analysis decomposes the change in aggregate use of task j between time t and *t-1*, $\Delta T_{jt} = T_{jt} - T_{jt-1}$, into a term reflecting the reallocation of employees between occupations and a term reflecting changes in task j within occupation. The mathematical formulation is: $\Delta T_{jt} = \sum_c (\Delta E_{ct} \bar{\gamma_{cj}}) + \sum_c (\Delta \gamma_{cjt} \bar{E_c}) = \Delta T^b_{jt} + \Delta T^w_{jt}$, where c indexes occupations, E denotes employment and E_{ct} is the share of employment in occupation c in total employment at time t, γ_{cjt} is measure of task j in occupation c at time t. An overstrike denotes an average over time, that is $\bar{\gamma_{cj}} = (\gamma_{cjt} - \gamma_{cjt-1})/2$ and $\bar{E_c} = (E_{ct} - E_{ct-1})/2$. ΔT^b_{jt} reflects the change in aggregate employment of task j attributable to changes in the occupational distribution of employment and ΔT^w_{jt} reflects the within-occupation task changes.

Table 3.7: Shift-Share Analysis of Changes in Skill Requirements

	10 x Annual Changes in Task Measures									
	non-routine analytic		non-routine interactive		routine cognitive		routine manual		non-routine manual	
	Overall									
1979-85	8.82		3.35		-8.43		-7.83		9.52	
1985-91	2.12		10.12		-8.05		-4.50		-0.21	
1991-99	4.21		24.63		-6.94		-8.98		8.94	
1979-99	5.01		13.34		-7.76		-7.20		6.23	
	Between and Within Occupational Decomposition									
	btwn	wthn	btwn	wthn	btwn	wthn	btwn	wthn	btwn	wthn
1979-85	-0.27	9.10	0.15	3.21	-1.40	-7.03	-1.26	-6.57	0.77	8.75
1985-91	0.44	1.68	0.10	10.02	0.87	-8.92	-0.00	-4.50	0.34	-0.55
1991-99	2.67	1.55	5.24	19.39	0.06	-7.00	-6.04	-2.94	-0.97	9.91
1979-99	0.77	4.24	1.70	11.64	-0.06	-7.70	-0.98	-6.22	0.12	6.11

The sample includes workers aged 18-65 with residence in West Germany and of German nationality. Occupations are defined according to the 2-digit level of the classification of occupational titles.

the view that the higher the educational attainment, the higher the measures in analytical and interactive tasks. In contrast, the figures indicate that employees with low levels of education are mainly occupied with routine cognitive, routine manual and non-routine manual tasks. Employees with medium levels of education have relatively high measures for all five task categories, but most interestingly, the value of their task measures for routine manual and routine cognitive activities are even higher than those for employees with low levels of education.

The educational upgrading and the changes in occupational skill requirements took place at the same time as information technology began to spread at the workplace. Whereas at the beginning of the IT revolution mainframe computers dominated the data-processing units of large firms, personal computers began to spread to business users from the late 1970s onwards. Owing to the steady fall in prices, this spread has become more pronounced. Table 3.9 shows the percentage of computer users at work. The table shows that within twenty years, more than half of the workforce has come to use computers at work.[26] Between 1979 and 1999,

[26]These figures on computer penetration at the workplace in West Germany are similar to those

Table 3.8: Distribution of Task Inputs by Education Groups

	non-routine analytic	non-routine interactive	routine cognitive	routine manual	non-routine manual
level of education...					
...high	22.72	33.98	29.91	9.76	11.13
...medium	8.44	15.51	31.38	27.10	22.57
...low	4.89	7.84	21.86	23.85	13.35

The sample includes workers aged 18-65 with residence in West Germany and of German nationality.

the spread of computers increased on average by more than 40 percent per annum. Table 3.9 also shows that the level of computer usage increased with the educational attainment of employees. In 1979, more than 10 percent of employees with high levels of education already used a computer at the workplace compared to less than 4 percent of employees with low levels of education and around 6 percent of employees with medium levels of education. This proportion had increased to more than 80 (30, 55) percent of employees with high (low, medium) levels of education in 1999. However, it is worth noting that, with an increase of around 45 percent per annum, the pace of computer diffusion was most pronounced among employees with low levels of education between 1979 and 1999 (compared to around 42 percent per annum for employees with medium levels of education and 30 percent for employees with high levels of education).

As Table 3.10 shows, computer adoption has been quite different for different occupational groups. It has been particularly pronounced in professional, technical, managerial, administrative and clerical occupations. The spread of computer capital has been much broader among clerical occupations than among sales occupations. This may indicate the division of office work into back and front office functions, as ,for example, Bresnahan (1999) pointed out, with employees in the back office (clerks) being occupied with routine cognitive and routine manual tasks such as data-entry and data-processing, and employees in the front office (sales personnel) spending most of their time serving customers and clients. In contrast to the wide spread of computers in most white-collar bureaucracies, operatives and crafts people witnessed a much slower penetration rate of IT at the workplace.

reported for other countries for example in Card, Kramarz and Lemieux (1999).

Table 3.9: TRENDS IN AGGREGATE COMPUTER USE* AND WITHIN DIFFERENT EDUCATIONAL GROUPS

	overall	low level of education	medium level of education	high level of education
1979	6.06	3.44	6.31	12.22
1985/86	18.11	10.19	20.00	25.58
1991/92	34.52	16.13	33.77	60.73
1998/99	55.38	32.65	56.52	83.15

The sample includes workers aged 18-65 with residence in West Germany and of German nationality. *Spread of Computers, Terminals, Laptops, Electronic Data-Processing Devices.

Table 3.10: SPREAD OF COMPUTER USE BY OCCUPATIONAL GROUPS

occupational group	1979	1985/86	1991/92	1998/99
white-collar workers				
professionals, technical workers, managers, administrators	8.53	23.47	47.34	72.25
clerical	12.85	43.87	70.76	91.99
sales	3.65	15.18	23.46	45.12
blue-collar workers				
operatives and craft people	1.40	4.18	12.33	27.52
laborers	0.52	1.82	11.17	17.11
personal service workers	3.03	6.79	15.30	40.99

The sample includes workers aged 18-65 with residence in West Germany and of German nationality.

The descriptive evidence shows that educational upgrading, increased demand for analytical and interactive activities and the spread of computer technologies evolved together in recent decades. This development is consistent with the argument that IT increases the demand for employees with high levels of education through shifting the task composition towards analytical and interactive activities.

3.5 Skill Requirements, Education and Technology in the Workplace

3.5.1 Technological Change and Changes in Occupational Skill Requirements

Based on the model by Autor, Levy and Murnane (2003) outlined in Section 3.2, there are two empirically testable hypotheses: (1) that IT substitutes for routine manual and routine cognitive activities, and (2) that IT is complementary to analytic and interactive activities. The framework emphasizes that the causal force by which IT affects skill demand is the declining price of IT. As the price of IT falls steadily, these two mechanisms have raised relative demand for employees with high levels of education who are assumed to have a comparative advantage in performing analytical and interactive activities.

The analysis that follows will investigate this substitution and complementarity hypothesis. Because there are no hypotheses on the relationship between IT and changes in non-routine manual task inputs derived from this theoretical model, I do not analyze this relationship in the following sections.

Table 3.11, Panel A, shows the first-difference relationship between workplace computerization and changes in occupational skill requirements. Each column represents a separate OLS regression of the annual changes in occupational task measures on the annual changes in occupational computer use. Annual changes are estimated between successive waves, that is between 1979 and 1985/86, between 1985/86 and 1991/92 as well as between 1991/92 and 1998/99. The regressions are based on the stacked data set. They are performed including time dummies for 1985/86-1991/92 and 1991/92-1998/99 capturing the trend in within occupational tasks changes for the corresponding time period relative to the base period 1979-1985/86.

The results show that occupations that saw greater increases in computerization witnessed significantly larger increases in analytical and interactive task requirements, whereas they witnessed greater declines in routine manual and routine cognitive task requirements. The coefficients are not only statistically significant but also economically large. For example, they indicate that 50 percent of changes in analytical task inputs were accounted for by computerization.[27] Similar calcula-

[27] At the bottom of Table 3.11, the unconditional (weighted) means of the dependent variables are shown. The figures indicate an average annual increase in the analytical task measure of 0.425 percentage points. Using the coefficient of 0.086 and the mean value of changes of computer

Table 3.11: OLS Regressions: Technological Change and Changes in Skill Requirements

Dep. Variables: (Annualized Changes in Task Inputs)				
	Δ non-routine analytic	Δ non-routine interactive	Δ routine cognitive	Δ routine manual
Panel A				
Δ computer use	0.086***	0.188***	-0.312***	-0.561***
	(0.032)	(0.031)	(0.105)	(0.148)
dummy 1985/86-1991/92	-6.160***	3.536**	-1.960	-2.462
	(1.129)	(1.767)	(3.098)	(7.712)
dummy 1991/92-1998/99	-7.987***	8.915***	16.394**	-7.436
	(1.381)	(1.440)	(7.726)	(7.065)
R^2	0.183	0.337	0.079	0.131
no. of observations:		237		
Panel B				
lagged Δ computer use	-0.022	0.160***	-0.796***	-0.173***
	(0.035)	(0.031)	(0.202)	(0.065)
dummy 1985/86-1991/92	1.470	-4.632***	-23.444***	6.005*
	(1.350)	(1.703)	(7.237)	(3.637)
R^2	0.015	0.195	0.205	0.053
no. of observations:		156		
Weighted mean of dependent variable:	0.425	0.980	-0.849	-0.504

Robust standard errors are in parentheses; regressions are weighted by the number of individuals within occupation group; ***,**,*-indicate significance at the 1, 5, 10 percent level.

tions show that 47 percent of changes in interactive task inputs are accounted for by computerization and it explains 90 percent of the decline in routine cognitive skill requirements. In the case of routine manual task inputs, computerization more than fully accounts for the observed task changes.

The time dummies show that, conditional on workplace computerization, the trend change in analytical skill requirements was negative in both periods 1985/86-

utilization of 2.465 percentage points, this implies that around 50 percent of changes in analytical tasks is accounted for by changes in IT usage.

1991/92 and 1991/92-1998/99 relative to the base period of 1979-1985/86 indicating that computerization more than fully accounts for the trend towards analytical task inputs in these later periods. In contrast, the trend change towards interactive skill inputs accelerated with time even after conditioning on computerization. In the routine tasks equations, the coefficients of the time dummies are mostly insignificant, except for a large positive trend in 1991/92-1998/99 in routine cognitive skills.

Panel B shows the result when lagged annual changes in computer use within occupation cell is used as regressor instead of contemporaneous changes in workplace computerization. The results of the lagged specification confirm the previous findings reported in Panel A, with the exception of the analytical task equation that now has an insignificant coefficient. The coefficient in the routine cognitive equation even increases in absolute terms suggesting that there might be a time lag until the full impact of computerization is reflected in occupational skill requirements. Unreported regressions in which the lagged proportion of computer users are included as an alternative measure confirm these results. These lagged results favor the argument derived from the theory that workplace computerization, brought about by the declining prices of IT-equipment, induced task shifts and not vice versa.

Table 3.12, Panel A, shows the result of a richer specification that tests whether changes in occupational skill requirements are implicitly captured by changes in the educational structure or changes in the gender structure of occupations. Neither of the additional regressors alters the qualitative relationship between computerization and changes in occupational skill requirements found in the bivariate regressions, and even the size of the coefficients are relatively insensitive to the additional controls. Only in the analytical task equation, the coefficient drops slightly more than ten percent. Changes in the proportion of employees with high levels of education turn out to play a significant role with respect to changes in interactive and analytical skill requirements, whereas changes in the proportion of employees with medium levels of education appear to be weak predictors of changes in occupational task inputs. Changes in the proportion of female employees are even negatively related to changes in analytical skill requirements, hence they fail to provide an alternative explanation for increasing analytical skill requirements. However, occupations with greater increases in the proportion of female employees witnessed relatively larger declines in routine cognitive skill requirements.[28]

[28]I also performed regressions that include changes in work-based learning (average years of work experience and average years of tenure with current employer) into the analysis. Both measures of work-based learning were not significantly related to changes in occupational task inputs. The

Table 3.12: Changes in Skill Requirements and Changes in the Educational and Gender Distribution

Dep. Variables: Annualized Changes in Task Inputs				
	Δ non-routine analytic	Δ non-routine interactive	Δ routine cognitive	Δ routine manual
Panel A				
Δ computer use	0.076***	0.181***	-0.311***	-0.529***
	(0.031)	(0.033)	(0.108)	(0.163)
Δ proportion w/	0.064**	0.081**	-0.195*	0.049
high educ. level	(0.033)	(0.039)	(0.115)	(0.178)
Δ proportion w/	0.006	0.038	-0.177*	0.257
medium educ. level	(0.025)	(0.034)	(0.104)	(0.184)
Δ proportion	-0.119***	0.026	-0.607***	-0.068
female employees	(0.049)	(0.049)	(0.191)	(0.175)
R^2	0.222	0.348	0.112	0.148
no. of observations:		237		
Panel B				
lagged Δ computer use	-0.009	0.153***	-0.752***	-0.187***
	(0.032)	(0.031)	(0.211)	(0.072)
lagged Δ proportion w/	-0.056	0.011	-0.680***	0.244***
high educ. level	(0.067)	(0.048)	(0.195)	(0.094)
lagged Δ proportion w/	-0.015	-0.103*	-0.123	0.145**
medium educ. level	(0.036)	(0.060)	(0.140)	(0.066)
lagged Δ proportion	0.110	0.177***	-0.714***	0.045
female employees	(0.068)	(0.054)	(0.268)	(0.178)
R^2	0.059	0.274	0.275	0.084
no. of observations:		156		

Control variables are: time dummies. Robust standard errors are in parentheses. Regressions are weighted by the number of individuals within occupation group. ***,**,*-indicate significance at the 1, 5, 10 percent level.

results are not reported because the inclusion of these additional variables did not alter the main findings reported in Table 3.12.

Panel B shows the results when lagged annual changes are included as regressors in the analysis instead of contemporaneous changes. The results for the relationship between computerization and changes in occupational skill requirements are similar to those reported in Table 3.11, Panel B. For changes in analytical skill requirements, contemporaneous changes in all variables seem to pick up more of the relevant information. Unlike the variable for workplace computerization, a comparison of the results for education and gender variables with those in Panel A reveals, however, that they are not insensitive to the change in specification.

Table 3.13 shows the relationship between workplace computerization and changes in occupational skill requirements for each education group separately. For each occupation-education group, the results are consistent with the hypotheses of a complementary relationship between computer technology and analytical and interactive activities, and a substitutive relationship between computer technology and manual and cognitive routine tasks. However, for part of the coefficients, the level of significance drops considerably. This is particularly pronounced for the group of employees with a high level of education.[29] I see two potential explanations for this finding. First, that changes in the task composition owing to workplace computerization are less pronounced for employees with high levels of education because their values of the task measures were already at the extreme of the distribution in 1979. Second, that for this group of workers the analysis might be particularly impaired by the fact that the task measures do not include information about the time spent with the different activities. This time dimension might be more important for employees who always had a high number of activities that they perform. In line with these arguments, the results for employees with a low level of education are the clearest with respect to the magnitude and significance of the coefficients. For this group of employees, workplace computerization has had a large effect on the occupational production function.

The last dimension analyzed in the present study are cohorts. If younger labor market entry cohort have both higher levels of, for example, analytical abilities and higher levels of computer use, the above findings may be the result of a spurious correlation. Table 3.14 shows the results of the above regressions for each birth cohort separately.[30]

[29] Autor, Levy and Murnane (2003) report similar findings on the industry level.

[30] Only cohorts that are observed over the entire period 1979-1998/99 are shown.

Table 3.13: Technological Change and Changes in Skill Requirements by Education

Dep. Variables: Annualized Changes in Task Inputs				
	Δ non-routine analytic	Δ non-routine interactive	Δ routine cognitive	Δ routine manual
Employees with High Level of Education				
Δ computer use	0.027	0.058	-0.253**	-0.052
	(0.065)	(0.060)	(0.120)	(0.077)
dummy 1985/86-1991/92	-0.356	17.304***	-10.983	0.393
	(4.368)	(4.483)	(7.911)	(7.312)
dummy 1991/92-1998/99	-9.898***	10.594***	-17.912**	4.761
	(3.870)	(3.987)	(8.395)	(6.494)
R^2	0.084	0.171	0.084	0.010
no. of observations:		121		
Employees with Medium Level of Education				
Δ computer use	0.069*	0.127***	-0.131	-0.521***
	(0.040)	(0.029)	(0.114)	(0.171)
dummy 1985/86-1991/92	-7.465***	2.646*	-2.880	-3.525
	(1.159)	(1.628)	(3.243)	(8.226)
dummy 1991/92-1998/99	-8.208***	10.095***	18.047**	-9.451
	(1.400)	(1.481)	(8.854)	(8.006)
R^2	0.186	0.299	0.067	0.113
no. of observations:		234		
Employees with Low Level of Education				
Δ computer use	0.128***	0.151***	-0.196*	-0.309***
	(0.042)	(0.044)	(0.120)	(0.129)
dummy 1985/86-1991/92	-3.685***	0.230	1.498	-2.267
	(1.176)	(1.762)	(3.814)	(7.916)
dummy 1991/92-1998/99	-5.472***	4.760***	31.453***	-11.904**
	(1.438)	(1.616)	(7.780)	(6.445)
R^2	0.149	0.148	0.161	0.056
no. of observations:		226		

Robust standard errors are in parentheses. Regressions are weighted by the number of individuals within occupation group. ***,**,*-indicate significance at the 1, 5, 10 percent level.

Table 3.14: Technological Change and Changes in Skill Requirements by Birth Cohort

Dep. Variables: Annualized Changes in Task Inputs				
	Δ non-routine analytic	Δ non-routine interactive	Δ routine cognitive	Δ routine manual
Employees born between 1956 and 1961				
Δ computer use	0.113***	0.152***	-0.202	-0.647***
	(0.034)	(0.041)	(0.130)	(0.171)
dummy 1985/86-1991/92	-5.231***	.543	0.378	5.933
	(1.561)	(2.229)	(4.923)	(9.799)
dummy 1991/92-1998/99	-10.853***	5.416***	14.226	-1.759
	(1.675)	(1.685)	(8.869)	(9.112)
R^2	0.205	0.118	0.036	0.117
no. of observations:	220			
Employees born between 1950 and 1955				
Δ computer use	0.049	0.216***	-0.226**	-0.513***
	(0.044)	(0.055)	(0.111)	(0.160)
dummy 1985/86-1991/92	-4.805**	6.301***	-3.230	-3.639
	(1.878)	(2.249)	(4.407)	(8.854)
dummy 1991/92-1998/99	-8.950***	7.753***	11.791	-10.845
	(1.960)	(2.062)	(8.977)	(7.960)
R^2	0.092	0.178	0.047	0.087
no. of observations:	211			
Employees born between 1940 and 1949				
Δ computer use	0.111***	0.203***	-0.255**	-0.411***
	(0.030)	(0.041)	(0.113)	(0.130)
dummy 1985/86-1991/92	-7.972***	2.846	-5.388	-3.357
	(1.504)	(2.010)	(3.765)	(8.137)
dummy 1991/92-1998/99	-7.210***	10.067***	9.019	-8.326
	(1.773)	(1.755)	(7.841)	(7.244)
R^2	0.170	0.280	0.059	0.071
no. of observations:	224			

<*Table continues on next page*>

<*Table 3.14 continued*>

Dep. Variables: Annualized Changes in Task Inputs				
	Δ non-routine analytic	Δ non-routine interactive	Δ routine cognitive	Δ routine manual
Employees born before 1940				
Δ computer use	0.150***	0.240***	-0.339***	-0.450***
	(0.034)	(0.039)	(0.106)	(0.145)
dummy 1985/86-1991/92	-9.768***	0.177	-9.521***	-5.500
	(1.160)	(1.902)	(3.025)	(7.011)
dummy 1991/92-1998/99	-5.463***	11.077***	13.355*	-8.665
	(1.850)	(2.230)	(7.305)	(6.681)
R^2	0.265	0.258	0.145	0.071
no. of observations:		213		

Robust standard errors are in parentheses. Regressions are weighted by the number of individuals within occupation group. ***,**,*-indicate significance at the 1, 5, 10 percent level.

The results suggest a complementary relationship between computer technologies and analytical and interactive activities and a substitutive relationship between computer technologies and cognitive and manual routine activities within each occupation-cohort group. Therefore, the previous findings do not seem to be a mere reflection of cohort effects.

3.5.2 Changes in Skill Requirements and Educational Upgrading

3.5.2.1 Contribution of Changes in Occupational Skill Requirements to the Educational Upgrading

In this section, I calculate the potential contribution of shifts in occupation skill requirements to shifts in employment of labor with high levels of education and with medium levels of education. This is done by firstly estimating an equation of educational requirements as a function of task inputs, an exercise that aims to translate occupational skill requirements into education-equivalents. The regression equation is:

$$ED_{ict} = \alpha_{0it} + \sum_{j=1}^{4} S_{jct}\alpha_{ijt} + \upsilon_{ict} \quad (3.2)$$

$t = $ 1979, 1985/86, 1991/92, 1998/99
$j = $ 1,...,4.
$i = $ high or medium
$c = $ occupation

$$j = \begin{cases} 1 & : \text{ non-routine analytic task measure} \\ 2 & : \text{ non-routine interactive task measure} \\ 3 & : \text{ routine cognitive task measure} \\ 4 & : \text{ routine manual task measure} \end{cases}$$

where ED_{ict} is the proportion of employees with education level i in occupation c at time t. S_{jct} is the measure of task j in occupation c at time t. The α_{ijt}s estimated in the regression provide an estimate of the demand for employees with high (medium) level of education as a function of occupation skill requirements. This is what Autor, Levy and Murnane (2003) call a "fixed coefficient" model because, by assuming the α_{ijt}s to be constant over the period, it neglects the impact of task prices on task demand. If the prices of analytical and interactive task inputs relative to routine task inputs has risen, for example, this model will lead to an underestimation of shifts towards analytical and interactive tasks and thus to an underestimation of the educational upgrading of the workforce.

The estimated coefficients α_{ijt} of equation (3.2) are used to predict changes in the demand for employees with high and medium levels of education.

$$\Delta \hat{ED}_{ic\tau} = \sum_{j=1}^{4} \Delta S_{jc\tau}\hat{\alpha}_{ij(t-1)} \quad (3.3)$$

$\tau = t - (t-1)$ with t= $1979, 1985/86, 1991/92, 1998/99$.

The results of estimating equation (3.2) separately for employees with high and medium levels of education and for each wave are shown in Table 3.15. Panel A presents the results for the proportion of employees with high levels of eduction. In each wave, the results indicate a strong (and mostly highly significant) positive relationship between analytical and interactive task inputs and the proportion of employees with high education levels. In 1979, for example, a one percentage point increase in analytical skill requirements results in a 1.3 percentage point increase in the demand for employees with high level of education. The results for the routine cognitive and routine manual task measures are also in line with the *a priori* expectations, although the coefficients are often insignificant.

Table 3.15: OLS Results: Educational Requirements within Occupation Group as a Function of Task Inputs

A. Dep. Variable: Proportion of Employees with High Level of Education								
	1979		1985/86		1991/92		1998/99	
non-routine analytic	1.321***	(0.337)	1.639***	(0.416)	1.102***	(0.217)	1.267***	(0.279)
non-routine interactive	1.322***	(0.307)	0.129	(0.566)	1.464***	(0.232)	0.706***	(0.186)
routine cognitive	-0.061	(0.110)	-0.301*	(0.159)	-0.576***	(0.131)	-0.039	(0.223)
routine manual	-0.206	(0.120)	-0.476***	(0.157)	-0.021	(0.077)	0.086	(0.232)
R^2	0.468		0.388		0.673		0.583	
no. of observations:	83		83		80		80	
B. Dep. Variable: Proportion of Employees with Medium Level of Education								
	1979		1985/86		1991/92		1998/99	
non-routine analytic	-0.436	(0.466)	-1.007*	(0.534)	-0.622*	(0.328)	-1.110***	(0.364)
non-routine interactive	-0.241	(0.424)	-0.047	(0.726)	-0.980***	(0.351)	-0.087	(0.343)
routine cognitive	0.019	(0.152)	0.631***	(0.205)	0.642***	(0.198)	0.290	(0.291)
routine manual	0.209	(0.167)	1.013***	(0.202)	0.171	(0.116)	-0.194	(0.303)
R^2	0.065		0.272		0.251		0.249	
no. of observations:	83		83		80		80	

Robust standard errors are in parentheses. Each regression includes an intercept term. Regressions are weighted by the number of individuals within occupation group. ***,**,*- indicate significance at the 1, 5, 10 percent level.

Panel B shows the results for the proportion of employees with medium level of education. With most of the coefficients being insignificant, the results are less clear-cut than those for employees with high levels of education. The overall picture suggests, however, a positive relationship between routine cognitive and routine manual task inputs and the proportion of employees with medium levels of education, whereas the relationship with respect to analytical and interactive task inputs is negative.

Panel A of Table 3.16 shows the observed annual changes in the proportion of employees with high and medium level of education for the subperiods 1979-85/86, 1985/86-91/92, 1991/92-98/99 and for 1979-1998/99. The pace of educational upgrading was relatively stable since the mid-1980s with average annual changes of 0.5 percentage points. Between 1979 and 1998/99 the proportion of employees with high level of education grew on average by 0.4 percentage points per annum. The proportion of employees with medium levels of education decreased considerably between 1979 and 1985/86, increased between 1985/86 and 1991/92 and declined again in the 1990s. Over the whole period, however, this resulted in an average annual decrease of 0.1 percentage points.

In what follows, I will largely concentrate the discussion of results on the whole period 1979-1998/99, although the results for the different subperiods are mostly comparable. However, macroeconomic shocks might affect the outcomes in these subperiods such as the recessions that West Germany experienced at the beginning of the 1980s and around 1992/1993, and also the unification boom just at the beginning of the 1990s might be important with this respect.

Two different measures of $\Delta S_{jc\tau}$ are used to calculate $\Delta \hat{ED}_{ic\tau}$ of equation (3.3): first, observed changes in occupation skill requirements and second, predicted changes in occupation skill requirements implied by computerization. In the calculations that follow, I will only use the α_{ij}s of the year 1979. The relationship between task inputs and education in 1979 is closest to the pre-computer era. Desktop computing, for example, only became widespread in the 1980s and 1990s.

Panel B shows the observed changes in occupation skill requirements. Requirements for analytical and interactive skills within occupation grew between 1979 and 1998/99, with the pace of increases in interactive inputs accelerating steadily. The figures show a steady decline in occupation requirements for routine cognitive skills and also for routine manual skills.

Inserting the observed changes in occupation skill requirements, together with the $\hat{\alpha}$s of Table 3.15-first column, into equation (3.3) shows that the observed changes in occupational skill requirements account for nearly 50 percent of the changes in the proportion of employees with high level of education between 1979 and 1998/99 (Panel C). With respect to the observed changes in the proportion of employees with

Table 3.16: SHIFTS IN HIGH-EDUCATED-EQUIVALENT LABOR DEMAND AND MEDIUM-EDUCATED-EQUIVALENT LABOR DEMAND IMPLIED BY CHANGES IN OCCUPATIONAL TASK INPUTS

	1979-1985/86	1985/86-1991/92	1991/92-1998/99	1979-1998/99
A. 10 x Observed Annual Changes in the Proportion of Employees with...				
high Level of Education	3.667	5.333	5.167	4.250
medium Level of Education	-6.833	5.000	-1.167	-0.947
B. 10 x Observed Annual Changes in Within Occupation Task Inputs				
non-routine analytic	9.037	1.716	1.774	4.242
non-routine interactive	3.046	9.981	16.430	10.705
routine cognitive	-6.059	-9.054	-10.416	-8.965
routine manual	-5.875	-5.216	-4.028	-7.305
C. Predicted Proportion of Changes in the Share of Employees with High/Medium Level of Education Explained by Observed Changes in Within Occupation Skill Requirements (in Percent)				
high Level of Education	47.934	32.237	49.741	48.997
medium Level of Education	8.815	-8.834	49.463	64.698
D. Predicted Annual Changes in Occupation Task Inputs Implied by Computerization (10 x Annual Changes)				
non-routine analytic	8.901	2.991	0.519	4.129
non-routine interactive	4.243	9.572	15.013	9.664
routine cognitive	-5.547	-9.001	6.519	-2.375
routine manual	2.171	-0.134	-4.503	-0.964
E. Predicted Proportion of Changes in the Share of Employees with High/Medium Level of Education Explained by Predicted Changes in Occupation Task Inputs Implied by Computerization (in Percent)				
high Level of Education	47.184	32.298	47.900	41.736
medium Level of Education	6.669	-7.506	46.546	46.171

medium levels of education, observed changes in the occupational skill requirements even accounted for around 65 percent of observed changes.

Panel D shows the results of the predicted changes in occupation skill requirements that are implied by computerization. These figures are based on the regression specification shown in Table 3.11, Panel A. The overall picture complies with the figures in Table 3.16, Panel B. Computerization implies an increase in occupational requirements for analytical and interactive tasks and a reduction in routine manual and routine cognitive tasks. The deviation between observed changes in skill requirements and the predictions implied by computerization is most pronounced in the nineties, where the predicted figures show a shift towards routine cognitive tasks.

Panel E shows the proportion of observed changes in the share of employees with high and medium level of education explained by predicted changes in occupation skill requirements implied by computerization. Between 1979 and 1998/99, occupational task changes induced by computerization account for more than 40 percent of the overall skill upgrading. This figures reaches with 47 (32) percent its height (low) in the first and last (second) subperiod. With respect to changes in the proportion of employees with medium levels of education, task shifts induced by computerization account for nearly 50 percent of the observed pattern of employment.

Given that these changes in skill requirements are only those within occupations, these figures show the substantial economic impact of changes in the skill requirements on the educational upgrading of the workforce. In addition, the analysis shows the role of workplace computerization in reshaping the occupational production process. Changes in occupational skill requirements implied by computerization account for 85 percent of the proportion of educational upgrading that is explained by observed task shifts.

3.5.2.2 Changes in Occupational Skill Requirements Using a Scalar Index

The question that has been neglected in the analysis so far is, whether there has been a polarization of work in recent decades.[31] The argument is that the substitution of, for example, routine cognitive tasks by computer technologies effects occupations such as bookkeepers and bank employees that are traditionally held by employees with medium levels of education. Non-routine manual activities, on the other hand, that, at present, cannot be accomplished by computers, are frequent in occupations that are often held by employees with low levels of education such as waiters.

In order to further investigate this question, I construct a scalar index of occupational skill requirements. This skill index is the predicted value derived from the regressions presented in Table 3.15, Panel A, for 1979. Based on the 1979 value of this skill index, I classify occupations into four groups. Occupations whose value of

[31] See, for example, Levy and Murnane (1992) and Goos and Manning (2003).

the skill index in 1979 was in the lowest quartile are the first group, occupations in the second quartile are the second group and so on. I first analyze how skill requirements have changed within the four occupation groups, then I examine how the employment distribution has changed among these groups in order to investigate the question of "polarization".

Table 3.17 shows the evolution of the skill index for each occupation group. In addition, the table also includes the proportion of employees with low, medium and high educational attainment within this occupation groups. As can be seen, the value of the skill index increased within each group of occupations. The increase was particularly pronounced for the group of occupations whose 1979 value was in the fourth quartile.

Figures 3.5-3.8 show the absolute changes in the skill index (relative to the 1979 values) within each of the four groups. In addition, the absolute changes in the proportion of employees with high, medium and low levels of education are included. Figure 3.5 shows the developments for occupations that were the least demanding in terms of the value of the skill index in 1979. For this group of occupations the skill index has risen by more than 15 percentage points. This development has been accompanied by an increase in the proportion of employees with high and medium levels of education, whereas the proportion of low educated employees has declined over time. Figure 3.6 and 3.7 show the patterns for the group of occupations whose 1979 value of the skill index was in the second and third quartiles. The development in these groups of occupations can also be characterized by a shift towards employees with high and medium levels of education and away from employees with low education since 1985/86. As Figure 3.8 shows, occupations with the highest skill index in 1979, have witnessed both a large increase in skill requirements and a pronounced educational upgrading. For this group of occupations the proportion of both employees with low and medium levels of education has declined.

Table 3.17: Trends in Occupational Skill Requirements for Occupations Grouped by the 1979 Value of the Skill Index (weighted by the number of individuals within group)

	1979	1985/86	1991/92	1998/99
First Quartile				
Mean Value of the Skill Index	-4.450	3.347	3.811	11.805
Proportion of empl. w/ high education	0.931	0.920	2.475	2.762
Proportion of empl. w/ medium education	67.306	67.561	71.817	73.338
Proportion of empl. w/ low education	32.043	31.519	25.707	23.900
Second Quartile				
Mean Value of the Skill Index	-2.333	1.458	2.154	8.436
Proportion of empl. w/ high education	0.887	1.388	2.564	4.096
Proportion of empl. w/ medium education	71.057	69.548	73.240	75.623
Proportion of empl. w/ low education	28.449	29.064	24.196	20.281
Third Quartile				
Mean Value of the Skill Index	0.056	5.693	8.749	15.451
Proportion of empl. w/ high education	2.127	2.407	3.859	4.671
Proportion of empl. w/ medium education	80.237	76.872	80.698	80.453
Proportion of empl. w/ low education	18.368	20.721	15.443	14.876
Fourth Quartile				
Mean Value of the Skill Index	18.653	27.800	40.232	44.675
Proportion of empl. w/ high education	33.147	31.553	45.561	47.885
Proportion of empl. w/ medium education	59.635	49.312	48.256	46.877
Proportion of empl. w/ low education	16.381	19.134	6.184	5.238

Figure 3.5: Occupations in the First Quartile

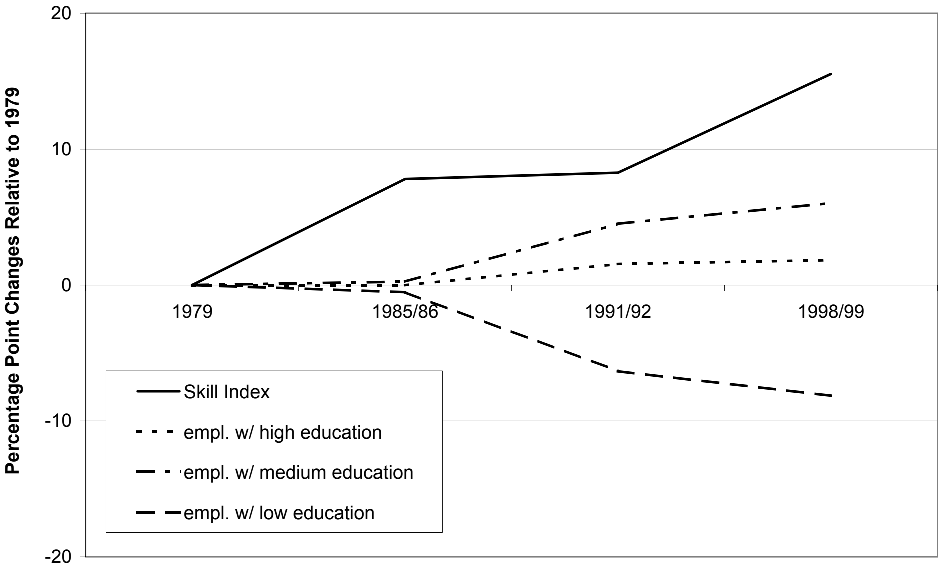


Figure 3.6: Occupations in the Second Quartile

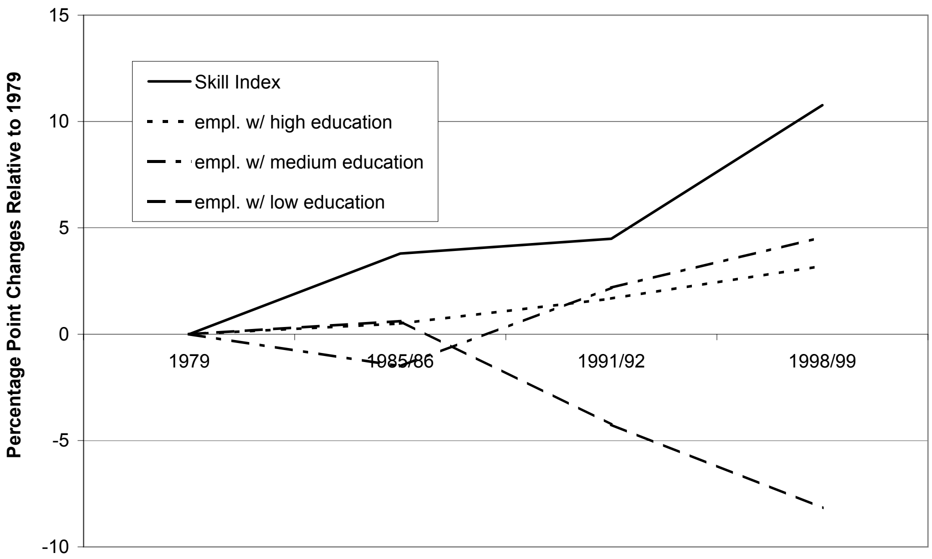


Figure 3.7: Occupations in the Third Quartile

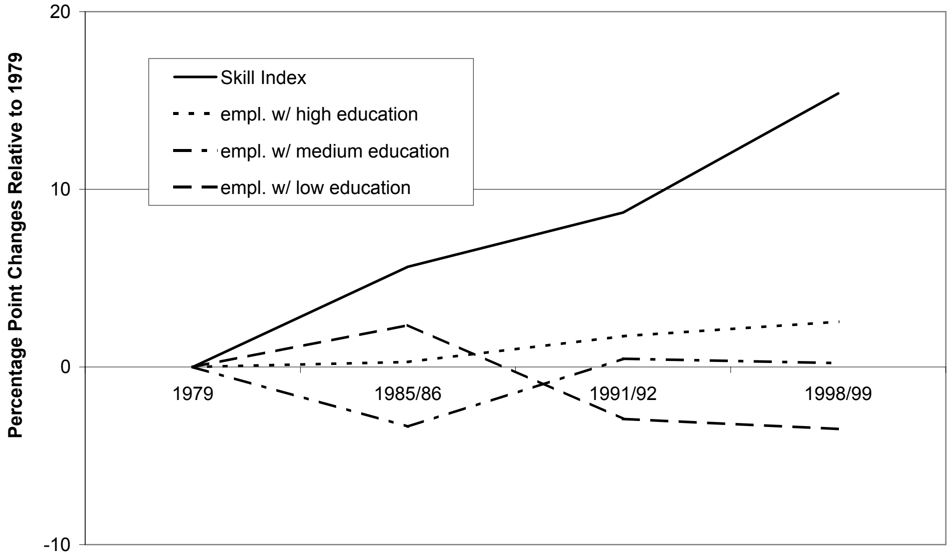
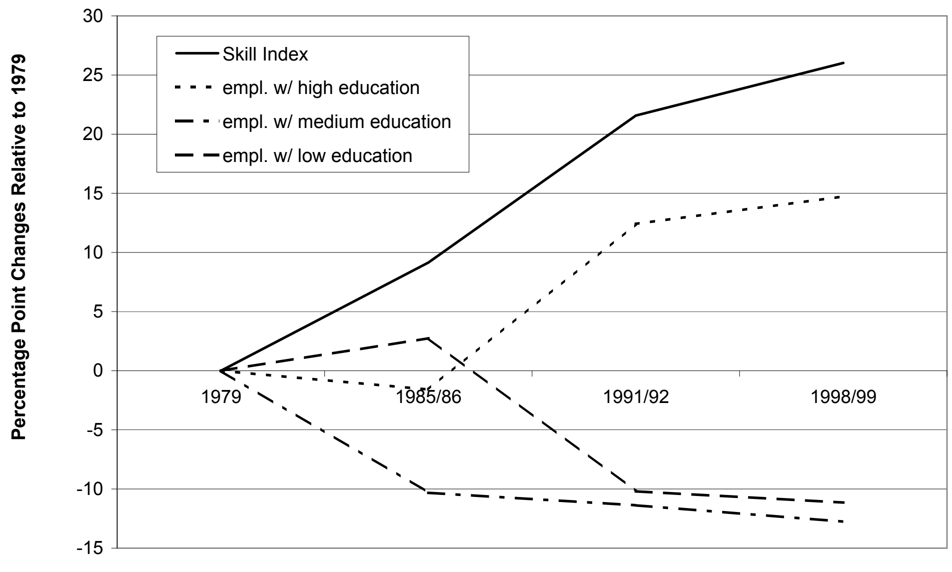


Figure 3.8: Occupations in the Fourth Quartile



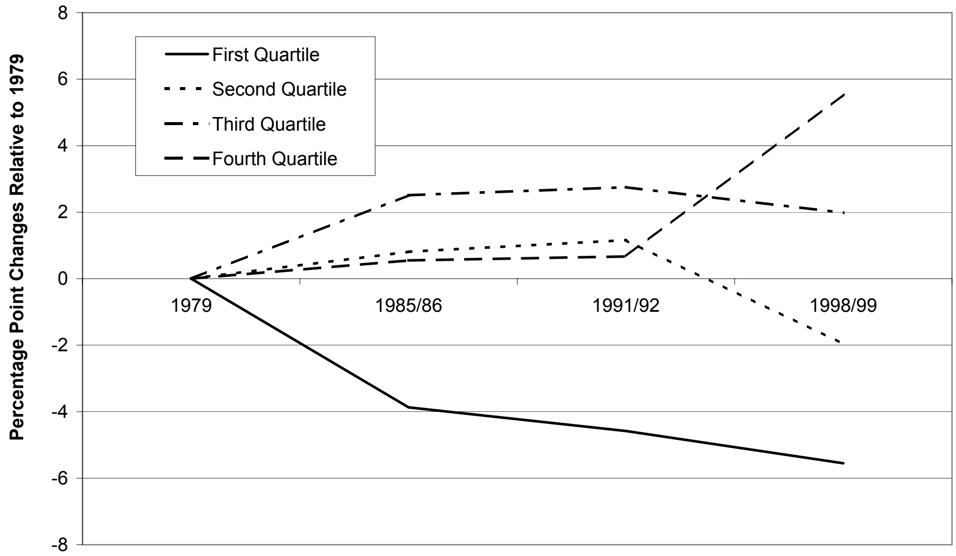
Based on these tables and figures it is difficult to assess whether the educational upgrading within each occupation group was "appropriate" giving the evolution of skill requirements, but the steep increase in occupational skill requirements even in occupation groups that were the least skill demanding in 1979 suggest that medium or high educated employees who moved into these groups of occupations are now performing tasks that are different from those that have been performed by low educated employees. This finding corroborates the previous evidence that, for each education group, tasks shifted towards analytical and interactive activities and away from manual and cognitive routine activities (page 28). The overall pattern does not indicate that "over-education" has occurred, on average, owing to the large inflow of employees with high levels of education into the labor market.

The question of whether there has been a "hollowing out" of middle-class occupations concerns the employment trends across these groups of occupations. Therefore, I calculated the distribution of employment among the different groups of occupations over time. Table 3.18 shows the employment shares for each occupation group over time, Figure 3.10 shows the absolute employment changes. Employment in occupations of the second group has always been the smallest. However, the decline in their employment share has been less pronounced than for occupations in the first group. As Figure 3.10 shows, employment in both the first and second occupation group has declined, whereas occupations in the third and fourth quartile have experienced a relative increase. These figures thus do not indicate that there was a "hollowing out" of middle-class occupations, at least not in terms of occupational skill requirements. They rather suggest a monotone shift towards more skill intensive occupations.

Table 3.18: Employment Trends for Occupations Grouped by the 1979 Value of the Skill Index

	1979	1985/86	1991/92	1998/99
First Quartile	25.64	21.77	21.06	20.09
Second Quartile	17.74	18.55	18.90	15.77
Third Quartile	34.19	36.70	36.94	36.17
Fourth Quartile	22.43	22.98	23.10	27.97

Figure 3.9: Employment Trends in Occupations Grouped by the 1979 Value of the Skill Index



3.6 Are the Results Robust to Changes in the Task Measure?

The individual task measures used so far assumed values between 0 and 100 for each task category j and time t (see Equation 3.1). Alternatively, one can restrict the task measures to sum up to 100 for each individual i and time t:

$$Task_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in cross-section } t}{\text{total number of activities performed by } i \text{ at time } t} * 100 \tag{3.4}$$

as previously

$t = 1979, 1984/85, 1991/92$ and $1998/99$, and

$$j = \begin{cases} 1 & : \quad \text{non-routine analytic tasks} \\ 2 & : \quad \text{non-routine interactive tasks} \\ 3 & : \quad \text{routine cognitive tasks} \\ 4 & : \quad \text{routine manual tasks} \\ 5 & : \quad \text{non-routine manual tasks.} \end{cases}$$

The underlying model of this task measure is one in which survey participants have their working day in mind while answering the questionnaire. It assumes that the activities asked for in the questionnaire include all activities employees perform at the workplace and that the denominator encompasses all activities individual i performs during the working day. A higher number of activities within a particular category then implicitly means that employees spend more time performing tasks of this category. But the questionnaire does not include information about time. I therefore prefer the measure that was introduced first and used throughout the paper. However, in order to test the robustness of findings I perform additional analyses using the alternative task measure.

Table 3.19 shows the overall trends using the alternative task measure. The alternative measure shows a larger absolute increase in analytical task inputs and larger decreases in the routine cognitive task inputs than in Table 3.4. The trends in the interactive and routine manual task measures are broadly comparable. Non-routine manual inputs hardly change in terms of the alternative task measure. The overall picture suggests that the task measure used throughout this study is a more conservative measure of changes in task inputs than the alternative measure.

Table 3.20 and 3.21 show some results of specifications using the alternative task measure. Annualized changes in task measures are regressed on annualized changes of computer usage. For each panel the equations are estimated simultaneously as a system of seemingly unrelated regressions (SUR) since, by construction, for each observation the task measures T_j sum up to 100 over all equations. This leads the ΔT_j to sum to zero. Only four out of the five task equations are linearly independent and for each observation the disturbances across equations must sum to zero. The system estimation technique allows the consideration of cross-equation constraints. One procedure is to estimate four out of the five 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

Table 3.19: Replication of Table 3.4 Using the Alternative Task Measure

	non-routine analytic	non-routine interactive	routine cognitive	routine manual	non-routine manual
1979	8.70	22.19	28.99	24.29	15.82
1985/86	14.25	26.77	22.08	20.52	16.38
1991/92	15.56	42.53	9.87	17.84	14.19
1998/99	26.05	43.25	5.00	8.62	17.08

The sample includes workers aged 18-65 with residence in West Germany and of German nationality.

specifications are invariant to the choice of the "left–out" equation.[32] However, given the focus in this analysis, it seems straightforward to drop the non-routine manual equation. Weighted SUR-estimations are performed, with the number of individuals within occupation group as weights.

Table 3.20 shows that, except for the analytical task equation, the results are robust to changes in the way the task measures are constructed. Occupations that saw greater increases in computerization witnessed significant larger increases in interactive task requirements, and significantly greater declines in cognitive and manual routine task requirements. The coefficient in the analytical task equation is negative. However, it is estimated very imprecisely.

Table 3.21 shows the results for each education group separately. For employees with high and low levels of education, the results are consistent with the hypotheses of a complementary relationship between computer technology and analytical and interactive activities, and a substitutive relationship between computer technology and cognitive and manual routine activities. For employees with medium levels of education, the results for interactive, routine cognitive as well as routine manual activities are consistent with the hypotheses. The results largely correspond to the findings shown in Table 3.13, although the coefficients shown in Table 3.21 are less precisely estimated.

Additional results not reported here confirm this picture. My interpretation of these findings is that the overall conclusions drawn from the analyses in this chapter are robust to changes in the construction of the task measure.

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

Table 3.20: Replication of Table 3.11 (Panel A) Using the Alternative Task Measure

Dep. Variables: (Annualized Changes in Task Inputs)				
	Δ non-routine analytic	Δ non-routine interactive	Δ routine cognitive	Δ routine manual
Δ computer use	-0.067	0.242***	-0.167***	-0.347***
	(0.053)	(0.087)	(0.067)	(0.085)
dummy 1985/86-1991/92	-6.798***	15.416***	-10.000***	-0.902
	(2.362)	(3.917)	(3.039)	(3.696)
dummy 1991/92-1998/99	5.631***	-16.417***	3.776	-4.931
	(2.327)	(3.859)	(2.994)	(3.642)
$Pseudo-R^2$	0.111	0.237	0.108	0.086
χ^2	29.46***	73.25***	28.59***	22.19***
no. of observations:		237		

The four equations are estimated simultaneously as a system of seemingly unrelated regressions (SUR). Standard errors are in parentheses. Regressions are weighted by the number of individuals within occupation group; ***,**,*-indicate significance at the 1, 5, 10 percent level.

Table 3.21: Replication of Table 3.13 Using the Alternative Task Measure

Dep. Variables: Annualized Changes in Task Inputs				
	Δ non-routine analytic	Δ non-routine interactive	Δ routine cognitive	Δ routine manual
Employees with High Level of Education				
Δ computer use	0.053	0.107	-0.279***	-0.02
	(0.097)	(0.149)	(0.096)	(0.051)
dummy 1985/86-1991/92	-18.430***	53.735***	-33.052***	1.460
	(5.341)	(8.246)	(5.296)	(2.837)
dummy 1991/92-1998/99	-8.408*	5.366	-12.875***	4.913
	(4.768)	(7.362)	(4.727)	(2.533)
$Pseudo - R^2$	0.108	0.400	0.401	0.039
χ^2	13.06***	75.90***	76.38***	4.67
no. of observations:		121		
Employees with Medium Level of Education				
Δ computer use	-0.034	0.173**	-0.074	-0.407***
	(0.053)	(0.081)	(0.069)	(0.080)
dummy 1985/86-1991/92	-6.806	12.105***	-9.493***	2.186
	(2.361)	(3.604)	(3.081)	(3.540)
dummy 1991/92-1998/99	7.033***	-18.007***	1.572	-1.822
	(2.337)	(3.568)	(3.050)	(3.504)
$Pseudo - R^2$	0.130	0.240	0.240	0.109
χ^2	34.57***	73.07***	15.92***	28.49***
no. of observations:		234		
Employees with Low Level of Education				
Δ computer use	0.055	0.225**	-0.207***	-0.353***
	(0.056)	(0.109)	(0.074)	(0.123)
dummy 1985/86-1991/92	-3.641	7.110	0.193	-16.022***
	(2.505)	(4.909)	(3.340)	(5.533)
dummy 1991/92-1998/99	12.516***	-15.066***	20.905***	-31.727***
	(2.590)	(5.077)	(3.454)	(5.722)
$Pseudo - R^2$	0.146	0.080	0.175	0.165
χ^2	37.73***	19.18***	46.55***	43.47***
no. of observations:		226		

The four equations are estimated simultaneously as a system of seemingly unrelated regressions (SUR). Standard errors are in parentheses. Regressions are weighted by the number of individuals within occupation group. ***,**,*-indicate significance at the 1, 5, 10 percent level.

3.7 A Note on Wages

So far, the analyses completely neglected task prices. If the prices for analytical and interactive task inputs relative to routine cognitive and routine manual task inputs had declined, for example, the overall trend towards analytical and interactive activities wouldn't be very surprising. In addition, the model in Section 3.5.2 would lead to an overestimation of shifts towards analytical and interactive activities and thus to an overestimation of the educational upgrading of the workforce.

The survey contains information on monthly earnings, according to 18 categories. In order to calculate hourly wages, a midpoint is assigned for each category. These midpoints are then divided by the number of hours an individual usually spends at work.[33] In a next step, individuals are classified according to task categories. Individuals who have the largest task measure in the analytical or interactive categories are classified as "non-routine" employees. Individuals who have their largest task measures in the manual or cognitive routine categories are classified as "routine" employees.

Figure 3.10 shows the evolution of the logarithm of mean hourly (nominal) wages for "non-routine" and "routine" employees.[34] Wages increased for both groups of employees at a similar pace, which results in the "non-routine/routine wage premium" to remain stable over time. The stability of relative task prices over time suggests that the "fixed" coefficient model used in Section 3.5.2 is appropriate, meaning that, on average, it neither leads to an overestimation nor to an underestimation of task shifts.

Of course, this evidence aggregates various developments on the individual level. However, the overall picture is in line with earlier studies that find that the German wage structure remained fairly stable in the 1980s and 1990s, in particular compared to the vast changes in the wage structure that have been going on in the U.S. during that time.[35]

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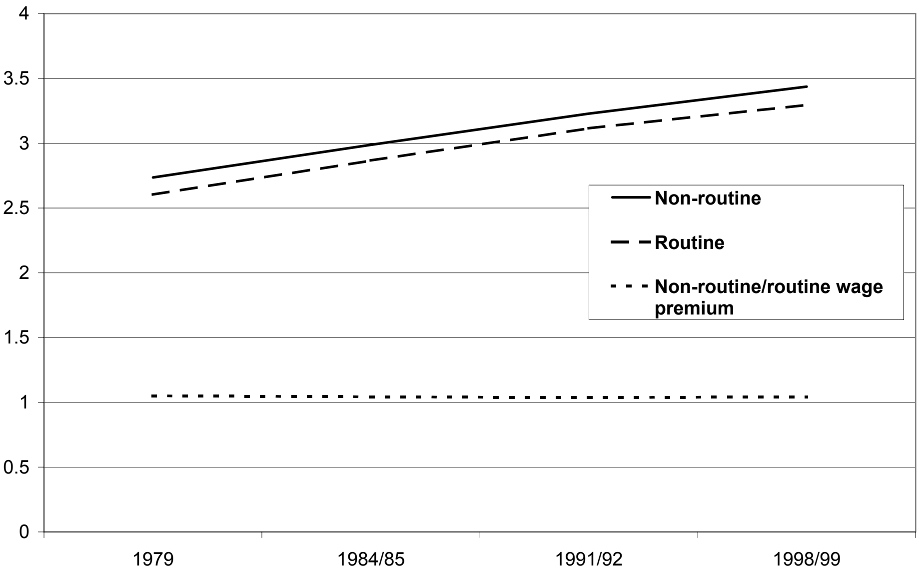
[33] Comparable procedures are often used in literature, for example, by DiNardo and Pischke (1997) and by Entorf and Kramarz (1997).

[34] The results are invariant to the use of the logarithm of mean hourly wages or the use of the mean of the logarithm of hourly wages.

[35] See, for example, Abraham and Houseman (1995) and Prasad (2000). Fitzenberger (1999) and Fitzenberger, Hujer, McCurdy and Schnabel (2001) provide evidence that the wage structure in West Germany is less stable than commonly believed. However, the changes are still small in comparison with changes in the wage structure in the U.S. or in the United Kingdom.

Figure 3.10: Logarithm of average hourly wages for "non-routine" and "routine" employees as well as the "non-routine/routine wage premium"



3.8 Conclusions

Are skill requirements in the workplace rising? The analysis in the present paper answers this question, first, by investigating whether skill requirements within formally identical occupations have changed between 1979 and 1999, and second, by exploring the role of workplace computerization in this development.

The results suggest that formally identical occupations today involve greater complexity than two decades ago. In recent decades, occupations have experienced a shift towards analytical and interactive activities, and away from cognitive and manual routine tasks. This development was ubiquitous in the sense that it occurred within occupations, within occupation-education groups and within occupation-age groups. Even those occupations that were the least demanding in 1979 now require a greater degree of complexity. In addition, the results indicate that the diffusion of computer technologies in the workplace has intensified these changes in the occupational production function. This comes from the fact that computers substitutes for workers in performing manual and cognitive routine tasks, but complement workers in performing analytical and interactive activities.

These findings indicate that previous studies that analyzed changes in skill demand, which focused on changes in the occupational distribution of employment and assumed the content of occupations to be constant over time, have largely underestimated the changes that have been going on in recent decades. There has not only been a shift towards more skill demanding occupations, the changes within occupations have been at least equally important. In addition, the analyses give information about the meaning of educational categories, which are often used as measures of skills. Using the task composition of occupations as output measures of the educational process, the analyses demonstrate that the skill content of educational categories have changed considerably in recent decades.

The results emphasize the importance of education and training in order to enable employees to cope with the challenges brought about by the changing task composition of occupations. It draws a particularly pessimistic perspective for the labor market prospects of employees with low levels of education. This group of employees has experienced the least favorable labor market development in recent decades. It has experienced either a decrease in wages or has been crowded out of the labor market in most industrialized countries. As the skill level of employees with low levels of education no longer meets the minimum occupational skill requirements, they become increasingly marginalized.

3.9 Appendix

Table A: Industry Classification

Manufacturing incl. construction and mining	
10	Mining
11	Chemical Industry, Rubber and Synthetic Material
12	Stone and Clay, Glass 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	Hairdressing
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

Chapter 4

Using Methods of Treatment Evaluation to Estimate the Wage Effect of IT Usage

4.1 Introduction

The widening wage structure in most industrialized countries in the 1980s has often been attributed to the impact of skill-biased technological change (SBTC), founded upon the notion that employer's demand for more skilled workers has been brought about by the extensive spread of information technologies (IT) at the workplace.[1] The idea is that IT increase productivity, but that only some employees possess the necessary skills to use them. Employees who use IT at the workplace then receive a wage payoff for their higher productivity owing to the use of IT.

The empirical evidence with respect to the relationship between the use of IT and wages on the individual level strongly depends on methodological issues. Cross-sectional analyses typically find significant positive wage markups for IT users. However, these rewards are strongly reduced in studies using panel data methods. As a result, most studies favor the argument that the observed positive correlations are spurious, that is, attributable to unobserved heterogeneity.

The exercise of estimating the wage effect of IT usage is one of the classical problems of selection bias, a special case of the more general problem of causal inference

[1] Comprehensive reviews of this literature can be found in Katz and Autor (1999), Acemoglu (2002) and Chennells and van Reenen (2002). For a critical assessment see Card and DiNardo (2002). Machin (2001) summarizes and discusses the most prominent points of criticism.

from non-experimental data.[2] Employers choose employees to use IT or employees themselves choose to use IT, hence, the assignment of persons to treatment is non-random. It is not clear whether differences in measured wages among employees are due to IT use or due to other factors that result in employees earning different wages even if there were no causal effect of IT usage. In the absence of genuine experimental data, some assumptions must be made to account for the problem of selection bias. The choice of assumptions must be justified in an economically convincing way depending on the context and the availability of data.

In this study, I primarily use two methods: regression based matching and matching on the propensity score. Both approaches rest upon the assumption that, conditional on a set of covariates, the difference in wages for IT users and IT non-users is attributable on average to the use of IT.[3] The particular feature of the data set used in this study backs this assumption. It has several advantages over other individual-level data sets:

1. It includes a large number of control variables that have been identified as important determinants of IT usage and wages in previous analysis. In contrast to other individual-level data sets that are usually limited to information about employees, it includes information on employers. This information is important since employers may differ in a way that systematically influences both individual wages and IT usage. It is, for example, very likely that an IT user would be employed at another employer in the counterfactual situation. The data set allows me to take various company characteristics into account, such as company size, industry affiliation, innovation strategy and company performance.

2. It is a sample of West German employees that includes both IT non-users, the potential comparison group, and IT users, the treatment group. They answered identical questionnaires. Wages and all other characteristics are therefore measured in the same way for both groups.

3. As the data set includes information on the regional affiliation of employees and employer characteristics such as company size and company performance, IT users and IT non-users operating in a common economic environment can be compared.

[2]See, for example, Heckman and Robb (1986).

[3]The measure of technology in this study is computer usage, which serves as a proxy for IT usage.

The most interesting parameter is the average treatment effect for the treated (ATT), that is, the expected benefit of IT usage on the users themselves, as opposed to the average treatment effect (ATE), the expected benefit of IT usage on a person drawn randomly from the work force. It is often argued in literature that the latter is not a very useful concept in the case of IT usage because computers are productive only in certain occupations (for example, for financial market analysts but not for ballet dancers). I additionally argue that it is important to allow for the possibility that treatment effects differ between individuals. How much IT increases the productivity of employees crucially depends on the tasks they have to perform, their qualification and the characteristics of the company. The results of Entorf and Kramarz (1998), for example, suggest that the increase in productivity is related to the experience employees have with new technologies.

In spite of the above arguments, I will also estimate the ATE. It provides a benchmark for assessing how important the arguments actually are. In addition, it allows me to compare my results with those found in other studies.

As in most cross-section studies, I find a robust positive relationship between wages and computer usage in West Germany in 1998/99. In addition to the methodological issues, this study contributes more recent evidence on the computer wage differential to literature. I do not interpret the result as causal in the sense that it suffices to give a computer to randomly drawn people of the working population for their wages to rise. Instead, I argue that given the extensive and rapid changes that have occurred in the workplace in recent decades, IT users would be worse off had they not started to work with computers.[4] This interpretation is in the spirit of Entorf, Gollac and Kramarz (1999), who found that computer users in France are less vulnerable to job losses.

This paper is organized in 6 sections. In the next section, I introduce the estimation problem at hand in a slightly more formal way following the program evaluation literature. I also discuss previous empirical results and present the empirical strategy of this study. After a general introduction, I discuss the regression based matching approach and matching on the propensity score. Regression based matching aims at purging the regression specification from potential correlation between unobservables and IT usage. The purpose of matching, on the other hand, is to re-establish the condition of an experiment when no such data are available. The differences in assumptions and interpretation of both methods are also discussed. In Section 4.3, I

[4]See Spitz (2004) for empirical evidence on how skill requirements in the workplace in West Germany have changed in recent decades.

present the data set and the variables of interest. Section 4.4 presents and discusses the estimation results. Section 4.5 concludes.

4.2 Empirical Strategy

4.2.1 Why Is It So Difficult to Estimate the Returns from IT Usage?

This study focuses on the problem of estimating the wage impact of IT usage. To state this more formally, I designate wages Y. Wages are assumed to be determined by a set of exogenous variables X, and by a dummy variable D, such that $D_i = 1$ indicates that employee i uses IT on the job, and $D_i = 0$ that employee i does not. Assuming, for the ease of illustration, that the decision to use IT was made in period s, so that, in each period t,

$$Y_{it} = \begin{cases} X_t\beta + D_i\alpha_i + U_{it} & \text{if} \quad t > s \\ X_t\beta + U_{it} & \text{if} \quad t \leq s \end{cases} \tag{4.1}$$

where α_i measures the heterogeneous impact of IT usage on wages. If α_i is constant across individuals, the impact is homogeneous. The set of parameters β defines the relationship between the observable variables X and the outcome Y, and U_{it} is an error term of mean zero and is assumed to be uncorrelated with X.

Most of the discussions on the wage effects of IT usage evolve because the group of IT users is most probably not random. This situation arises because the decision of individual i or, more likely, the decision of an employer e to choose individual i to use IT is based on personal characteristics P, workplace characteristics W and employer characteristics E that may also affect wages Y. If this is the case, and the set of observable variables X is only a subset of characteristics P, W or E, then correlation between the error term U and the IT use variable D is very likely to exist. Hence, as a consequence of such a non-random assignment, IT usage ($D_i = 1$) would be correlated with the error term U_{it} in the wage equation, which results in the standard econometric approach that regresses Y on X and D, producing biased results.

The decision rule may be described in a very stylized form as a latent single index function $IN_e(i)$, which specifies the gain in profitability of employer e if employee i (working at e) uses IT. $IN_e(i)$ thus represents the difference between the productivity increases of employer e owing to the implementation of IT and the higher wages employer e has to pay to employee i for the IT usage. $IN_e(i)$ is a function of observable variables X and unobservable variables V: $IN_e(i) = X\gamma + V$. The entire set of characteristics I, which are relevant to the decision about IT usage and wages, are then the combination of variables X and V, $I = (X, V)$. Employer e decides that employee i uses IT on the job if $IN_e(i) > 0$, in which case $(D_i = 1)$ is observed. A simple behavioral model is one in which employers select employees into IT usage based on a comparison of the present value of expected profits with and without employee i using IT: $IN_e(i) = PV_e(1) - PV_e(0)$, where $PV(1)$ is the present value of expected profits if employee i uses IT on the job and $PV(0)$ without IT usage.[5]

Previous empirical studies have addressed the issue of non-random assignment of computers in one form or another. All of these studies consider observed differences between computer users and non-users, though there is a large difference with respect to the number of available observables. The methods used to account for unobserved heterogeneity range from including proxies for individual ability into the regression specification to applying panel data methods.

Krueger (1993), who was the first to address the question of whether workers who use computers at work are paid more as a result of their computer skills, uses four empirical strategies to take into account unobserved heterogeneity in cross-section data. First, he considers computer use at home because computer use at home may reveal unobserved characteristics on the basis of which employers may select workers to use computers at work. Including computer usage at home in the regression specification then captures at least some of the unobserved heterogeneity that is associated with computer usage at work. Second, he restricts the sample to narrowly defined occupational groups, for example, secretaries. Third, he includes test score results and parental education in the specification. These variables are commonly used as proxies for individual ability. Fourth, he analyzes the relationship between changes in the proportion of computer users and changes in hourly earnings on the occupational level. The successive inclusion of additional controls attenuates the raw logarithmic wage differential for computer use of more than 30 percent to around 10 percent in the 1980s. However, none of the specifications alters the main result of a significant positive relationship between computer use and wages.

In subsequent years, various studies have presented empirical evidence suggesting that Krueger's results are driven by unobserved heterogeneity. DiNardo and Pischke (1997) make their point by showing that there is also a wage premium for

[5]For a more comprehensive model of computer assignment see, for example, Borghans and ter Weel (2004).

workers using a pencil, calculator or telephone at work or who work while sitting. Entorf and Kramarz (1997) and Entorf, Gollac and Kramarz (1999) use French data and estimate fixed-effects models. They do not find a wage premium for computer usage once they control for time-invariant unobserved individual and company heterogeneity, while the corresponding cross-section results lead to a computer-wage differential of around 16 percent – a common figure in cross-section analyses of the early 1990s. The results indicate that it is the increased productivity owing to the experience employees gain with new technologies that leads to the wage premium rather than the effect of merely using new technologies. Bell (1996), on the other hand, finds that 60 percent of the cross-sectional computer wage premium still remains in first-difference regressions using UK data.

The panel methods hinge crucially on the assumption of time-invariant unobserved heterogeneity. In the presence of changing returns on unobserved skills, differencing the data will not remove the wage effect of unobservables that might be correlated with computer use. As DiNardo and Pischke (1997) already emphasized, this factor may be a plausible explanation for the differing results of the two studies because the wage structure has widened in the UK since the early 1980s but not in France. In addition, Dolton and Makepeace (2004) criticize the simple panel methods for not allowing the coefficient to vary between individuals or, in other words, for ignoring variation in the parameter values. Exploring information on whether individuals used a computer in 1991 and 2000 (stayers), in 1991 only (leavers) or in 2000 only (enterers), they find, for example, a positive wage effect of 9 percent for male leavers in panel regressions.

As this short review of research demonstrates, previous results are mixed. To my knowledge, none of the studies considers explicitly that IT usage may be interpreted as a treatment. This notion is very attractive for this question of analysis because the main interest lies on the ATT. By contrast, previous studies focus on estimating the average wage effect of IT usage.

4.2.2 Estimation Methods

The empirical strategy in this study is to use methods most often applied in the active labor market program evaluation literature. In the tradition of this literature, I interpret IT usage as a treatment D_i, that is, estimating the coefficient of IT usage translates into a problem of estimating an average treatment effect (ATE).[6] The

[6] ATE is an average partial effect in the case of a binary variable.

ATE is usually estimated using a counterfactual framework (Rubin, 1974), where each individual i has an outcome with ($D_i = 1$) and without ($D_i = 0$) treatment (conventionally denoted as Y_{1i} and Y_{0i} respectively). Since both states are never observed for one person simultaneously, different methods have been developed in literature to overcome this "omitted variable" problem depending on the specific circumstances of the question of interest.

The observed outcome may be expressed as:

$$Y_i = Y_{0i}(1 - D_i) + Y_{1i}D_i = Y_{0i} + D_i(Y_{1i} - Y_{0i}). \tag{4.2}$$

This body of literature distinguishes between the average treatment effect (ATE), $E(Y_{1i} - Y_{0i})$, that is, the expected effect of treatment on a person drawn randomly from the population, and the average treatment effect on the treated (ATT), $E(Y_{1i} - Y_{0i}|D_i = 1)$, that is, the expected effect of treatment of those who actually have been treated. Since $E(Y_{1i}|D_i = 1)$ is directly identifiable from the sample, the problem of estimating the ATT is equivalent to the problem of estimating the counterfactual average, $E(Y_{0i}|D_i = 1)$. Thus, in order to be able to estimate the average non-treatment outcome for treated employees based on the outcomes for non-treated, identifying assumptions are needed. Estimating the ATE, on the other hand, involves estimating both counterfactual averages, $E(Y_{0i}|D_i = 1)$ for the non-treated workers in the sample and $E(Y_{1i}|D_i = 0)$ for the treated workers in the sample. In the case of IT usage, the effect on the subpopulation of treated employees (ATT) is probably of more interest than the effect on the overall population (ATE). As already discussed earlier in this paper, one of the reasons is that computers are of value only in certain jobs, for example, for computer scientists but not for artistic painters. The overall focus of the analysis will therefore be on the ATT. However, for ease of comparison with previous analyses and for the purpose of having a benchmark, I will also estimate the ATE.

The observed difference in outcomes between those treated and those untreated equals $E(Y_{1i} - Y_{0i}|D_i = 1)$ plus a bias term:

$$\begin{aligned} E(Y|D_i = 1) - E(Y|D_i = 0) &= E(Y_{1i}|D_i = 1) - E(Y_{0i}|D_i = 0) && (4.3)\\ &= E(Y_{1i} - Y_{0i}|D_i = 1) && (4.4)\\ &+ \underbrace{[E(Y_{0i}|D_i = 1) - E(Y_{0i}|D_i = 0)]}_{\text{bias term}}. \end{aligned}$$

If IT usage were randomly assigned to employees, that is, if the treatment and control group had the same distribution of both observed and unobserved characteristics, this would be an easy task: the ATE and ATT would be the difference in sample average of those using IT and those not using IT at the workplace.[7] However, this scenario is very unlikely, in particular as recent empirical studies document that IT users differ systematically from IT non-users, for example, with respect to their education. Table 4.9 shows the non-randomness of IT usage based on the data set at hand. The major differences are in the distribution of formal education between IT users and IT non-users. In contrast to IT being randomly assigned, employers select employees with specific favorable traits for treatment. The decision about who uses IT on the job is related to the question of how much an employer's profitability increases from IT use and, hence, to the outcomes Y_{1i} and Y_{0i}.

Since data from a social experiment or instrumental variables that allow purging of the regression from the presence of a possible omitted variable bias are not available for this research project, my strategy is based on the assumption of "strict ignorability" of treatment conditional on a set of controls (Rosenbaum and Rubin, 1983): $(Y_{1i}, Y_{0i}) \perp\!\!\!\perp D_i|X$. That is, conditional on X, D_i and (Y_{1i}, Y_{0i}) are independent, where X denotes a vector of observable covariates, D_i denotes the treatment (in our case $D_i = 1$: IT usage, $D_i = 0$: no IT usage) and Y_{1i} is the logarithm of hourly wages for IT users and Y_{0i} for IT non-users. This assumption implies that $E(Y_{0i}|X, D_i) = E(Y_{0i}|X)$ and $E(Y_{1i}|X, D_i) = E(Y_{1i}|X)$, referred to as the conditional mean independence assumption (CIA) in literature. That is, conditional on X, the non-treatment outcome for the treated and non-treated are comparable in expectation. For the estimators used in this study it suffices that this weaker assumption holds.

The intuition behind this assumption is that systematic differences in wages between IT users and IT non-users with the same values for the covariates X are attributable to the use of IT. Since the moments of the distribution of Y_{1i} for the treated can be estimated directly, it suffices for the assumption $E(Y_{0i}) \perp\!\!\!\perp D_i|X$ to hold in order to be able to estimate the ATT.

The present data set is particularly suited for this strategy because it contains a large number of observables that have been identified as important determinants of the IT use-wage relationship in earlier studies. In spite of this merit, one must keep in mind that the CIA is a strong assumption and that, stricly speaking, the

[7] An additional assumption is that there are no general equilibrium effects in the sense that IT use by one employee does not affect wages of other employees (so-called stable unit treatment value assumption: SUTVA; see, for example, Angrist, Imbens and Rubin, 1996). This is synonymous to stating that there are no macroeconomic effects. The analysis in this study is based on a random sample, which implies SUTVA.

estimation strategy accounts solely for selection on observables. Differences between IT users and IT non-users in the distribution of unobserved attributes such as ability are not considered. Heckman, Ichimura, Smith and Todd (1998b) decompose the bias term of equation 4.3 into three components:

$$\text{bias term} = [E(Y_{0i}|D_i = 1) - E(Y_{0i}|D_i = 0)] = B_1 + B_2 + B_3 \tag{4.5}$$

The first two components, B_1 and B_2, arise due to differences in the distribution of observed characteristics X whereas the last component, B_3, refers to the "classical" selection bias resulting from selection on unobservable attributes. B_1 corresponds to the bias due to differences in the support of regressors between IT users and IT non-users. B_2 corresponds to the bias owing to differences in the shape of distributions of regressors in the two groups in the region of common support.

I use two methods to overcome the bias due to B_2, regression based matching and matching on the propensity score. The two approaches differ in how they deal with the bias due to B_1, which I will discuss in Section 4.2.3. None of them is able to resolve problems due to the presence of B_3. However, Heckman, Ichimura and Todd (1997) and Heckman, Ichimura, Smith and Todd (1998b) find that the selection bias part, B_3, is the smallest of the three components of bias in their application. How important the different bias components are depends, of course, on the application. However, the richness of the data set in the present study largely reduces the scope for a potential bias owing to unobservables.

Both approaches have already been widely discussed in literature (see, for example, Heckman and Robb, 1985, Heckman, Ichimura and Todd, 1997 and 1998a, or Wooldridge, 2002, Chapter 18). I will review the basic concepts in order to demonstrate their usefulness for the estimation problem at hand.

4.2.2.1 Regression Based Matching

The aim of regression based matching (RBM) is to purge the outcome equation from potential correlation between the error term U_{it} and D_i (see equation 4.1). The basic logic of the RBM is analogous to the proxy solution to the omitted variable problem.[8]

[8] The omitted variable bias can be mitigated, or even eliminated, if a proxy variable is available for an unobserved variable q. The formal requirements for a proxy variable can be found, for example, in Wooldridge (2002, p.63ff.). The intuition is that, conditional on the proxy variable, the unobservable variable q is uncorrelated to each of the observable variables X in the specification.

To illustrate this approach it is useful to decompose the counterfactual outcomes for IT user Y_{1i} and IT non-user Y_{0i} into their means and a stochastic part:[9]

$$\begin{aligned} Y_{0i} &= \mu_0 + U_{0i} \qquad E(U_{0i}) = 0 && (4.6) \\ Y_{1i} &= \mu_1 + U_{1i} \qquad E(U_{1i}) = 0 && (4.7) \end{aligned}$$

where $\mu_j = E(Y_{ji}), \quad j = 0, 1$. As in the previous part of the paper, i refers to individuals and j to the treatment status. For the case of linear regressions $\mu_j = X\beta_j$. Inserting these into equation (4.2) of observed outcomes gives:

$$Y_i = \mu_0 + (\mu_1 - \mu_0)D_i + U_{0i} + (U_{1i} - U_{0i})D_i \tag{4.8}$$

Under the CIA assumption and assuming the $E(U_{1i}|X) = E(U_{0i}|X)$ it follows that standard regression methods can be used to estimate ATE. This is because equation (4.8) may be rewritten as:

$$\begin{aligned} E(Y_i|D_i, X) &= \mu_0 + (\mu_1 - \mu_0)D_i + E(U_{0i}|X) + \underbrace{E(U_{1i} - U_{0i}|X)}_{=0} D_i && (4.9) \\ &= \mu_0 + \alpha D_i + g_0(X) && (4.10) \end{aligned}$$

where $\alpha = \mu_1 - \mu_0 = E(Y_{1i} - Y_{0i}|X) = ATE = ATT$ and $g_0(X) = E(U_{0i}|X)$. In addition, $E(U_{0i}|X)$ might be expressed as a function of some vector function $h_0(X)$, such as $E(U_{0i}|X) = \eta_0 + h_0(X)\beta_0$. Then, equation (4.9) translates into

$$E(Y_i|D_i, X) = \gamma_0 + \alpha D_i + h_0(x)\beta_0 \tag{4.11}$$

where $\gamma_0 = \mu_0 + \eta_0$. $h_0(X)\beta_0$ is an example of a control function and its purpose is to provide an approximation for $E(U_{0i}|X)$. When inserted into equation (4.9) and therefore implicitly subtracted from U_{0i}, it purges the equation from the covariance between D_i and U_{0i}. The idea is that the purged disturbance term $[U_{0i} - h_0(X)\beta_0]$ is orthogonal to all variables on the right-hand side of the equation. If the assumptions hold, the control function accounts for a possible self-selection bias.[10]

[9] The structure of illustration follows Wooldridge (2002), chapter 18.

[10] This is a special case of a control function that does not rely on instruments. For a discussion on the control function approach involving instruments refer, for example, to Heckman and Robb (1985) or Blundell, Dearden and Sianesi (2003). In contrast to the instrument approach that rests upon the exclusion restriction, identification in the approach used in this study is achieved through a functional form restriction.

The previous specification rests upon the assumption that there are on average no person-specific gains conditional on X, $E(U_{1i} - U_{0i}|X) = 0$. Relaxing this assumption implies that ATE and ATT are no longer identical. However, a regression specification can still be used:

$$E(Y_i|D_i, X) \quad = \quad \mu_0 + \alpha D_i + g_0(X) + D_i[g_1(X) - g_0(X)] \tag{4.12}$$

where $\alpha = ATE$, $g_0(X) \equiv E(U_{0i}|X)$ and $g_1(X) \equiv E(U_{1i}|X)$. $g_0(X)$ and $g_1(x)$ are both operationalized by replacing them with a parametric function of X. The intuition is analogous to the approach in equation (4.11).

Assuming that these functions are both linear in X, equation (4.12) can be written as

$$E(Y_i|D_i, X) \quad = \quad \gamma_0 + \alpha D_i + X\beta_0 + D_i[X - E(X)]\delta \tag{4.13}$$

where β_0 and δ are unknown parameters (the intermediate steps are shown in the appendix to this chapter). As can be seen, the control function then involves both the level effect of X and the interactions of X (which have been previously demeaned by $E(X)$, approximated with the sample averages) with the treatment indicator. Based on the $A\hat{T}E$, the ATT is estimated using[11]

$$A\hat{T}T = \hat{\alpha} + (\sum_{i=1}^{N} D_i)^{-1}(\sum_{i=1}^{N} D_i(X - \bar{X})\hat{\delta}). \tag{4.14}$$

I take account of the fact that the demeaned variables are generated regressors by applying a bootstrap method to construct the standard errors of the estimated coefficients. All bootstrap results are based on 100 resamples.

4.2.2.2 Propensity Score Matching

The CIA assumption, introduced in Section 4.2.2, is the basis of the matching technique. The traditional matching approach estimates the expected non-treatment outcome for an IT user i with observable characteristics X by the fitted value of a nonparametric regression in the sample of IT non-users with identical X. This can be represented in the following formula:

[11] A method to estimate the ATT directly would be to demean the X using the averages of the "treated" sample instead of the averages of the "whole" sample.

$$ATT = \frac{1}{N_1} \sum_{i \epsilon D_i = 1} \{Y_{i1} - \sum_{i \epsilon D_i = 0} w_{N_0} Y_{i0}\}, \tag{4.15}$$

where N_1 is the number of IT users and N_0 is the number of IT non-users. w_{N_0} is a weight function that weights the observations of an IT non-user according to its similarity with respect to X to IT user i. The literature discusses different matching estimators, which differ with respect to the weight function. I will discuss the estimators used in this study at the end of this section. Beforehand, I shortly refer to the so-called "curse-of-dimensionality" problem that arises when the vector of observable characteristics X is high-dimensional (as it is the case in this study). As the dimension of the data increases and, hence, the information content increases, the complexity of the estimation problem increases exponentially. The "curse-of-dimensionality" arises because in high-dimensional settings, the data requirements needed to find counterfactuals that are similar along every dimension of X increase exponentially in the dimension of X.

Rosenbaum and Rubin (1983) introduced the propensity score as a means to overcome the dimensionality problem that arises when the set of conditioning variables X is large. They showed that when outcomes Y_0 are independent of the treatment conditional on variables X (CIA assumption), then outcomes Y_0 are also independent of the treatment conditional on the propensity score $p(X)$, defined as $P(D_i = 1|X)$, with $0 < P(D_i = 1|X) < 1$. As can be seen from this formula, the propensity score is the probability of treatment given the covariates X. In conditional independence notation, this is $(Y_{1i}, Y_{0i}) \perp\!\!\!\perp D_i|p_i(X)$. This property allows it to use the one-dimensional propensity score $P(D_i = 1|X)$ instead of the high-dimensional vector X in the matching approach. $P(D_i = 1|X)$ instead of X now determines the similarity of treated and non-treated employees. Dehejia and Wahba (1999, 2002), among others, have drawn attention to this class of estimators because their analyses suggest that propensity score matching is a powerful tool to resolve the selection bias problem inherent in non-experimental data.[12]

To implement this estimator, one first needs an estimate for the propensity score. I choose a flexible probit model that includes various covariates (described below),

[12] Others also investigated the properties of matching methods in different settings (see, for example, Heckman, Ichimura and Todd, 1997, 1998a). However, Dehejia and Wahba (1999, 2002) explicitly make the case for matching on the propensity score in order to overcome LaLonde's criticism of non-experimental estimators (LaLonde, 1986). Criticism of Dehejia and Wahba (1999, 2002) comes from Smith and Todd (2004).

their quadratics and interactions. However, logit models as proposed by Rosenbaum and Rubin (1983) or non-parametric models may also be used (Powell, 1994, Heckman, Ichimura and Todd, 1997). I take account of the sampling variability in the estimated propensity scores by applying a bootstrap method to estimate the standard errors of the estimated treatment effects. The bootstrap results are based on 100 resamples.

Matching estimators differ with respect to the weights they attach to members of the non-treated group. The traditional pairwise matching method, nearest neighbor matching, weights the nearest non-treated employee with 1 and all others with 0, that is, only the closest member of the comparison group is used as the comparison level for the treated employee i. In order to guarantee that the "closest" neighbor is not too far away in terms of the propensity score, one usually sets a caliper. In the nearest neighbor matching estimations in this study the caliper is set to 0.001.

Extensions to this method are, for example, kernel or local linear matching estimators (Heckman, Ichimura and Todd, 1997 and Heckman, Ichimura, Smith and Todd, 1998), which have the advantage of reducing the asymptotic mean squared error. In this study, I present results using an Epanechnikov kernel.

4.2.3 Discussion of Methods

In this paper, I present two different approaches for estimating the ATE and ATT. They both rely on the CIA, but each of them uses different additional assumptions to overcome the omitted variable problem associated with the counterfactual framework. This has implications for the economic interpretation of estimated coefficients. Both methods are, however, similar with respect to the fact that they impute the missing potential outcomes. The data set is particularly suited for these approaches because it includes a large number of potential controls.

None of the approaches considers an instrument variable Z as a source of exogenous variation to approximate random assignment to IT usage. This is the case because I did not find convincing candidates that are correlated with IT usage but do not simultaneously determine wages. Therefore, selection models, which are otherwise powerful tools, cannot be applied in this study (see Heckman, 1979, and Heckman and Robb, 1985, 1986).[13] However, having an instrument at hand would have been helpful only in the case of homogeneous treatment effects (see, for exam-

[13] In contrast to matching and control function approaches, which are considered "selection on observables," selection models additionally account for selection on unobservables.

ple, Heckman and Robb, 1985, Blundell and Costa Dias, 2000, or Blundell, Dearden and Sianesi, 2003).[14] Assuming a homogeneous impact of treatment is always restrictive, but seems to be particularly cumbersome for the question of interest in this study, as previous research suggests that the effects of IT usage do vary across individuals (see, for example, Entorf and Kramarz, 1997, 1998, Dolton and Makepeace, 2004). The fact that the productivity of IT depends on the occupational circumstances favors the argument that the effects of IT usage are heterogenous across individuals. Employers select those employees into IT usage from which they expect the largest increases in profitability. These expectations rely on workplace characteristics, individual characteristics and company characteristics. Employees share in the gains of IT usage in terms of higher wages.

In the case of heterogeneous treatment effects, the composite error term is given by $U_i + D_i(\alpha_i - \bar{\alpha})$. To see this consider the outcome equation 4.1 (for $t > s$): $Y_i = \beta + D_i\alpha_i + U_i$ (abstracting from other regressors), where α_i is the treatment impact of individual i. Define $\bar{\alpha}$ as the population mean impact ($E(\alpha_i) = \bar{\alpha} = ATE$), ϵ_i as worker i's deviation from the population impact, and then $\alpha_i = \bar{\alpha} + \epsilon_i$. The outcome equation may then be written as: $Y_i = \beta + D_i\bar{\alpha} + [U_i + D_i\epsilon_i] = \beta + D_i\bar{\alpha} + [U_i + D_i(\alpha_i - \bar{\alpha})]$. Therefore, $U_i + D_i(\alpha_i - \bar{\alpha})$ is the composite error term. Even if the instrument Z is uncorrelated with U_i, it is, by assumption, not uncorrelated with $U_i + D_i(\alpha_i - \bar{\alpha})$.

Regression assumes a functional form that is linear in parameters. It imputes the missing potential outcome using the estimated regression function. For example, if $D_i = 1$, then Y_{1i} is observed and Y_{0i} is missing. The regression approach imputes Y_{0i} with a consistent estimator $\hat{\mu}_0(X)$ for the conditional expectation. Simple OLS hinges crucially on the assumption $E(U_{1i} - U_{0i}|X) = 0$ (see equation 4.9). The resulting estimate will not in general recover the ATT. The additional regression specification used in this study, which includes interactions between the observable variables X and the treatment dummy recovers the ATT. In addition, the interaction terms provide evidence of the presence and extent of heterogeneous effects, firstly, through the statistical significance of the estimated coefficients and, secondly, through the quantitative magnitude of effects for various subgroups that might be of particular interest.

Matching, on the other hand, does not assume that the functional form is linear

[14] An exception is the local average treatment effect interpretation of instrument estimates in the heterogeneous treatment effect case (see Imbens and Angrist, 1994).

in parameters. It is a non-parametric approach in which a comparison group among the non-treated is chosen, such that the selected group is as similar as possible to the treated group in terms of their observable characteristics. It is a very attractive approach in this study because the main interest lies on the average treatment effect for the treated (ATT)[15] and the data set has properties that have been identified as being favorable in the context of the evaluation of active labor market programs (Heckman, Ichimura and Todd, 1997). Matching estimators impute the potential outcome using only the outcome of the nearest neighbor of the opposite treatment group. However, various studies point to the importance of the choice of the matching variables (for example, Blundell, Dearden and Sianesi, 2003).

Both matching and OLS produce weighted averages of the treatment effects $E(Y_{1i} - Y_{0i}|X)$. Matching recovers the ATT by weighting the heterogeneous effects according to the proportion of treated at each value of X (that is, proportionally to the propensity score at X). OLS, in contrast, weights the heterogeneous effects proportionally to the variance of treatment status at X (Angrist, 1998).

One issue is whether the support of the observable variables overlaps for the treated and the non-treated group (bias B_1 in equation 4.5). This problem is particularly evident for matching. If there are regions where the support does not overlap, it is not possible to find a sufficiently comparable observation in the other group. Then matching is often performed only over the common support region.[16] The estimated effect must then be redefined as the mean treatment effect for those treated falling within the common support region, which, in the heterogeneous treatment case, might be quite different from the average treatment effect on the treated. This problem is less severe in the regression approach, because the parametric model can in general be used to predict the expected outcome even in regions outside the common support. However, the reliability of the estimated coefficients then hinges crucially on the ability of the model to predict outside its common support. Regression is not a transparent tool in this respect. Researchers are often not aware of the fact that the observables do not overlap much. The advantage of matching is that it quickly reveals the extent to which treated and non-treated groups overlap in terms of pre-treatment variables.

[15] It is also possible to recover the ATE with the matching approach. This requires the estimation of the average treatment effect for the non-treated in addition to the average treatment effect on the treated. The ATE can then be calculated as a weighted average of the effect on the treated and the effect on the non-treated.

[16] For a detailed discussion of this problem see Lechner (2000).

Neither approach overcomes the potential bias due to unobservables (B_3 in equation 4.5). If IT usage and wages are still positively correlated with some unobserved individual traits, such as ability, both ATT and ATE are upward biased. This situation is equivalent to arguing that the CIA does not hold in the present estimation problem. Given the large set of controls that are taken into account in the analysis, it is hard to imagine exactly what the remaining unobservables might be. For example, the specifications control for individual education, which takes into account that high ability persons choose higher levels of education. I therefore argue that the informational richness of the data set justifies the CIA.

4.3 Data and Empirical Framework

The analysis is based on the "Qualification and Career Survey", which is a survey of employees 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). I use the most recent cross-section, launched in 1998/99, in this study. It covers more than 30,000 individuals (men and women).[17]

In addition to the main variable of interest, IT usage, three types of variables are considered in the analyses: individual characteristics, company characteristics and workplace characteristics. I include variables reflecting individual characteristics in order to account for the fact that employees may systematically differ with respect to characteristics that may affect both computer use and wages. As more highly educated workers are more likely to use computers at work and earn higher wages, I control for the level of formal education of employees, work experience and tenure with the current employer. As wages of civil servants are determined in a process that differs from the process for wages of employees in private companies, a dummy variable for civil servants is also included in the regressions.

One drawback of most estimates on individual-level data is that they generally do not provide information on the employers. Employer information may however be important if it determines systematic effects on wages and IT usage. The data set

[17] I restrict the sample to West German residents with German nationality: in other words, East German residents and non-German employees are excluded from the sample. Moreover, the sample does not include self-employed, employees with agricultural occupations and employees working in the agricultural sector. Persons younger than 18 or older than 65 are also excluded from the sample.

allows me to take various company characteristics into account such as company size, industry affiliation, innovation strategy and company performance. This ability is a substantial improvement over other studies in this area. Based on previous empirical research, I expect, for example, that larger companies and innovative companies pay higher wages and that they are more likely to use IT intensively.

Another feature that distinguishes this data set from others is that it includes information on the task composition of occupations.[18] These tasks describe the occupational context in which IT is introduced. In addition, this information on occupational skill requirements allows me to further reduce unobserved heterogeneity.

The variables used in the estimates are constructed as follows (Summary statistics can be found in Table 4.1):

Hourly Wages: The survey contains information on monthly earnings, according to 18 categories. A midpoint is assigned for each category. These midpoints are then divided by the number of hours an individual usually spends at work.[19] Compared to other data sets that are usually used in comparable analyses such as the CPS for the U.S. or the IAB-S for Germany, this data set has the advantage that earnings of highly paid workers are not censored from above. In all estimates, the logarithm of wages is used as dependent variable. On average, employees in West Germany earned about 27 German Marks in 1998/99 (Table 4.1).

IT equipment: The data set includes detailed information on the tools and machines used by the employees in the workplace. The "IT use" variable is a dummy that takes the value 1 if the employee uses a computer, terminal or electronic data processing device on the job. As shown in Table 4.1, 57 percent of employees have used one or more of the above devices on the job in West Germany in 1998/99.

Individual characteristics: I distinguish three levels of formal education attained by employees. Employees with a low level of education are those with no vocational training. Employees with medium levels of education have a vocational qualification either from an apprenticeship or they have graduated from a vocational college. Employees holding a degree from a university or a technical college are classified as having a high level of education. As shown in Table 4.1, the majority of the survey participants, 70 percent, has a medium qualification level, whereas 17 percent are

[18]For a detailed analysis of how the task composition of occupations changed in West Germany since 1979 see Spitz (2004).

[19]Comparable procedures are often used in literature, for example, by DiNardo and Pischke (1997) and by Entorf and Kramarz (1997).

highly qualified and only 12 percent have a low education level.

The survey participants also indicate their first year of work. Based on these answers, I calculate the years of (potential) work experience (1999 - first year of work). In addition, employees indicate the year when they started to work for the current employer. This information is used to calculate tenure (1999 - first year with current employer).

The data set includes information about previous unemployment spells (dummy variable: "Have you ever been unemployed before?"), marital status, gender and whether survey participants were born in East Germany. It also contains information about whether an employee is working as a civil servant. In addition, I constructed a dummy variable indicating whether employees live in a city (place of residence is larger than 100,000 inhabitants).

Workplace Characteristics: The analyses by Autor, Levy and Murnane (2003) and Spitz (2004) document how IT has changed the content of work towards analytical and interactive activities and away from manual and cognitive routine activities. The data set at hand is a cross-section, thus changes in the task composition of occupations cannot be taken into account. However, the data set allows me to consider task levels, capturing the content of jobs, and therefore, it gives a description of the context in which IT is used. Survey participants are asked what kind of activities they perform at the workplace. Based on these activities five categories are constructed, which classify the occupational skill requirements: analytic tasks, interactive tasks, repetitive cognitive tasks, repetitive manual tasks and non-repetitive manual tasks. Table 4.2 shows the list of activities that employees were asked for in the questionnaire and how the activities are classified in the five task categories. On the individual-level i, the task measures ($Task_{ik}$) are defined as:

$$Task_{ik} = \frac{\text{number of activities in category } k \text{ performed by } i \text{ in 1998/99}}{\text{total number of activities in category } k \text{ in 1998/99}} * 100 \tag{4.16}$$

where

$$k = \begin{cases} 1 & : \text{ non-routine analytic tasks} \\ 2 & : \text{ non-routine interactive tasks} \\ 3 & : \text{ routine cognitive tasks} \\ 4 & : \text{ routine manual tasks} \\ 5 & : \text{ non-routine manual tasks.} \end{cases}$$

Table 4.1: Summary Statistics

	Mean	Std. Deviation	Min.	Max.	Observations
IT	0.57	0.50	0	1	21816
Pencil	0.92	0.27	0	1	18775
(hourly) wages (in DM)	27.19	11.82	3.13	98.68	18561
Qualification					
high education level	0.17	0.37	0	1	21816
medium education level	0.71	0.46	0	1	21816
low education level	0.12	0.33	0	1	21816
experience	20.76	11.58	0	47	21816
tenure	11.75	9.84	0	47	21816
Workplace Characteristics:					
analytic task measure	14.01	23.80	0	100	18041
interactive task measure	30.26	28.18	0	100	21754
repetitive cognitive task measure	21.73	41.24	0	100	21813
repetitive manual task measure	17.43	30.83	0	100	21768
non-repetitive manual task measure	24.32	24.99	0	50	12319
Company Characteristics					
product innovation	0.37	0.48	0	1	20802
process innovation	0.51	0.50	0	1	20857
very good company performance	0.18	0.39	0	1	14450
good company performance	0.65	0.48	0	1	14450
rather bad company performance	0.14	0.35	0	1	14450
bad company performance	0.03	0.17	0	1	14450
Other Controls					
ever unemployed	0.30	0.46	0	1	22545
married	0.69	0.46	0	1	22677
civil servants	0.11	0.31	0	1	22677
born in East Germany	0.04	0.19	0	1	22677
woman	0.44	0.50	0	1	22677
lives in city	0.38	0.48	0	1	22677

For example, if the analytical task category includes 4 activities and employee i performs 2 of them, the analytical task measure for employee i is 50.

The data set also contains information about the current occupation of the employees. Occupations are grouped according to the (2-digit) classification of occupational titles by the Federal Employment Bureau in 1999, leading to 78 occupational groups.

Company characteristics: Company size has been identified as an important com-

Table 4.2: Assignment of Activities

Classification	Tasks
non-routine analytic	researching, evaluating and planning, making plans, constructing, designing, sketching working out rules/regulations using and interpreting rules
non-routine interactive	negotiating, lobbying, coordinating, organizing teaching or training selling, buying, advising customers, advertising entertaining or presenting employing or managing personnel
routine cognitive	calculating, bookkeeping correcting of texts/data measuring of length/weight/temperature
routine manual	operating or controlling machines setting up machines
non-routine manual	repairing or renovation houses/apartments/machines/vehicles restoring art/monuments serving or accomodating

ponent of wage determination in previous studies, finding that larger companies pay higher wages to employees with similar characteristics (see, for example, Brown and Medoff, 1989, Schmidt and Zimmermann, 1991). In addition, IT usage increases in company size (see Table 4.3). Company size measured as the number of employees is captured by 7 size classes. Companies with one to four employees are classified to belong to the first size bracket and companies with more than 1,000 employees to the last one. Based on these size classes, 7 dummy variables are formed. Most of the survey participants, 28 percent, belong to companies with a size class from 10 up to 49 employees, followed by the size class from 100 up to 499 employees. Companies with more than 1000 employees are represented by 12 percent of the survey participants. About 20 percent of the interviewed employees belong to small companies with less than ten employees.

The data set also includes information about the performance of companies. The survey participants were asked whether the company was doing very good, good,

Table 4.3: IT usage by Company Size Distribution

No. of employees	Freq.	Percent	IT usage (in percent)
1 to 4	1,707	7.8	42.9
5 to 9	2,716	12.3	45.3
10 to 49	6,186	28.1	50.1
50 to 99	2,790	12.7	57.1
100 to 499	4,457	20.2	63.8
500 to 999	1,447	6.6	68.3
1000 and more	2,721	12.4	72.1
Total	22,024		

rather bad or bad. For each of these categories, I constructed a dummy variable. Table 4.1 shows that 18 percent of employees report to work in companies that are doing very well and 65 percent work in companies that are doing well. 17 percent of employees work in companies that are either doing rather bad or bad.

Companies are classified according to 48 detailed industry codes. Based on these codes we group companies into three sectors: manufacturing, trade, and services.[20] The inclusion of these variables accounts for inter-industry wage differentials that are not already captured by the observed individual and company characteristics (see, for example, Krueger and Summers, 1987, Dickens and Katz, 1987, Gibbons and Katz, 1992 and Abowd, Kramarz and Margolis, 1999).

4.4 Empirical Results

Table 4.4 displays the estimation results of the wage regressions. Unreported results show that the raw log wage differential for IT use in Germany is 0.275 (about 31 percent) in 1998/99. This figure is slightly lower than the raw log wage differential of 0.288 that DiNardo and Pischke (1997) report for Germany based on the 1991/92 cross-section of the BIBB/IAB data. Thus, in contrast to the period between 1979 and 1991/92, when the raw log wage differentials for computer use increased steadily (although at a declining pace), as shown in the paper by DiNardo and Pischke, this

[20] I also ran regressions that included more detailed industry dummies. The results reported in Section 4.4 are robust to this change in specification.

differential remained stable or even declined slightly in the 1990s.

Columns (1)-(5) show the results of specifications that are successively extended with additional controls. Including individual characteristics such as the level of formal education, work experience, tenure, gender, marital status or residence in a city reduces the coefficient of IT usage by more than 30 percent (column 1). The coefficients of the controls have the expected sign, therefore I will not discuss them in detail. In column (2), workplace characteristics are included in the specification. The higher the measure for non-routine cognitive activities, both analytical and interactive, the higher the wages. By contrast, wages decrease in the measure for non-routine manual activities. Including the workplace characteristics additionally reduces the IT coefficient by 30 percent (compared to the coefficient in column 1). In column (3), company characteristics such as company size and information about the innovation strategy of the company are included in order to control, for example, for company size effects in remuneration. Industry dummies are also included to account for cross-sectoral differences in pay. In addition, dummies indicating company performance are included. Most interestingly, the inclusion of the company characteristics hardly affect the IT coefficient. By contrast, the returns to education decrease and the dummy for employees born in East Germany as well as the dummy for employees living in the city now are insignificant. Column (4) includes 10 dummies for West German states that control for cross-state differences in wage levels owing to, for example, differing economic conditions. However, these variables neither affect the IT coefficient nor the coefficients of the other controls. The specification in column (5) includes 77 two-digit occupation dummies. The occupation dummies have a large impact on the estimated IT wage differential. From column (1) to column (5), the IT coefficient drops by more than 70 percent, indicating that the largest part of the raw logarithm wage differential for IT users has been due to observable differences that would have resulted in employees earning different wages even in the absence of IT. The results indicate that observable workplace characteristics such as workplace tasks and occupational affiliation account for the largest proportion of the bias in the raw logarithm wage differential. However, conditional on all the controls, the results still suggest that employees who use IT on the job earn around 8 percent higher wages.

Table 4.4: OLS Regressions for the Effect of IT on Wages

Dependent Variable: Log(Hourly Wages)						
	(1)	(2)	(3)	(4)	(5)	(6)
IT	0.182***	0.123***	0.122***	0.122***	0.076***	0.061***
	(0.005)	(0.006)	(0.008)	(0.008)	(0.010)	(0.024)
Individual Characteristics						
high educ. level	0.437***	0.379***	0.330***	0.329***	0.222***	0.089
	(0.011)	(0.014)	(0.018)	(0.018)	(0.020)	(0.068)
medium educ. level	0.126***	0.102***	0.083***	0.082***	0.052***	0.042*
	(0.009)	(0.011)	(0.014)	(0.014)	(0.014)	(0.026)
experience	0.017***	0.018***	0.018***	0.017***	0.017***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
experience^2 *(1/100)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tenure	0.009***	0.008***	0.006***	0.006***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
woman	-0.092***	-0.083***	-0.098***	-0.098***	-0.088***	-0.110***
	(0.009)	(0.010)	(0.013)	(0.014)	(0.014)	(0.036)
married	0.105***	0.097***	0.088***	0.088***	0.083***	0.082***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.020)
woman*married	-0.120***	-0.107***	-0.104***	-0.103***	-0.105***	-0.120***
	(0.011)	(0.012)	(0.012)	(0.016)	(0.015)	(0.034)
ever unemployed	-0.022***	-0.024***	-0.037***	-0.037***	-0.036***	-0.008
	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.018)
born in East Germany	-0.045***	-0.031**	-0.021	-0.019	-0.015	0.004
	(0.013)	(0.015)	(0.018)	(0.018)	(0.014)	(0.038)
civil servant	-0.064***	-0.076***	-0.094**	-0.094**	-0.107***	0.003
	(0.009)	(0.009)	(0.041)	(0.041)	(0.045)	(0.103)
lives in city	0.016***	0.014**	0.008	0.005	0.002	-0.000
	(0.005)	(0.006)	(0.007)	(0.008)	(0.008)	(0.020)

<*Table continues on next page*>

<Continued from previous page>

Dependent Variable: Log(Hourly Wages)						
	(1)	(2)	(3)	(4)	(5)	(6)
Company Characteristics						
product innovation			0.004	0.004	0.008	0.016
			(0.008)	(0.008)	(0.007)	(0.018)
process innovation			0.036***	0.034***	0.025***	0.018
			(0.008)	(0.008)	(0.008)	(0.018)
very good company performance			0.044**	0.038*	0.045**	-0.017
			(0.026)	(0.021)	(0.022)	(0.048)
good company performance			0.007	0.003	0.010	-0.025
			(0.025)	(0.020)	(0.020)	(0.044)
rather bad company performance			-0.012	-0.016	-0.011	-0.027
			(0.021)	(0.021)	(0.021)	(0.046)
Workplace Characteristics: Measure of...						
non-routine analytic tasks		0.087***	0.120***	0.120***	0.077***	0.048
		(0.012)	(0.016)	(0.016)	(0.016)	(0.052)
non-routine interactive tasks		0.154***	0.154***	0.155***	0.150***	0.179
		(0.011)	(0.014)	(0.014)	(0.015)	(0.038)
routine cognitive tasks		0.031***	0.005	0.004	-0.001	-0.002
		(0.012)	(0.014)	(0.014)	(0.014)	(0.028)
routine manual tasks		-0.006	-0.040**	-0.037**	-0.033*	-0.043
		(0.017)	(0.018)	(0.018)	(0.020)	(0.038)
non-routine manual tasks		-0.119***	-0.096***	-0.095***	-0.083***	-0.041
		(0.011)	(0.014)	(0.014)	(0.014)	(0.034)
77 occupation dummies	No	No	No	No	Yes	Yes
7 company size dummies	No	No	Yes	Yes	Yes	Yes
dummies for manufacturing & trade	No	No	Yes	Yes	Yes	Yes
10 dummies for West German states	No	No	No	Yes	Yes	Yes
$IT * [x - E(x)]$	No	No	No	No	No	Yes
R^2	0.348	0.340	0.399	0.401	0.443	0.455
Number of observations	18547	15266	8936	8936	8897	8897

Employees with low levels of education working in large companies in the services sector are the base category. Heteroscedasticity-consistent standard errors are in parentheses in column (1)-(5). Column (6): $IT * [x - E(x)]$ means that the specification includes interaction terms between IT usage and all the level variables X, where all the X had previously been demeaned by the sample averages. Bootstrapped standard errors using 1000 resamples. ***, **, *-indicate significance at the 1, 5, 10 percent level.

Ideal control variables are only those that are attributes of the assignment to IT usage and the earnings process but are unaffected by the treatment itself (for example, time-invariant individual characteristics such as gender and place of birth). However, some of the controls used in this study such as work experience or the incidence of previous periods of unemployment might be affected by the treatment itself. IT users are, for example, less likely to become unemployed. Therefore, the treatment effect estimated here does not capture the indirect effects of IT usage on wages (for example, through productivity).

Up to now, the coefficient of IT usage has been constrained to be homogeneous on average conditional on the observable variables. I now extend the specification by adding a control function that includes interactions between all covariates X (previously demeaned using sample averages) and the IT use dummy D_i. Although the above specifications already include a large number of controls, the remaining 8 percent wage markup for IT users may still be due to characteristics that are not observable in the data set at hand if these unobservables are positively correlated with both IT usage and wages. The aim of control functions is to purge the specification from the remaining covariance between unobservables and IT usage (see Section 4.2.2.1). The results in column (6) show that including the control function in the specification reduces the estimated coefficient of IT usage to 6 percent ($= ATE$).[21]

The interaction terms are jointly significant ($F_{(112,8666)} = 8.34, p{-}value = 0.0000$) and therefore provide evidence of the presence of heterogeneous effects. Table 4.5 shows the results for selected interaction terms. The empirical evidence suggests, for example, that IT user with a university degree benefit particularly in terms of wages. Differences in gender, work experience or workplace tasks, by contrast, do not have a significant effect on the gains from computer use.

The estimated ATT is 0.083 with a standard error of 0.024. The ATT is estimated using Formula (4.14), the standard error is bootsrapped using 1000 resamples (see Footnote 21 for details). The ATT is significantly different to the ATE. Therefore, on average, treatment effect heterogeneity seems to be important. The result that the ATT is higher than the ATE suggests that there has been selection into treatment based on expected returns. If IT non-user had started to use IT instead

[21] The standard errors in column (6) are estimated using a design-matrix bootstrap approach in order to account for the generated regressors in the specification. Because of the large number of dummy variables in the specification the resamples are chosen to be twice as large as the sample in order to guarantee that all coefficients can be estimated. The estimated covariance matrix then is doubled in accordance with the rate of convergence of the estimator.

of those who actually did, they would have enjoyed a substantial lower benefit than the group of actual IT users.

Table 4.5: Selected Interaction Terms

Dependent Variable: Log(Hourly Wages)		
high educ. level * IT	0.160***	(0.077)
medium educ. level * IT	0.023	(0.035)
woman * IT	0.040	(0.040)
non-routine analytic tasks * IT	0.035	(0.062)
non-routine interactive tasks * IT	-0.030	(0.048)
routine cognitive tasks * IT	0.007	(0.044)
routine manual tasks * IT	0.021	(0.064)
non-routine manual tasks * IT	-0.059	(0.046)
experience * IT	0.005	(0.004)
experience^2 * IT	-0.000	(0.000)
civil servant * IT	-0.154	(0.108)
tenure * IT	-0.000	(0.002)
born in East Germany * IT	-0.026	(0.052)
married * IT	0.007	(0.026)
very good company performance * IT	0.091	(0.084)
good company performance * IT	0.053	(0.088)
rather bad company performance * IT	0.021	(0.080)

Results of selected interaction terms from Table 4.4, column (6). Bootstrapped standard errors using 1000 resamples in parentheses. ***, **, *-indicate significance at the 1, 5, 10 percent level.

One of the most powerful criticisms of the "returns on computer use" literature comes from DiNardo and Pischke (1997) who show that there is also a considerable wage effect of the use of pencils (and other "white-collar" tools) in their cross-section estimates. They convincingly argue that if we don't believe that pencils changed the wage structure, why should we believe that computers did. Hence, they attribute the estimated wage differentials for IT usage to unobserved skills.

One part of their analysis deserves special attention. Table 4.6 reports parts of their Table III. Panel A reports the coefficients for computer use when separate regressions are performed for each workplace tool. Panel B shows the results when all tools are included together in the specification. Controlling for the different workplace tools attenuates the coefficient for computer use in each period, but the effect declines over time. Including the tools reduces the estimated coefficient on computer use by around 40 percent in 1979, by around 33 percent in 1985/86 and by 26 percent in 1991/92. In 1991/92, the coefficient of computer use has a magnitude of 13 percent even after controlling for all the tools. I reproduced their estimates for the most recent wave of the data set (last column). Relative to the result in Panel A, the estimated coefficient for computer use decreases by around 30 percent due to the inclusion of the dummies for the different workplace tools (Panel B). The coefficient of computer use still has a magnitude of around 15 percent. In contrast to the previous years, in which the different tools have always had a significant positive impact on wages, only the coefficients for the use of calculators and working while sitting remained significantly positive in 1998/99. The coefficient for using a telephone at work is now even significantly negative.

These results suggest that the changes in computer technology over time has also altered its role in the workplace. Computer technology has decreased the costs of accessing and processing information in the 1980s and early 1990s, whereas in the late 1990s it additionally reduced the costs of communication. The convergence of information technology and communication technology, once two distinct technological areas, has been the central feature of technological change in the 1990s.

I take up the DiNardo and Pischke (1997) idea and estimate regressions that include dummies indicating the use of various workplace tools instead of the computer dummy. The results are shown exemplarily for pencils in Table 4.7. Unreported results show that the first-order relationship between pencil use and wages is 5.7 percent (significant at the 1-percent level). Similar to the specifications in Table 4.4, I successively augment the specifications with additional controls. In contrast to the IT effect, the estimated pencil effect disappears as soon as controls for individual and workplace characteristics are included in the specification (column 2). The variables that have had only attenuating effects on the coefficient of IT usage, now result in the pencil effect to disappear. Column (2) shows the results of the regression specification that includes the minimum number of controls that are necessary to eliminate the wage effect of pencil use. It is interesting to notice that the coefficient in the comparable IT equation (Table 4.4, column 2) still is about 12 percent. This result also suggests that changes in computer technology over time altered its function in the workplace.

Table 4.8 displays the results of the matching estimations. Column (1) shows that,

Table 4.6: OLS Regressions For The Effect Of Different Tools on Pay

Dependent Variable: Log(Hourly Wages)				
	Germany 1979	Germany 1985–86	Germany 1991–92	Germany 1998–99
A. Tools entered separately				
Computer	0.112	0.157	0.171	0.204
	(0.010)	(0.007)	(0.006)	(0.006)
B. Tools entered together				
Computer	0.066	0.105	0.126	0.146
	(0.010)	(0.008)	(0.007)	(0.007)
Calculator	0.017	0.053	0.044	0.051
	(0.008)	(0.007)	(0.007)	(0.006)
Telephone	0.072	0.043	0.045	-0.019
	(0.007)	(0.008)	(0.008)	(0.006)
Pen/Pencil	0.062	0.031	0.035	0.003
	(0.007)	(0.008)	(0.008)	(0.011)
Work while sitting	0.058	0.050	–	0.065
	(0.007)	(0.007)	–	(0.006)

Standard errors are in parentheses. Source of columns 1-3: DiNardo and Pischke (1997, p. 299, Table III, 2nd part). Column 4: own regressions. Similar to the specification in DiNardo and Pischke education, experience, experience squared, dummies for part-time, city, female, married, female*married, and for civil servants are included in the regressions.

using nearest neighbor matching, the average wage effect of IT usage for employees who use IT is 7.8 percent. The coefficient is significant on the 1-percent level. In the matching, 3,461 controls are used to estimate the potential missing outcome of IT users had they not adopted computer technology.[22] Owing to the restriction that only observations within the region of common support are used, there are 400 IT users who are not considered in the analysis. Column (2) shows the results when an Epanechnikov kernel is used in the matching process. This change in the weighting scheme barely alters the result.

[22]Owing to missing values in the matching variables, the sample reduces to 9,240 individuals (5,779 IT user and 3,461 IT non-user) in the matching specification.

Table 4.7: OLS Regressions for the Effect of Pencil Use on Wages

Dependent Variable: Log(Hourly Wages)					
	(1)	(2)	(3)	(4)	(5)
Pencil	0.033***	0.016	0.016	0.016	0.005
	(0.010)	(0.011)	(0.013)	(0.013)	(0.013)
Individual Characteristics					
high educ. level	0.495***	0.398***	0.358***	0.357***	0.231***
	(0.013)	(0.015)	(0.020)	(0.020)	(0.021)
medium educ. level	0.151***	0.112***	0.096***	0.095***	0.057***
	(0.011)	(0.013)	(0.016)	(0.016)	(0.016)
experience	0.018***	0.019***	0.017***	0.017***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
experience^2 *(1/100)	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tenure	0.009***	0.008***	0.005***	0.006***	0.005***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
woman	-0.079***	-0.075***	-0.088***	-0.089***	-0.095***
	(0.010)	(0.011)	(0.014)	(0.014)	(0.015)
married	0.120***	0.103***	0.091***	0.091***	0.086***
	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)
woman*married	-0.119***	-0.101***	-0.095***	-0.093***	-0.098***
	(0.012)	(0.013)	(0.017)	(0.017)	(0.016)
ever unemployed	-0.036***	-0.033***	-0.046***	-0.046***	-0.044***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.008)
born in East Germany	-0.056***	-0.035**	-0.024	-0.023	-0.010
	(0.015)	(0.015)	(0.020)	(0.020)	(0.020)
civil servant	-0.065***	-0.081***	-0.105***	-0.105***	-0.107**
	(0.009)	(0.009)	(0.040)	(0.040)	(0.045)
lives in city	0.023***	0.017***	0.011	0.007	0.002
	(0.006)	(0.006)	(0.008)	(0.009)	(0.008)

<Table continues on next page>

<*Continued from previous page*>

Dependent Variable: Log(Hourly Wages)					
	(1)	(2)	(3)	(4)	(5)
Company Characteristics					
product innovation			0.002	0.002	0.005
			(0.008)	(0.008)	(0.008)
process innovation			0.057***	0.056***	0.036***
			(0.008)	(0.009)	(0.008)
very good company performance			0.053**	0.048**	0.055**
			(0.023)	(0.022)	(0.023)
good company performance			0.008	0.004	0.013
			(0.021)	(0.021)	(0.021)
rather bad company performance			-0.012	-0.016	-0.009
			(0.023)	(0.023)	(0.022)
Workplace Characteristics: Measure of...					
analytic tasks		0.110***	0.139***	0.139***	0.082***
		(0.012)	(0.017)	(0.017)	(0.017)
interactive tasks		0.185***	0.185***	0.186***	0.158***
		(0.011)	(0.014)	(0.014)	(0.015)
routine cognitive tasks		0.047***	0.023	0.022	0.008
		(0.014)	(0.016)	(0.016)	(0.016)
routine manual tasks		-0.032*	-0.067***	-0.064***	-0.038*
		(0.019)	(0.020)	(0.020)	(0.022)
non-routine manual tasks		-0.171***	-0.135***	-0.134***	-0.095***
		(0.012)	(0.015)	(0.015)	(0.015)
77 occupation dummies	No	No	No	No	Yes
7 company size dummies	No	No	Yes	Yes	Yes
dummies for manufacturing & trade	No	No	Yes	Yes	Yes
10 dummies for West German states	No	No	No	Yes	Yes
R^2	0.300	0.323	0.383	0.385	0.437
Number of observations	15951	13986	8037	8037	8001

Employees with low levels of education working in large companies in the services sector are the base category. Heteroscedasticity-consistent standard errors are in parentheses. ***, **, *-indicate significance at the 1, 5, 10 percent level.

Table 4.8: Results of the Propensity Score Matching - ATT

Dependent Variable: Log(Hourly Wages)				
	(1)	(2)	(3)	(4)
IT	0.078***	0.077***	0.062*	0.082***
	(0.023)	(0.023)	(0.038)	(0.022)
Number of Treated	5,379	5,379	5,076	5,076
Number of Controls	3,461	3,461	3,461	3,461

(1) shows the ATT of IT usage using nearest neighbor matching (random draw version, bootstrapped standard errors using 1000 replications). (2) shows the ATT using kernel matching (Epanechnikov kernel, bootstrapped standard errors using 1000 replications). (3) shows the ATT of IT usage using nearest neighbor matching (random draw version, bootstrapped standard errors using 1000 replications) with the additional restriction that treated and controls have the same level of education. (4) shows the ATT using kernel matching (Epanechnikov kernel, bootstrapped standard errors using 200 replications) with the additional restriction that treated and controls have the same level of education. For details on the bootstrap methods see Footnote (21). Only observations that are on the common support are used. The caliper is set to 0.001. The propensity score is estimated using the level of formal education, age, age^2, work experience, work experience^2, interaction between work experience and education, workplace tasks, born in East Germany, ever unemployed, living in a city, woman, married, married woman, 8 company size dummies, 39 industry dummies, 3 dummies reflecting company performance, 79 occupation dummies, 10 dummies for West German states and a constant as regressors.

Table 4.9, last column, shows the means of the main individual characteristics of the IT non-users that are used as controls in the matching approach. It is evident that, although there is a convergence between treated and controls with respect to most of the observable characteristics, the difference in educational level is still significant. Therefore, columns (3) and (4) of Table 4.8 show estimates that, in addition to having close propensity scores, restrict matches to be within groups of employees with equal levels of education. This extension increases the number of IT users that are off the common support to 703. The estimate of the nearest neighbor matching declines to 6.2 percent, whereas the coefficient of the estimate that uses

Table 4.9: MEAN COMPARISON FOR IT USERS AND IT NON-USERS

	IT user	IT non-user prior to matching	selected controls§
high education level	0.25	0.07*	0.17*
medium education level	0.69	0.72*	0.74*
low education level	0.06	0.21*	0.09*
age	39.99	40.29*	40.20
experience	20.04	21.52*	21.22*
tenure	12.37	10.82*	12.33
ever unemployed	0.26	0.34*	0.29
married	0.70	0.65*	0.70
woman	0.44	0.44	0.44
civil servants	0.15	0.05*	0.13
born in East Germany	0.03	0.05*	0.04

* indicates that the means differ with statistical significance of 5 percent in a two-tailed t-test between IT user and either IT non-user prior to matching (column 3) or the selected IT non-user (last column).
§ IT non-users who are selected by the matching procedure.

an Epanechnikov kernel increases to 8.2 percent. Both estimates are significant, although the coefficient of the nearest neighbor matching loses precision.

I also estimate the ATE using the matching technique (see Footnote 15). Table 4.10 shows the results. The structure of the table follows Table 4.8. The ATE of IT usage using nearest neighbor matching is 6.8 percent (column 1). This result hardly changes when an Epanechnikov kernel is used as the weighting scheme (column 2). Column (3) and (4) show the results when the matches are additionally restricted to be within groups of employees with equal levels of education. This additional restriction results in the coefficient to decline in the nearest neighbor matching, whereas it is hardly changed in the Epanechnikov kernel matching.

Comparing the ATT and ATE of the matching estimations reveals that the ATT is larger than the ATE, which was already the finding in the RBM estimates. Thus, the matching results corroborate the notion that there is treatment heterogeneity. In addition, the matching results also suggest that there has been selection into treatment based on expected returns.

As for the ATT and ATE, the estimates using RBM are very close to those

Table 4.10: Results of the Propensity Score Matching - ATE

Dependent Variable: Log(Hourly Wages)				
	(1)	(2)	(3)	(4)
IT	0.068***	0.067***	0.053**	0.065***
	(0.028)	(0.028)	(0.028)	(0.018)
Number of Treated	5,379	5,379	5,076	5,076
Number of Controls	3,461	3,461	3,461	3,461

(1) shows the ATE of IT usage using nearest neighbor matching (random draw version, bootstrapped standard errors using 1000 replications). (2) shows the ATE using kernel matching (Epanechnikov kernel, bootstrapped standard errors using 1000 replications). (3) shows the ATE of IT usage using nearest neighbor matching (random draw version, bootstrapped standard errors using 1000 replications) with the additional restriction that treated and controls have the same level of education. (4) shows the ATE using kernel matching (Epanechnikov kernel, bootstrapped standard errors using 200 replications) with the additional restriction that treated and controls have the same level of education. For details on the bootstrap methods see Footnote (21). Only observations that are on the common support are used. The caliper is set to 0.001. The propensity score is estimated using the level of formal education, age, age^2, work experience, work experience^2, interaction between work experience and education, workplace tasks, born in East Germany, ever unemployed, living in a city, woman, married, married woman, 8 company size dummies, 39 industry dummies, 3 dummies reflecting company performance, 79 occupation dummies, 10 dummies for West German states and a constant as regressors.

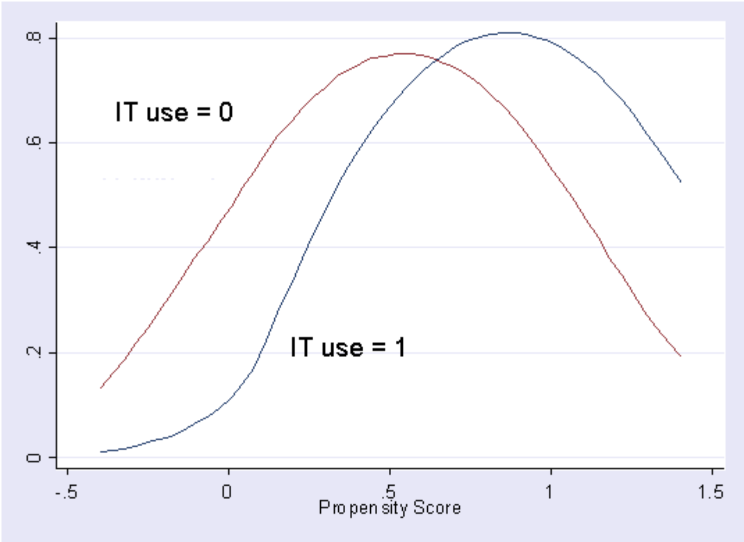
estimated by the propensity score matching procedure. This finding may occur because (i) there is no common support problem, (ii) there is little heterogeneity in treatment effects or all the propensity scores are small, and (iii) there is no serious mis-specification in the no-treatment outcome (see Blundell, Dearden and Sianesi, 2003).

Figure 4.1 shows the kernel density estimates of the distribution of propensity scores for IT users and IT non-users. The two distributions greatly overlap. However, the results of the matching procedure reveal that 400 (703) of the 5,779 IT users are outside the region of common support. In this application imputing the values that are outside the common support by relying on a functional form assumption (RBM) or discarding the IT users without similar counterfactuals from the analysis (matching) does not lead to different results.

The difference in the ATE and ATT in both approaches suggest that heterogenous treatment effects are important. This notion is also supported be the joint significance of the interaction terms in the RBM specification, although selected interaction terms only point to weak effects.

The propensity scores in the analysis assume values between 0 and 1. The mean is 0.64 and the median is 0.73. This information does not suggest that propensity scores are particularly clustered at certain points in the distribution.

Figure 4.1: Kernel Density Estimations of Propensity Scores for IT Users and IT Non-Users



4.5 Conclusions

This paper deals with the question of whether IT users earn higher wages than employees who do not use IT on the job. In addition to the average treatment effect of IT usage, which was the focus of previous studies, I estimate the average treatment effect for the treated. The ATT is more interesting than the ATE for the question of IT wage differentials because the implementation of IT cannot be analyzed without considering the occupational context. Employers choose employees to use IT on the basis of expected profitability increases owing to the implementation of IT, which depends on occupational characteristics, individual characteristics and company characteristics. The prevailing circumstances greatly influence the impact of IT on productivity and thus individual wages.

The analysis rests upon the advantage of the data set that includes a large number of controls that have been identified as important determinants of the IT use-wage relationship in previous studies. This feature of the data set allows me to use methods that assume that, conditional on the controls, the differences in wages of IT users and IT non-users are attributable to the use of IT.

I find a robust average treatment effect for the treated of around 8 percent. This indicates that IT users would be worse off had they not started to use IT in the workplace. I also find evidence for the presence of heterogeneous treatment effects. A comparison of the ATE and ATT reveals that IT non-user would have witnessed lower benefits in terms of wages had they started to use IT instead of those who actually have. However, the difference in ATT and ATE is only about 2 percentage points.

A 8 percent wage markup appears to be small, in particular in comparison with the 10-15 percent that have typically been found in cross-section analyses in the 1990s. The size of the effect is rather similar to results previously found in panel analyses. The data set does not include unemployed. I therefore argue that the 8 percent wage markup for IT users represents a lower bound. Analyses of Entorf et al. (1999), for example, suggest that people who do not use computers have a higher probability of becoming unemployed. Therefore, the IT non-users observed in my data set are probably already a positive selection.

4.6 Appendix

Intermediate steps between equation 4.12 and 4.13:

$$\begin{aligned}
E(Y_i|D_i,X) &= \mu_0 + \alpha D_i + g_0(X) + D_i[g_1(X) - g_0(X)] \\
g_0(X) &= \eta_0 + X\beta_0 \quad Eg_0(X) = 0 \\
g_1(X) &= \eta_1 + X\beta_1 \quad Eg_1(X) = 0 \\
E(Y_i|D_i,X) &= \mu_0 + \alpha D_i + \eta_0 + X\beta_0 + D_i[\eta_1 + X\beta_1 - \eta_0 - X\beta_0] \\
&= \mu_0 + \eta_0 + \alpha D_i + X\beta_0 + D_i[\eta_1 - \eta_0 + X(\beta_1 - \beta_0)] \\
&= \underbrace{\mu_0 + \eta_0}_{\gamma_0} + \alpha D_i + X\beta_0 + D_i[\frac{\eta_1 - \eta_0}{\beta_1 - \beta_0} + X]\underbrace{(\beta_1 - \beta_0)}_{\delta}
\end{aligned}$$

To be shown: $\dfrac{\eta_1 - \eta_0}{\beta_1 - \beta_0} = -E(X)$

$$\begin{aligned}
\frac{\eta_1 - \eta_0}{\beta_1 - \beta_0} &= \frac{1}{\beta_1 - \beta_0}(g_1(X) - X\beta_1 - g_0(X) + X\beta_0) \\
\eta_1 - \eta_0 &= g_1(X) - g_0(X) + X(\beta_0 - \beta_1) \\
X &= \frac{1}{\beta_1 - \beta_0}(g_1(X) - g_0(X) - \eta_1 + \eta_0) \\
E(X) &= \frac{1}{\beta_1 - \beta_0}(\underbrace{Eg_1(X)}_{=0} - \underbrace{Eg_0(X)}_{=0} - \eta_1 + \eta_0) \\
&= -\frac{\eta_1 - \eta_0}{\beta_1 - \beta_0}
\end{aligned}$$

Chapter 5

IT, Organizational Change and Wages[§]

5.1 Introduction

The effects of information technology (IT) on skills and wages are an extensively discussed topic in the labor market literature, with the skill-bias technological change (SBTC) hypothesis being one of the most prominent themes.[1] However, recent studies on the company-level emphasize that, in order to result in efficiency gains, the use of IT should be accompanied by appropriate organizational changes, so-called high-performance-workplace-organizations (HPWO), with favorably decentralizing character such as teamwork, flat hierarchies, job rotation or quality circles.[2] The use of IT and organizational changes (OC) are increasingly viewed as strategic complements. In addition, the hypothesis that organizational change itself is skill-biased emerged.[3]

[§]This chapter is a strongly revised version of Bertschek and Spitz (2003b).

[1]See, for example, the comprehensive reviews by Katz and Autor (1999), Acemoglu (2002), Card and DiNardo (2002), or by Chennells and van Reenen (2002).

[2]Microeconometric evidence for this hypothesis is given, for example, by Bresnahan, Brynjolfsson and Hitt (2002) and by Brynjolfsson and Hitt (2000). Evidence on the quantitative importance of organizational changes can be found in Osterman (1994, 2000).

[3]See Caroli and van Reenen (2001). Aguirregabiria and Alonso-Borego (2001) present evidence suggesting that the reorganization of workplaces may even have a larger impact on the occupational structure of companies than technical capital. Goldin and Katz (1998) discuss the skill upgrading in a historical context. They show that the substitution of unskilled labor by skilled labor and capital began early in the twentieth century. They view this skill upgrading as a result of organizational changes, driven by technological changes. A growing literature emphasizes the

The empirical evidence so far relied heavily on company-level data sets, with most studies focusing on the impact of IT and OC on company productivity, whereas studies that investigate the impact on wages are rare. To the best of our knowledge, Cappelli and Carter (2000) is the only study that analyzes the joint effects of IT and OC on wages. They use data on about 3,300 U.S. establishments of the manufacturing industry and the service sector. They find that employees benefit from IT use and OC in terms of higher wages, however, their results suggest that the effect of OC is limited to the manufacturing sector.

Our study contributes to the discussion about the *joint* effects of IT and OC on wages. In contrast to the analysis by Cappelli and Carter (2000), we are in the favorable position to have individual-level data to investigate this question. Assuming that IT and OC - as complementary measures - have positive impacts on a company's productivity, we analyze whether employees share in the gains that companies obtain from using IT and from changing their organizational structure. The analyses are based on a large, representative cross-section of West German employees, which were surveyed in 1998 and 1999.

The use of individual-level data has several advantages compared to company-level data sets: We do not have to fall back upon aggregate information on employees. In particular, we know whether or not an employee uses IT on the job. A special feature of the data is that it includes detailed information about the company the interviewed employees work at. In particular, the employees were asked whether or not they work in companies that reorganized their organizational structure within the last two years. Three forms of organizational changes are considered: restructuring of departments, changes in the management structure and outsourcing of parts of the production process. In addition, there is a question that informs us about whether the employee has been personally affected by the organizational change in the company. This dual information, presence of organizational changes in companies and personal affectedness of employees, allows us to infer the potential reasons for wage differentials.

Our results suggest that even when controlling for a wide range of individual characteristics, workplace characteristics and company characteristics, IT users still earn around 6 percent higher wages than their peers. In addition, we find that

impact of organizational changes upon rising wage inequality, see, for example, Kremer and Maskin (1996), Acemoglu (1999), and Lindbeck and Snower (1996). Aghion, Caroli and Garcia-Penalosa (1999) suggest that the impact of organizational changes on wage inequality depends crucially on a companies' choices with respect to its management of human resources.

employees working in companies that have changed their organizational structure earn higher wages independent of the fact whether their workplace situation had been directly affected by the organizational change. This result points to wage differentials across companies rather than within companies.

The paper is organized as follows: Section 5.2 reviews previous empirical and theoretical results. Section 5.3 describes the data and the empirical framework. Estimation results are presented and discussed in section 5.4. Section 5.5 concludes.

5.2 Theoretical Background and Previous Empirical Results

The recent literature about organizational change is closely related to the historical debate about the division of labor and the gains from specialization.[4] Gains from specialization, that is, from the repetition of the same tasks, are due to an increased dexterity of an individual in specific tasks (in the sense of learning-by-doing), time-savings otherwise lost for switching from one activity to another, and increased potential for mechanization. There are, however, also limiting factors such as transaction costs (Yang and Borland, 1991), the extent and characteristics of the market (Piore and Sabel, 1984, Aoki, 1986, and Thesmar and Thoenig, 2000), coordinaton costs or the amount of knowledge possessed by specialists (Becker and Murphy, 1992). Whereas the division of labor, for example, increased enormously during industrialization, which was characterized by mass production, standardized products and a rather stable product mix, there is now vast empirical evidence that job roles have expanded both horizontally, through increased integration of tasks, and vertically, through the introduction of flat hierarchies and autonomous work teams.

In recent decades, empirical studies extolling the productivity effects of workplace innovations emerged, for example, by Black and Lynch (2000, 2001), Caroli and van Reenen (2001), Eriksson (2003) and Huselid (1995). Ichniowski, Shaw and Prennushi (1997) analyze complementarities between human resource management practices. Huselid and Becker (1996) and Wolf and Zwick (2002) concentrate on methodological issues. All of these studies deal with so-called high-performance workplace organizations (HPWO) or innovative human resource management (HRM) practices, meaning work practices with decentralizing character that allocate more decision-

[4] Adam Smith (1776) already described how the division of labor increases economic growth.

making rights as well as responsibility to employees.

Several studies relate these changes in the organization of work to the introduction of IT at the workplace. IT influences both the gains from specialization and the traditional limiting factors. Milgrom and Roberts (1990), for example, emphasize the role of IT embedded in machine tools making them a "programmable, multitask production equipment", which can be cheaply switched from one task to the other and, hence, allow the company to efficiently produce a variety of outputs in very small batches. Lindbeck and Snower (2000) emphasize overall changes in the nature of work, for which advances in IT is one important driving force. In addition to the characteristics of IT to allow machines to become flexible and versatile, they accentuate the greater access to information and the reduced communication time owing to the introduction of IT at the workplace, which facilitates decentralization of decision-making and enables employees to become more involved in each others tasks ("multitasking"). However, Lindbeck and Snower also stress the importance of the growth of human capital per worker, generated by education systems, which has ensured that workers have become more versatile as well, and that workers have become to prefer jobs that allow them to exercise a variety of skills.

There are, in general, two arguments for the joint technological and organizational changes. On the one hand, IT itself calls for a reorganization of work through its differing impact on different tasks employees have to perform on the job (see, for example, Autor, Levy and Murnane, 2003, and Spitz, 2004). On the other hand, IT enables organizational changes. For example, the flattening of a company's hierarchical layers (accompanied with a wider control span at each layer) is encouraged by the improved monitoring technology owing to the increased access to information and lower costs of communication. The implication of both arguments is that companies have to adapt their organizational structures when implementing IT in order to use these technologies efficiently.

Empirical company-level evidence for the hypothesis of IT as an enabling technology is given by Bresnahan et al. (2002) and Brynjolfsson and Hitt (2000) on the basis of different U.S. company data sets. Bertschek and Kaiser (2004) take into account the simultaneity between productivity and OC and provide evidence for companies belonging to the German business-related services sector.

The effect of OC on employees is much less studied. Cappelli and Neumark (2001) find that HPWO are associated with higher labor costs suggesting that the higher productivity of companies that introduced HPWO is to some extent offset by the higher costs. In an extreme scenario, this offsetting relationship may even result in a decline in profitability owing to OC. Appelbaum, Bailey, Berg and Kalleberg (2000) consider five worker outcome dimensions in their study: the extent to which workers trust their managers, the degree to which workers perceive their jobs to be intrinsically rewarding, a worker's commitment to the organization, job satisfaction and work-related stress. They find, for example, that the opportunity to participate substantially in the company's decision-making process is positively related to trust and intrinsic rewards. Their analyses focus on nonmonetary benefits that employees derive from performing their tasks. However, there are few studies investigating the effect of OC on worker's wages.[5]

From the point of view of the company, there are some arguments why employers should share parts of the gains with their employees. Foremost, employees may get more productive owing to the OC. But there are also a variety of additional arguments, not related to productivity considerations, as pointed out by Black and Lynch (2000): Firstly, companies may have to pay a wage premium in order to attenuate resistance to workplace changes of employees and to ensure that employees actively collaborate with respect to the implementation of OC. Secondly, employers may also have to pay a wage premium in order to indemnify employees for the increased job insecurity that may be associated with the workplace reorganizations. And thirdly, employees may acquire additional skills owing to the workplace restructuring that are valuable to outside companies, such as problem solving or interpersonal skills. Hence, employers may have an incentive to pay a wage markup in order to ensure that employees stay with their company. Appelbaum et al. (2000) provide additional theoretical arguments, why one would expect companies that change their organization to pay higher wages. The greater discretionary effort that is required from workers in more participatory work settings speaks in favor of a positive link between OC and wages. Higher wages give employees an incentive to exert such discretionary effort.

Reviewing the above arguments reveals that they generally fall either within the framework of efficiency wage models or in the context of compensating wage differential models. Efficiency wage models, on the one hand, provide rationales why employers pay wages (to all their employees) that are above market-clearing level.[6]

[5]There is now a growing literature that investigates the impact of organizational changes on wage inequality (see Aghion, Caroli and Garcia-Penalosa, 1999, for a review). The major argument is that organizational changes increase the productivity gap between individuals with different skill levels.

[6]See Yellen (1984) for a review of efficiency wage models. Akerlof and Yellen (1990) provide a

Efficiency wages are part of an employer's compensation policy. They are particularly important in work environments that involve unforeseeable contingencies and discretionary power by employees, which make the writing of explicit contracts very costly, if not impossible. Efficiency wages are one measure that provides incentives for employees to maximize their productivity and to remain attached to a company for long periods of time.[7] Employees are willing to exert effort (and stop shirking) because their wages are in excess of what they could earn elsewhere. In addition, a company's high pay strategy attracts a large pool of applicants, allowing the company to hire only the best applicants and, hence, to build up and maintain a high quality work force.

Compensating wage differentials, on the other hand, are wage markups that companies have to pay in order to compensate workers for undesirable working conditions. Typical examples for such undesirable working conditions are dirt, heat, danger or noise. However, in the context of this study, one might also think about increased job insecurity and aversion of workers to changes in job content as "unpleasant" features. The compensating wage differentials aim at giving the worker an incentive to adapt to the new working environment. Companies thus compensate employees who accept the new paradigm by paying them more than comparable employees in jobs that do not have these particular characteristics.

As the organizational changes of recent years focus on increased employee involvement and greater discretion for employees with respect to the organization of work, both efficiency wage and compensating wage arguments may be particularly important.

The first type of questions with respect to organizational changes in the survey on which this analysis is based asks for whether or not the survey participants work in companies that implemented organizational changes. Thus, wage differences found for this group of employees apply independent of whether or not the survey participant has been personally affected by organizational changes. This question allows it to investigate whether companies that implemented organizational changes pay systematically different wages to all members of their work force, that is, it hints to wage differentials across companies.

The second type of question asks for whether survey participants have been per-

collection of the classical studies in this body of literature.

[7]Another instrument of an employer's compensation policy is incentive pay, which relates employee's wages directly to some measure of output. However, monitoring and the measurement of output on which remuneration might be based is often costly.

sonally affected by OC, subject to the fact that their companies implemented organizational changes. This question allows us to analyze whether companies pay systematically different wages only to that part of their workforce that witnessed a particular change in their job content in recent years owing to OC. Thus, the question hints at wage differentials within companies.

The few empirical studies that investigate the relationship between HPWO and wages find contradictory results. Bauer and Bender (2001) find that HPWO are associated with higher wages and higher wage dispersion in Germany. The results of Black and Lynch (2000) and Appelbaum et al. (2000) suggest that companies that introduced HPWO have higher company performance and are paying higher wages. Cappelli and Neumark (2001) find that HPWO are associated with higher labor cost, which are very likely to result from increased employee compensation. Osterman (2000), in contrast, does not find that employees are profiting from the introduction of HPWO in terms of greater wage increases or increased job security.

None of these studies investigates the effects on wages when IT and OC are introduced jointly. As already mentioned in the Introduction, Cappelli and Carter (2000) is the only analysis studying the question of joint effects at the company-level. By contrast, our study analyzes this question at the individual-level.

5.3 Data and Empirical Framework

The analysis is based on the “Qualification and Career Survey”, which is a survey of employees 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). It is a rich source of information on the qualification and occupational career trends of German employees. We use the most recent cross-section, which was launched in 1998-1999, because it is the only one that contains information on both the diffusion of IT at the workplace and organizational changes in companies.

The complete sample contains more than 34,000 observations. For the purpose of the analysis at hand, we restrict the sample to male employees with residence in West Germany and German nationality. Self-employed were also withdrawn from the sample. These restrictions reduce the sample to around 12,300 individuals. The persons in the sample are between 18 and 65 years old. The companies employing these employees cover a wide range of industries both manufacturing and services, however, companies in the agricultural sector are excluded.

Our basic framework closely follows Krueger (1993) who estimates extended income functions originating from Mincer (1974) by ordinary least squares (OLS). In addition to the main variables of interest, IT and OC, three types of variables are considered in the analyses: individual characteristics, company characteristics and workplace characteristics. We include variables reflecting individual characteristics in order to account for the fact that employees systematically differ with respect to characteristics that may affect both computer usage and wages. As more highly skilled workers are more likely to use computers at work and earn higher wages, we control for the level of formal education of employees, work experience and tenure with the current employer. As wages of civil servants are determined in another process than wages of employees in private companies, we also include a dummy variable for civil servants into the regressions.

One drawback of most estimations on individual-level data is that they generally do not have much information on employers. Employer information may, however, be important for the analysis if they determine systematic effects on wages, IT usage and OC. Our data set allows us to take various company characteristics into account such as company size, industry affiliation, innovation strategy, IT intensity of the sector and company performance. Based on previous empirical research, we expect, for example, that larger companies pay higher wages and that they are more likely to introduce OC than smaller companies. Furthermore, we expect "IT-intensive" companies to pay higher wages and that they are more likely to introduce OC than companies with less IT-intensive production processes (Osterman, 1994).

Another feature that distinguishes our data set from others is that it includes information on the task composition of occupations.[8] These tasks describe the occupational context in which IT is introduced and organizational changes are made. In addition, this information on occupational skill requirements allows us to further reduce unobserved heterogeneity.

The variables used in the estimations are constructed as follows (Summary statistics are in Table 5.1):

Hourly Wages: The survey contains information on monthly earnings, according to 18 categories. To each category midpoints are assigned. These midpoints are then divided by the number of hours an individual usually spends at work.[9] Compared

[8] For a detailed analysis of how the task composition of occupations changed in West Germany since 1979 see Spitz (2004).

[9] Comparable procedures are often used in literature, for example, by DiNardo and Pischke (1997) and by Entorf and Kramarz (1997).

Table 5.1: Summary Statistic

	Mean	Std. Deviation	Min.	Max.	Observations
Information Technology					
IT	0.57	0.50	0	1	12334
Organizational Change					
restructuring of departments	0.42	0.49	0	1	11751
change in management structure	0.32	0.47	0	1	11785
outsourcing	0.19	0.40	0	1	11575
being directly affected by...					
...restructuring of departm.	0.19	0.39	0	1	11751
...change in management struct.	0.21	0.41	0	1	11785
...outsourcing	0.06	0.24	0	1	11575
Qualification					
high education level	0.19	0.39	0	1	12340
medium education level	0.70	0.46	0	1	12340
low education level	0.10	0.30	0	1	12340
experience	21.42	11.65	0	47	12340
tenure	12.98	1 0.49	0	47	12340
(hourly) wages (in DM)	29.72	12.24	3.19	98.68	10506
Workplace Characteristics:					
analytic task measure	15.95	25.07	0	100	12319
interactive task measure	0.74	29.52	0	100	12319
repetitive cognitive task measure	0.28	45.95	0	100	12319
repetitive manual task measure	24.03	34.51	0	100	12319
non-repetitive manual task measure	24.32	24.99	0	50	12319
Company Characteristics					
IT intensive industry	0.56	0.50	0	1	12340
product innovation	0.42	0.49	0	1	11803
very good company performance	0.19	0.39	0	1	8331
good company performance	0.63	0.48	0	1	8331
rather bad company performance	0.15	0.35	0	1	8331
bad company performance	0.03	0.17	0	1	8331

to other data sets that are usually used in comparable analyses such as CPS for the U.S. or the IAB-S for Germany, this data set has the advantage that earnings of highly paid workers are not censored from above. The summary statistics show that employees earned on average around 30 German Marks in 1998/99. Minimum wages were only slightly larger than 3 German Marks, whereas maximum wages approached nearly 100 German Marks. In all estimations, the logarithm of wages is used as dependent variable.

IT equipment: The survey participants indicate whether or not they use one or more of the following devices: personal computers, laptops, other kinds of computers, scanners or computerized control devices such as computer numerical control machines. Based on these questions an IT-dummy is formed that indicates whether an employee uses one or more of the above devices on the job. Table 5.1 shows that around 60 percent of employees used one of the IT devices at the workplace in 1998/99.

Organizational Changes (OC): The data set contains information about three measures of organizational changes. Employees are asked whether the company for which they work had introduced one or more of the following three different kinds of measures of organizational change in the previous two years: reorganization of departments (RD), changes in the management structure (MS), and outsourcing (OUT) of a part or parts of the production process. These different measures are used in the analysis as dummy variables that indicate whether or not the respective measure had been implemented. In addition, we construct a dummy variable "organizational change" that takes the value one if companies had introduced at least one of the above measures. The use of this variable in the estimation attempts to take account of potential collinearity between the OC variables.[10]

According to the summary statistics in Table 5.1, 42 percent of the employees belong to companies that restructured departments. Management structures had been changed in the case of 32 percent of survey participants and 19 percent indicate to belong to companies in which parts of the production process had been outsourced. Table 5.2 indicates that the frequencies of all three types of OC increase with company size.

One drawback of this data set is that the variables capturing OC are less detailed and less precise than measures used in previous research, for example, Ichniowski et al. (1997) or Osterman (1994). Therefore, in the following paragraphs we will relate our measures to those previously used. As Ichniowski, Kochan, Levine, Olson and Strauss (1996) emphasize, the term "innovative work practice" has no settled meaning. As a result, there is a large variety of measures used in literature. They all have in common that they characterize a shift away from traditional forms of work organization, which was associated with "...tightly defined jobs with associated rates

[10]The correlation between the restructuring of departments and outsourcing (changes in the management structure) is 0.359 (0.464). The correlation between changes in the management structure and outsourcing is 0.309.

Table 5.2: Company Size Distribution

			Perc. share of companies with		
Number of employees	Freq.	Percent	RD	MS	OUT
1 to 4	581	4.79	14.95	10.42	8.16
5 to 9	1088	8.97	15.24	12.64	5.94
10 to 49	3266	26.93	25.29	20.86	10.24
50 to 99	1609	13.27	36.29	28.68	13.38
100 to 499	2697	22.24	54.44	39.88	24.83
500 to 999	963	7.72	62.74	48.04	29.15
1000 and more	1950	16.08	71.13	56.05	39.94
Total	12127	100.00			

of pay, clear lines of demarcation separating the duties and rights of workers and supervisors, decision-making powers retained by management...", toward workplaces with "...greater degree of flexibility in work organization, cooperation between labor and management, and worker participation in decisions and financial well-being of the company (Ichniowski et al., 1996, p.300)". This widely observed shift is the basis for our interpretation of the variables measuring OC in the data set.

Restructuring of departments (RD):[11] The most common organizational change that affected the structure of departments during the 1990s was the introduction of self-managed teams and employee problem-solving groups, instruments that largely decentralized decision-making and increased employee involvement. While it is true that the survey question is an imprecise measure of the implementation of teamwork, we argue that, since the restructuring of department has taken place between 1997 and 1999, it is justified to consider this measure as an organizational change with decentralizing character. This notion is supported by the respondent's answers to questions of how their work had changed between 1997 and 1999. For example, 30 percent of employees that work in companies that reorganized their departments between 1997 and 1999 report that they have greater discretionary power with respect to the planning and performing of their own work in 1999 than in 1997, whereas only 16 percent of employees that work in companies that did not reorganize their departments report so (see Table 5.3).[12] For 39 (62) percent of employees, who

[11]The exact wording of the question is: "In the last two years, has there been a restructuring or reorganization of departments in your company?"

[12]The exact wording of the question is: "In the last two years, did your discretionary power of planning and executing your work increase, stayed the same or decreased?"

report that their companies reorganized their departments, the variety of tasks (the amount of specialist knowledge) they have to perform increased between 1997 and 1999, whereas this is the case for only 22 (39) percent of employees who work in companies that did not reorganize their departments. Interestingly, for the question of whether control by supervisors increased, employees who work in companies that reorganized their department have higher fraction in the "increased" and "decreased" category than those in companies that did not change the structure of their departments. This pattern may reflect the better monitoring technologies that are now available owing to IT, which are, most probably, implemented and used to a greater extent by companies that changed their organization. Overall, the answers to these four questions are, however, in line with the characteristics that are usually attributed to a more decentralized organization of work.

Changes in the management structure (MS):[13] Given the time period (1997-1999), we assume that this measure reflects the flattening of a company's hierarchy. This may have an inverse effect on managers who loose power and potentially their job owing to the abolishment of hierarchy levels. However, a flattening of a company's hierarchical layer is usually accompanied with an increased control span at each layer. In addition, this measure enhances the decision-making authority of the individual employee and enriches the range of tasks as employees often rotate across jobs. This theoretical thinking is supported by the survey results. Table 5.4 shows how work has changed between 1997 and 1999 depending on whether or not companies had changed their management structure. The results are similar to those in Table 5.3. The fraction of employees who report that they had more discretionary power over their work (had more versatile and interesting work) in 1999 than in 1997 is larger in companies that changed their management structure. The amount of specialist knowledge required to perform the work increased also for a larger fraction of workers. Similar to the above result, a larger proportion of employees that work in companies that changed the management structure report an increase of control by supervisors and a decrease of control by supervisors. Our conclusion from the answers to these four questions is again that they are in line with the characteristics of flatter hierarchies. The results by Appelbaum et al. (2000) suggest that this feature of flatter organizational structures has a positive impact on an employee's motivation and is beneficial to an employee's identification with his company.

[13]The exact wording is: "In the last two years, has there been a change in the structure of management in your company?"

Table 5.3: Changes in Work between 1997 and 1999 for Employees in Companies that Reorganized their Departments

	RD=0	RD=1
A. Did your discretionary power over your work...		
increased	16.51	30.57
stayed the same	70.49	58.25
decreased	6.20	8.18
B. Has the versatility and interest of your work...		
increased	22.33	38.97
stayed the same	71.50	54.37
decreased	4.40	5.80
C. Has the extent of supervision...		
increased	9.52	16.80
stayed the same	72.78	62.73
decreased	10.60	14.38
D. Has the amount of specialist knowledge required to perform your job...		
increased	39.37	62.09
stayed the same	57.26	35.48
decreased	2.04	1.88

The figures refer to the percentage of employees who report that the respective scenario applied to their work. The figures in each category do not sum up to 100 percent because the questionnaire also included the possibility for respondents to indicate that the type of question does not apply to their work.

Outsourcing (OUT):[14] During the 1990s, companies have increasingly externalized certain tasks that were previously performed by their employees. They then buy these products and services from companies that are specialized in those tasks. Outsourcing allows the companies to concentrate on their core competencies, to replace fixed costs by variable costs, and to increase flexibility.

Being directly affected by organizational changes: The data set includes information on whether the survey participant has been directly affected by an organizational change. Thus, analogously, we construct dummy variables for whether or not employees have been directly affected by these measures. Six percent of survey

[14] The exact wording is: "In the last two years, has your company increasingly outsourced parts of the production process or bought more intermediate products from other companies?"

Table 5.4: Changes in Work between 1997 and 1999 for Employees in Companies that Changed their Management Structure

A. Did your discretionary power over your work...		
	MS=0	MS=1
increased	18.26	30.67
stayed the same	69.41	57.05
decreased	6.16	8.83
B. Has the versatility and interest of your work...		
	MS=0	MS=1
increased	24.90	38.30
stayed the same	69.05	54.65
decreased	4.41	6.18
C. Has the extent of supervision...		
	MS=0	MS=1
increased	9.50	18.89
stayed the same	72.23	61.05
decreased	10.72	15.19
D. Has the amount of specialist knowledge required to perform your job...		
	MS=0	MS=1
increased	42.50	61.98
stayed the same	54.14	35.83
decreased	2.05	1.80

The figures refer to the percentage of employees who report that the respective scenario applied to their work. The figures in each category do not sum up to 100 percent because the questionnaire also included the possibility for respondents to indicate that the type of question does not apply to their work.

participants indicate that they have been directly affected by outsourcing activities of their company (see Table 5.1). 19 percent report that their workplace has been directly affected by a restructuring of departments. Changes in the management structure directly affected 21 percent of employees. Focusing attention to only those employees who report that they work in companies that changed their organization also reveals interesting patterns: 44 percent of employees who report that their companies restructured departments have been directly affected by this measure, and 64 percent of employees who work in companies that changed the structure of management have been directly affected, whereas the majority (94 percent) of employees who report that their companies outsourced part of the production process has not been directly affected.

Table 5.5: Summary Statistics for IT users and IT non-users

	Sample Means by IT-use			
	IT user		IT non-user	
	Mean	Std. Deviation	Mean	Std. Deviation
restructuring of departments	0.54	0.50	0.26	0.44
change in management structure	0.41	0.49	0.21	0.41
outsourcing	0.23	0.42	0.15	0.36
being directly affected by...				
...restructuring of departm.	0.25	0.44	0.09	0.29
...change in management struct.	0.25	0.43	0.15	0.36
...outsourcing	0.07	0.26	0.04	0.19
high education level	0.30	0.46	0.05	0.22
medium education level	0.65	0.48	0.77	0.42
low education level	0.05	0.22	0.17	0.38
experience	20.85	11.38	22.18	11.95
tenure	13.82	10.59	11.87	10.26
wage	33.41	12.85	25.01	9.54

IT and OC are often viewed as strategic complements. As Table 5.5 shows, IT users are more likely to work in companies that reorganized their production processes. The higher incidence holds for all three practices. However, the difference is most pronounced for the restructuring of departments. 54 percent of the IT users reported to work in companies that restructured their department compared to 26 percent for IT non-users. In addition, IT users are also more likely to be directly affected by organizational changes. For example, 25 percent of IT users report to be directly affected by a restructuring of departments compared to 9 percent of IT non-users.

Table 5.5 also demonstrates major differences with respect to the educational attainment of IT users and IT non-users and their wage outcome indicating that IT users have a higher educational attainment and earn higher wages.

Workplace Characteristics: The analyses by Autor et al. (2003) and Spitz (2004) document how IT has changed the content of work towards analytical and interactive activities and away from manual and cognitive routine activities. The data set at hand is a cross-section, thus changes in the task composition of occupations cannot be taken into account. However, the data set allows us to consider task levels, capturing the content of jobs, and therefore, it gives a description of the context in which IT is used and organizational changes have been made. Survey participants are asked what kind of activities they perform at the workplace. Based on these activities five categories are constructed, which classify the occupational skill requirements: analytic tasks, interactive tasks, repetitive cognitive tasks, repetitive manual tasks and non-repetitive manual tasks. Table 5.6 shows the list of activities that employees were asked for in the questionnaire and how the activities are classified in the five task categories. On the individual-level i, the task measures ($Task_{ij}$) are defined as:

$$Task_{ij} = \frac{\text{number of activities in category } j \text{ performed by } i}{\text{total number of activities in category } j} * 100 \tag{5.1}$$

where

$$j = \begin{cases} 1 & : \text{ analytic tasks} \\ 2 & : \text{ interactive tasks} \\ 3 & : \text{ routine cognitive tasks} \\ 4 & : \text{ routine manual tasks} \\ 5 & : \text{ non-routine manual tasks.} \end{cases}$$

For example, if the analytical task category includes 4 activities and employee i indicates that she performs 2 of them, her analytical task measure is 50. Spitz (2004) includes further details on the concept of skill requirements of occupations. On average, employees perform, for example, 16 percent of analytical activities, whereas they perform 30 percent of repetitive cognitive activities (Table 5.1).

The data set also contains information about the current occupation of employees. Occupations are grouped according to the (2-digit-level) classification of occupational titles by the Federal Employment Bureau, 1999, leading to 78 occupational groups.

Individual characteristics: We distinguish three levels of formal educational attainment of employees. Employees with a low level of education are those with no further vocational training. Employees with medium levels of education have a vocational qualification either from an apprenticeship or they are graduated from a vocational college. Employees holding a degree from a university or a technical college are classified as having a high level of educational attainment. This categorization corresponds closely to the institutional setting of the German education

Table 5.6: Assignment of Activities

Classification	Tasks
analytic	researching, evaluating and planning,
	making plans, constructing, designing, sketching
	working out rules/regulations
	using and interpreting rules
interactive	negotiating, lobbying, coordinating, organizing
	teaching or training
	selling, buying, advising customers, advertising
	entertaining or presenting
	employing or managing personnel
routine cognitive	calculating, bookkeeping
	correcting of texts/data
	measuring of length/weight/temperature
routine manual	operating or controlling machines
	setting up machines
non-routine manual	repairing or renovation houses/apartments/machines/vehicles
	restoring art/monuments
	serving or accomodating

system and is often used in literature, see, for example, Bellmann, Reinberg and Tessaring (1994) or Fitzenberger (1999). In contrast, U.S. studies usually use the number of schooling years as a measure of education (see Card, 1999, for further discussions). As shown in Table 5.1, the largest part of the survey participants, 70 percent, has a medium qualification level, whereas 19 percent are highly qualified and only 10 percent have a low education level.

Survey participants also indicate their first year of work. Based on these answers, we calculate (potential) work experience (1999-first year of work). In addition, employees indicate the year in which they started to work with the current employer. This information is used to calculate company tenure (1999-first year with current employer).

Company characteristics: Company size has been identified as an important component of wage determination in previous studies, finding that larger companies pay higher wages to employees with similar characteristics (see, for example, Brown and

Medoff, 1989, Schmidt and Zimmermann, 1991). A recent contribution disentangling the sources for these firm-size wage differentials using employer-employee data is Abowd, Kramarz and Margolis (1999). In our analysis, company size measured as the number of employees is captured by 7 size classes. Companies with one to four employees are classified to belong to the first size bracket and companies with more than 1,000 employees to the last one. Based on these size classes, 7 dummy variables are formed. Most of the survey participants, 27 percent, belong to companies with a size class from 10 up to 49 employees, followed by the size class from 100 up to 499 employees (see Table 5.2). Companies with more than 1000 employees are represented by 16 percent of the survey participants. Less than 14 percent of the interviewed employees belong to small companies with less than ten employees.

The data set also includes information about the performance of companies. The survey participants were asked whether the company was doing very good, good, rather bad or bad. For each of these categories, we constructed a dummy variable. The results of Wolf and Zwick (2002), for example, suggest that company performance and the implementation of organizational changes are correlated. In addition, we expect a company's pay to its IT users to be related to its performance. Table 5.1 shows that 19 percent of employees report to work in companies that are doing very well and 63 percent work in companies that are doing well. 18 percent of employees work in companies that are either doing rather bad or bad.

Companies are classified according to 48 detailed industry codes. Based on these codes we group companies into three sectors: manufacturing, trade, and services.[15] The inclusion of these variables accounts for inter-industry wage differentials that are not already captured by the observed individual and company characteristics (see, for example, Krueger and Summers, 1987, Dickens and Katz, 1987, Gibbons and Katz, 1992 and Abowd, Kramarz and Margolis, 1999).

In order to identify companies operating in "IT-intensive" industries, we construct a dummy variable that takes the value one if the IT intensity of the industry is higher than the average IT intensity of the sector to which it belongs. In addition, the survey participants were asked whether or not their company introduced new products or services to the market within the last two years. Based on these answers a dummy variable for "product innovation" was constructed. We expect companies in technology intensive industries as well as innovative companies to pay higher wages and to have a higher likelihood to implement organizational changes.

[15]We also ran regressions that included more detailed industry dummies. The results that we report in Section 5.4 are robust to this change in specification.

5.4 Empirical Results

Table 5.7 displays the estimation results of the basic wage regressions. Each row represents a separate OLS regression. The result in the first row (Panel A) shows that the raw log wage differential for IT use in West Germany is 0.282 (about 32 percent) in 1998/99.[16] The regressions in Panel B show that employees who work in companies that restructured their departments, changed their management structure or outsourced parts of their production earn significantly higher wages. The coefficient in the bivariate regression that includes the dummy for "organizational change", which takes the value one if companies had introduced at least one of the measure of organizational changes, is also positive and highly significant. In addition, employees that have been directly affected (Panel C) by a restructuring of departments, changes in the management structure or a company's outsourcing activities earn significantly higher wages. The information in Panel A about an individual's usage of IT is the type of information that is usually available in individual-level data sets that in general do not provide information about company characteristics such as organizational changes. The information about organizational changes (Panel B) are usually available in company-level data sets that then include only aggregate information about wages and IT usage such as average wages of employees or the proportion of employees using IT. The advantage of this data set is that it includes information on both IT on the individual-level and organizational changes on the company-level. In addition, it includes individual information about whether employees had been personally affected by these organizational changes. This advantage will be taken into account in the analyses that follow.

These bivariate regressions suffer from some of the most prominent drawbacks of previous research. Estimates based on individual-level data, that is, the majority of studies analyzing the relationship between IT usage and wages, cannot adequately tell whether employers differ systematically in a way that affects wages (such as differences in work organization). Estimates based on company-level data, that is, the majority of studies on high-performance workplace practices, are not able to take into account individual differences that affect wages (such as IT usage on the job). For example, the positive relationships between IT usage and wages shown in Panel

[16] This figure is slightly smaller than the raw log wage differential of 0.288 that DiNardo and Pischke (1997) report for Germany based on the 1991-1992 cross-section of the BIBB/IAB data. Thus, in contrast to the period between 1979 and 1991-1992, where the raw log wage differentials for computer use increased steadily (although at a declining pace), as shown in the paper by DiNardo and Pischke, it remained stable or even slightly declined in the 90s.

Table 5.7: Bivariate OLS Regressions for the Effect of IT and Organizational Changes on Wages

Dependent Variable: Log(Hourly Wages)		
	Coeff. (Std. Error)	R^2 No. of Observations
A.		
IT	0.282***	0.120
	(0.007)	10501
B.		
restructuring of departments	0.182***	0.052
	(0.008)	10034
chg. in management structure	0.168***	0.040
	(0.008)	10067
outsourcing	0.144***	0.021
	(0.009)	9879
organizational change	0.204***	0.066
	(0.008)	10506
C.		
being directly affected by...		
...restructuring of departments	0.138***	0.019
	(0.010)	10034
...chg. in management structure	0.120***	0.015
	(0.009)	10067
...outsourcing	0.140***	0.007
	(0.015)	9879

Heteroscedasticity-consistent standard errors are in parentheses.
***, **, *-indicate significance at the 1, 5, 10 percent level.

A might reflect that IT users are more likely to work in companies that restructured their organization, which often pay higher wages, whereas the positive relationship between organizational changes and wages (Panel B) might reflect that companies that restructured their organization have a larger fraction of IT users, who generally earn higher wages. That is, owing to the covariation in the introduction of IT and the implementation of organizational changes, one might end up by incorrectly attributing the positive wage effect of one factor to the other.

The first extension, thus, is to estimate regressions that include both information about IT usage and about organizational changes simultaneously in the specification. The results are shown in Table 5.8, each column represents a separate OLS regression. Columns (1)-(3) show that the coefficient of IT use and the dummies for the different organizational changes decline compared to the bivariate results in Table 5.7. For example, conditional on the "restructuring of department" variable, the coefficient of IT use drops by 12 percent. However, IT users still earn around 28 percent higher wages than IT non-users. Conditioning on "changes in the management structure" reduces the IT-coefficient by 20 percent, whereas conditioning on "outsourcing" reduces the IT-coefficient only by 5 percent. The coefficients of the variables for the different measures of organizational changes decline even to a larger extent owing to the inclusion of the IT use variable. The coefficient of the "restructuring of departments" variable declines by 38 percent (column 1), the result in column 2 shows that the wage markup for employees that work in companies who changed their management decreased by 35 percent and the coefficient of the "outsourcing" variable drops by 22 percent.

The result is similar when the dummy for "organizational changes" is included in the regression instead of the separate measures (column 4) and also, when all variables reflecting organizational changes are included jointly in the specification (column 5). Column 5 shows that including the different measures for organizational changes jointly reduces the respective coefficients by around 60 percent, however, each of them still remains positive and highly significant. In addition, the coefficient for IT usage changes hardly.

Although these specifications only focus on the main variables of interest of this study, they already indicate that it is important to consider both individual and company information. The reduction in coefficients owing to the joint inclusion of variables of IT usage and organizational changes indicate that studies that are not able to account for the covariation in IT usage and the implementation of organizational changes overestimate the respective coefficients.

Unreported results in which the information about whether employees had been directly affected by the organizational changes are included in the specification instead of the "broad" information of organizational changes as in Table 5.8 show similar patterns, although the coefficients are generally smaller. The coefficient of IT use has always a magnitude of around 16 percent, whereas the coefficients for the different measures of "direct" organizational changes decline to around 7-10 percent. All coefficients remain highly significant.

As outlined in Section 5.2, IT and organizational changes are often viewed as strategic complements. Therefore, IT users might be particularly involved in the introduction of organizational changes by supporting the successful implementation

Table 5.8: OLS Regressions for the Effect of IT and Organizational Change on Wages

Dependent Variable: Log(Hourly Wages)					
	(1)	(2)	(3)	(4)	(5)
IT	0.248***	0.226***	0.269***	0.244***	0.241***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Organizational Changes					
restructuring of dept.	0.112***				0.072***
	(0.007)				(0.009)
chg. in management structure		0.110***			0.063***
		(0.008)			(0.009)
outsourcing			0.113***		0.061***
			(0.009)		(0.010)
organizational change				0.136***	
				(0.008)	
R^2	0.141	0.137	0.132	0.151	0.149
Number of observations	10030	10063	9876	10501	9633

Heteroscedasticity-consistent standard errors are in parentheses.
***, **, *-indicate significance at the 1, 5, 10 percent level.

from a technical point of view. Moreover, the productivity effects of OC might be more pronounced for IT users than for IT non-users. Therefore, IT users in companies that changed organization may be particularly rewarded.

The regressions in Table 5.9 include interactions between the IT use variable and the dummies for organizational changes in order to account for potential complementarities. The interaction term of the "restructuring of departments" variable and IT is positive but insignificant, whereas the interaction terms for the two other measures of organizational changes are negative. IT users working in companies that changed their management structure earn significantly (10 percent level) lower wages than their peers. In terms of wages, the results do not suggest that there is a complementary relationship between IT use and organizational changes.

However, IT and organizational changes may still be strategic complements in production as suggested by company-level studies (for example, Bresnahan et al., 2002). The weak evidence for interaction effects in the wage regressions may be informative about the type of computing that is important for companies that change their organizational structure. Bresnahan (1999) distinguishes between three main categories: *organizational computing* such as corporate accounting systems, supply chain management systems, customer relationship management systems or transaction processing systems, *scientific or technical computing* in factories and laboratories, and *individual productivity computing* such as word-processing or computer-aided design. The measure of IT equipment in this study reflects individual productivity computing and, partly, scientific or technical computing, but does not capture organizational computing. However, in the process of restructuring of departments, changes in the management structure or outsourcing, organizational computing is likely to be more important than individual computing or technical computing.

Table 5.9: Complementarities between IT and Organizational Change

Dependent Variable: Log(Hourly Wages)			
	(1)	(2)	(3)
IT	0.247***	0.264***	0.273***
	(0.010)	(0.009)	(0.008)
Organizational Changes			
restructuring of dept.	0.111***		
	(0.012)		
restructuring of dept. * IT	0.001		
	(0.016)		
chg. in management structure		0.129***	
		(0.013)	
chg. in management structure * IT		-0.028*	
		(0.016)	
outsourcing			0.129***
			(0.014)
outsourcing * IT			-0.025
			(0.018)
R^2	0.141	0.137	0.132
Number of observations	10030	10063	9876

Heteroscedasticity-consistent standard errors are in parentheses.
***, **, *-indicate significance at the 1, 5, 10 percent level.

Up to now, the analysis focused on the “broad” variables of organizational change and neglected the information about whether employees have been personally affected. The specification in Table 5.10 includes both types of variables for organizational changes. As before, each column represents a separate OLS regression. Column (1) shows that the positive relationship between a restructuring of departments and wages does not depend on whether or not employees have been directly affected by this measure. The two other measures of OC convey a different picture. Column (2) shows that employees who have been directly affected by a change in management structure earn significantly lower wages than employees who have not been directly effected. This suggests that employees rather lose than gain competencies owing to the reduction in hierarchical layers. The joint effect, that is, the sum of coefficients of the variable for the change in management structure and the variable for "being personally affect", is positive, however. The result in column (3) shows that employees who have been directly affected by outsourcing activities of companies earn significantly higher wages than their peers, suggesting that compensating wage differentials might play a role in the corresponding companies. However, the wage markup for being personally affected is rather small in size compared to the effect that accrues to all employees in companies that engaged in outsourcing. As will be seen in analyses that follow, the coefficients of the measures of OC for employees that had been directly affected become insignificant as soon as the specification accounts for additional observable differences. The coefficients of the measures for the direct affectedness by OC become insignificant owing to the controls, whereas the broad measures of OC remain (mostly) significant. It is interesting to note that in Table 5.10 the IT wage differential is hardly affected by the inclusion of the variables that measure the personal affectedness by OC.

The previous specifications are scarce in the sense that they focus solely on the relationships between the main variables of interest. They omit, however, a large number of factors that may be correlated with both IT usage and organizational changes. Results from previous empirical studies suggest, for example, that employees with high levels of education earn higher wages and are more likely to use IT at the workplace and that companies that implement organizational changes have a higher fraction of highly educated employees. Previous research also finds that larger companies and more innovative companies use more IT, are more likely to change their organizational structure and pay higher wages. In addition, previous analyses point to the fact that IT is complementary to analytical and interactive tasks, for which employees with high levels of education (who earn higher wages) have a comparative advantage, whereas IT substitutes for cognitive and manual routine activities, which are usually performed by employees with lower levels of education. In sum, previous analyses emphasize that there is a large number of observable and (for the researcher) unobservable factors that may influence IT use, organizational changes and wages.

Table 5.10: Wage Differentials across and within Firms

Dependent Variable: Log(Hourly Wages)			
	(1)	(2)	(3)
IT	0.248***	0.255***	0.269***
	(0.008)	(0.008)	(0.007)
Organizational Changes			
restructuring of dept.	0.114***		
	(0.009)		
chg. in management structure		0.131***	
		(0.011)	
outsourcing			0.112***
			(0.010)
Being Directly Affected By...			
restructuring of dept.	-0.005		
	(0.011)		
chg. in management structure		-0.031***	
		(0.012)	
outsourcing			0.002***
			(0.017)
R^2	0.141	0.138	0.132
Number of observations	10030	10063	9876

Heteroscedasticity-consistent standard errors are in parentheses.
***, **, *-indicate significance at the 1, 5, 10 percent level.

Having only a cross-section at hand, we are not able to control for (time-constant) unobserved heterogeneity by taking individual-specific fixed effects into account. However, this caveat is to some extent outweighed by the fact that the data set includes many variables that are potentially correlated with IT use, organizational changes and hourly wages. These variables fall within three broad categories: individual characteristics, company characteristics and workplace characteristics (for a detailed description see Section 5.3). In order to assess the importance of different factors, we are going to augment the specification step-by-step. First by individual characteristics, then by workplace characteristics, and last by company characteristics. Individual characteristics are: level of formal education, work experience, tenure with the current employer and a dummy for civil servants. Company characteristics are: company size, sector affiliation, innovative strategy, IT intensive industries and company performance. Workplace characteristics are: five task categories (analytic, interactive, routine cognitive, routine manual and non-routine manual) and occupational affiliation.

Table 5.11 shows the results of the specification that includes individual characteristics. The IT wage differential and the wage markup for organizational changes drops by around 30 percent (compared to Table 5.9) owing to the covariates. In addition, the coefficients of the variables that capture whether employees have been directly affected are now insignificant in all three specifications. The coefficients of the covariates are highly significant and convey the typical picture: wages increase in educational attainment, wages increase (with a decreasing pace) in years of work experience and tenure with the current employer tends also to increase wages.

The insignificant coefficients of variables capturing the affectedness reflect one important difference between traditional work systems, often termed Fordist or Tayloristic, and modern work systems. Modern measures of work organization are not directed to individual employees, their goal is to increase organizational efficiency. Maximizing organizational productivity dominates the maximization of individual productivity, which was the goal of work organization in the past. Therefore, it seems reasonable for employers to pay higher wages to all their employees instead of only rewarding a particular group of employees.

In the following regressions, we do not report the results for the variables that capture whether employees have been directly affected anymore. The coefficients are always insignificant and the inclusion of these variables in the specification does not alter the results for the other variables.

Table 5.11: OLS Regressions for the Effect of IT and Organizational Change on Wages: Individual Characteristics Only

Dependent Variable: Log(Hourly Wages)			
	(1)	(2)	(3)
IT	0.172***	0.174***	0.182***
	(0.007)	(0.007)	(0.007)
Organizational Changes			
restructuring of dept.	0.077***		
	(0.007)		
chg. in management structure		0.079***	
		(0.007)	
outsourcing			0.085***
			(0.008)
Being Directly Affected By...			
restructuring of dept.	-0.010		
	(0.011)		
chg. in management structure		-0.015	
		(0.011)	
outsourcing			-0.002
			(0.015)
Individual Characteristics			
high educ. level	0.435***	0.440***	0.441***
	(0.015)	(0.015)	(0.016)
medium educ. level	0.129***	0.131***	0.135***
	(0.013)	(0.012)	(0.013)
experience	0.020***	0.020***	0.020***
	(0.001)	(0.001)	(0.001)
experience^2 *(1/100)	-0.034***	-0.035***	-0.035***
	(0.002)	(0.002)	(0.002)
tenure	0.008***	0.008***	0.009***
	(0.000)	(0.000)	(0.000)
R^2	0.32	0.32	0.32
Number of observations	10030	10063	9876

Control variable is a dummy variable for civil servants. Employees with low levels of education are the base category. Heteroscedasticity-consistent standard errors are in parentheses. ***, **, *-indicate significance at the 1, 5, 10 percent level.

Table 5.12 shows the results when workplace characteristics and 77 occupation dummies are additionally included in the specification. Again, the coefficients for the IT use variables as well as the different measures of organizational changes drop considerably. Comparing the results from Tables 5.9, 5.11 and 5.12 shows that the inclusion of the workplace characteristics has a larger quantitative impact on the size of the IT use variable than the inclusion of the individual characteristics, suggesting that it is important to analyze the implementation of IT with the occupational context in mind. The results of the five task categories show that wages are positively related to the extent of non-routine cognitive activities both analytical and interactive, whereas they are negatively related to non-routine manual activities.[17] The coefficients of the individual characteristics decline owing to the inclusion of the workplace characteristics in the specification, but the functional form of the relationship remains unchanged.

The results of the richest specification additionally including company characteristics are shown in Table 5.13, which reports only the coefficients of the most interesting variables. The control variables are listed at the bottom of Table 5.13.[18]

As expected, both the IT use wage differential and the wage markup for organizational changes drop again owing to the inclusion of the company characteristics. The IT use wage differential is reduced to 6 percent, which is only 20 percent of the bivariate result of 0.282. It is robust across the different specifications in columns (1)-(5). Also, the coefficients of the different measures of organizational changes decline. The results now suggest that employees that work in companies that restructured their departments do not earn significantly higher wages (column 1). However, the coefficients for employees working in companies that changed their management structure (column 2) or outsourced part of their production (column 3) are still significant and positive, although they are quantitatively small.

The results show that companies operating in IT intensive industries pay significantly higher wages. However, we do not find significant effects for product innovators. The dummy variables for company performance indicate that wages are increasing in performance. Unreported results that did not include the information about company performance show that the IT coefficient as well as the coefficients

[17] We additional investigated potential complementary or substitutive relationships between workplace tasks and IT usage by including interaction terms in the specification (see Spitz, 2004). In terms of wages, the results do not hint to complementary or substitutive effects.

[18] The control variables convey the usual picture. For example, that manufacturing is the highest paying sector and that wages increase in company size.

for the different measures of OC are higher when company performance is included in the specification (everything else equal to specification in Table 5.13). This result suggests that companies with performance problems are more likely to introduce organizational changes and that they pay their IT users lower wages.[19]

Owing to the company controls, the negative relationship between routine manual tasks and wages now turns out to be significant. The negative relationship between non-routine manual tasks remains significantly negative, but the size of the effect declines. The results for the individual characteristics remain relatively unchanged by the company controls.

Overall, one might conclude that we find positive wage effects of both IT use and organizational changes, in particular changes in management structure and outsourcing activities. The size of the IT wage differential is in the order of magnitude of coefficients typically reported in studies using panel methods.[20] The richness of the data set thus seems to be equally successful in reducing unobserved heterogeneity as methods that remove time-constant unobserved heterogeneity. However, in line with findings of Entorf and Kramarz (1998), we do not interpret this result as causal in the sense that the introduction of IT at the workplace immediately increases individual productivity and thus wages. We rather argue that employees get more productive through the experience they gain with using IT. Our results do not hint to a complementary relationship between IT and OC in terms of wages.

The interpretation of our results might be encumbered with an important caveat: although the coefficients for the different OCs are small or even insignificant, they might be upward biased because those employees that have been mostly affected by the OCs have been dismissed. The survey on which our analyses are based, however, only includes employees, but not unemployed persons. Thus, we are not able to take account of persons who are affected by organizational changes in the sense that they lose their jobs. Using matched employer-employee data Jacobson, LaLonde and Sullivan (1993), for example, find that high-tenure workers that are displaced and then rehired end up with considerable wage losses. Rationalizing production processes in order to save costs might be involved with the dismissal of employees – an effect that cannot be captured by our data base.

This argument applies in particular to the case of outsourcing when companies

[19]Wolf and Zwick (2002) also find that companies with productivity problems tend to introduce organizational changes.

[20]Bell (1996), for example, report a coefficient of 0.047 in fixed-effects regressions using data for U.K.

not only source out certain tasks but whole workplaces. The fact that 94 percent of employees in our sample who report that their company outsourced part of the production has not been directly affected supports this conjecture.

According to a survey by the ZEW (Centre for European Economic Research) among more than 4,000 companies in the year 2000, the most important reasons for outsourcing of IT-related tasks have been the higher competency and quality of specialized companies, the possibility to save costs and the lack of time to do certain IT-tasks internally. In these company-level data, no significant correlation between outsourcing and the expected development of employment can be found.

Several studies name the concentration on core competencies, cost reductions and lack of qualified personnel as the most important reasons for outsourcing decisions, see, for example, Henkel and Kaiser (2002, p.13) for the case of IT-outsourcing. The results by Falk and Koebel (2002) suggest that rather output growth than input substitution drives the increasing use of imported materials and purchased services. There seems to be no significant relationship between outsourcing and labor demand. The study by Heshmati (2003) gives a comprehensive overview on the effects of general outsourcing. The decision to source out might differ across company size. For instance, large companies might source out whole departments, which will lead to dismissals if the corresponding tasks are not done within the company anymore. On the other hand, the employees working in the outsourced department might continue their work within a new enterprise as it is, for example, the case for the Deutsche Bank that outsourced its IT-department to IBM, thus, about 900 former Deutsche Bank employees are now working for IBM (Lamberti, 2003). Small companies, in contrast, will probably outsource single tasks rather than whole departments. In our data set, the percentage share of employees working in companies with organizational changes increases with company size for all three types of OC considered as shown in Table 5.2.

This caveat of neglecting dismissals seems to be less severe for "changes in the management structure" and "restructuring of departments". For example, 64 (44) percent of employees who report that their companies changed the structure of the management (restructured departments) have been directly affected. These types of organizational changes supposed to increase the degree of employee involvement in decision-making or increase the degree of flexibility in work organization, thereby increasing employees' motivation. Appelbaum et al. (2000), for example, report on a survey that investigates workers' attitudes and experience with modern forms of work organization. They report that participation in decisions has a strong and positive effect on employees' perception of the intrinsic rewards of jobs, that is they find the jobs more meaningful and challenging. In addition, Appelbaum et al. (2000) find that more participatory work systems enhances employees' trust in managers. It is very unlikely that employees would have these perceptions if the organizational changes had involved large scale dismissals.

The data set in this study includes information about employees' work satisfaction. Survey participants indicate their satisfaction with the career opportunity in the company, the working atmosphere, the task they have to perform and the pressure exerted on them. Descriptive statistics (not reported) show that, on average, employees who work in companies that changed their organization are more satisfied with their work, although the differences in means are often not significant.

Table 5.12: OLS Regressions for the Effect of IT and Organizational Change on Wages: Individual and Workplace Characteristics

Dependent Variable: Log(Hourly Wages)					
	(1)	(2)	(3)	(4)	(5)
IT	0.066***	0.062***	0.067***	0.062***	0.060***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Organizational Changes					
restructuring of dept.	0.052***				0.028***
	(0.007)				(0.008)
chg. in management structure		0.060***			0.043***
		(0.007)			(0.008)
outsourcing			0.053***		0.031***
			(0.008)		(0.008)
organizational change				0.065***	
				(0.008)	
Workplace Characteristics					
analytical tasks	0.040***	0.037***	0.041***	0.037***	0.041***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
interactive tasks	0.134***	0.138***	0.144***	0.134***	0.131***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)
routine cognitive tasks	0.021	0.022	0.017	0.019	0.017
	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)
routine manual tasks	-0.019	-0.018	-0.013	-0.018	-0.017
	(0.021)	(0.021)	(0.022)	(0.021)	(0.022)
non-routine manual tasks	-0.106***	-0.106***	-0.103***	-0.104***	-0.104***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)
Individual Characteristics					
high educ. level	0.231***	0.237***	0.2369***	0.238***	0.228***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
medium educ. level	0.069***	0.073***	0.074***	0.075***	0.068***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
experience	0.022***	0.022***	0.022***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
experience^2 *(1/100)	-0.037***	-0.037***	-0.038***	-0.038***	-0.037***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
tenure	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.38	0.38	0.38	0.39	0.38
Number of observations	8602	8609	8476	8910	8296

Control variables are: Dummy variable for civil servants and 77 occupation dummies. Employees with low levels of education are the base category. Heteroscedasticity-consistent standard errors are in parentheses. ***, **, *-indicate significance at the 1, 5, 10 percent level.

Table 5.13: OLS Regressions for the Effect of IT and Organizational Change on Wages: Individual, Workplace and Company Characteristics

Dependent Variable: Log(Hourly Wages)					
	(1)	(2)	(3)	(4)	(5)
IT	0.060***	0.056***	0.056***	0.056***	0.053***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Organizational Changes					
restructuring of dept.	0.006				-0.009
	(0.010)				(0.011)
chg. in management structure		0.035***			0.036***
		(0.010)			(0.010)
outsourcing			0.030***		0.026**
			(0.010)		(0.011)
organizational change				0.027***	
				(0.010)	
Workplace Characteristics					
analytical tasks	0.064***	0.061***	0.061***	0.061**	0.064***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
interactive tasks	0.155***	0.152***	0.158***	0.154***	0.154***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
routine cognitive tasks	0.014	0.018	0.013	0.016	0.012
	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)
routine manual tasks	-0.045**	-0.051**	-0.044*	-0.048**	-0.046**
	(0.023)	(0.023)	(0.023)	(0.022)	(0.023)
non-routine manual tasks	-0.091***	-0.091***	-0.089***	-0.092***	-0.090***
	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)
Individual Characteristics					
high educ. level	0.188***	0.184***	0.181***	0.189***	0.176***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
medium educ. level	0.041**	0.037***	0.039**	0.041**	0.035**
	(0.017)	(0.017)	(0.018)	(0.017)	(0.018)
experience	0.020***	0.020***	0.020***	0.020***	0.020***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
experience^2 *(1/100)	-0.034***	-0.034***	-0.034***	-0.034***	-0.034***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
tenure	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

<*Table continues on next page*>

<*Continued from previous page*>

Dependent Variable: Log(Hourly Wages)					
	(1)	(2)	(3)	(4)	(5)
Company Characteristics					
IT intensive industry	0.028***	0.027***	0.030***	0.027***	0.030***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
product innovation	0.017*	0.013	0.015*	0.012	0.014
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
very good company performance	0.072***	0.082***	0.077***	0.076**	0.086***
	(0.026)	(0.027)	(0.027)	(0.026)	(0.028)
good company performance	0.046*	0.054**	0.049**	0.050**	0.056**
	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)
rather bad company performance	0.036	0.044*	0.038	0.036	0.046*
	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
R^2	0.42	0.42	0.41	0.42	0.42
Number of observations	5495	5482	5395	5600	5305

Control variables are: Dummy variable for civil servants, sector dummies, dummies for 6 company size categories, 77 occupation dummies. Employees with low levels of education working in large companies in the services sector are the base category. Heteroscedasticity-consistent standard errors are in parentheses. ***, **, *-indicate significance at the 1, 5, 10 percent level.

5.5 Conclusions

In this study we analyze whether the use of IT at the workplace and organizational changes are positively related to individual wages taking possible complementarities between IT and OC into account. In addition, the data set allows us to investigate whether wage markups for employees that work in companies that have changed their organization accrue only to those that have been directly affected or to all employees. We use a large individual-level data set that includes information about individual characteristics, workplace characteristics and company characteristics referring to West Germany in 1998-1999.

Our findings suggest that IT users earn about 6 percent higher wages than observably similar IT non-users. We interpret this positive wage effect of IT use not as causal in the sense that only the implementation and use of IT at the workplace increases individual productivity and thus wages. In line with previous research, we rather believe that employees get more productive through their experience they gain with using IT.

Employees working in companies that have changed their management structure or have outsourced part of their production process earn significantly higher wages. Interestingly, this positive wage markup is not related to the fact of whether or not employees had been personally affected by these organizational changes. By contrast, companies that have implemented organizational changes seem to pay higher wages to all of their employees — a result that speaks in favor of wage differentials across rather than within companies. In addition, in terms of wages, we do not find evidence for a complementary relationship between IT and organizational changes.

One might argue that the quantitative importance of the wage effects, about 6 percent for IT usage and 3 percent for organizational changes, are small. In particular, as most studies on IT wage differentials conclude that there are no wage effects of IT usage if they find comparable figures. However, in the light of the fact that unions and employer associations in Germany typically bargain for wage increases of about 4 percent, the sizes of the estimated coefficients should not be disparaged in its importance for employees.

Chapter 6

Managerial Ownership and Company Performance in German Small and Medium-Sized Private Enterprises[§]

6.1 Introduction

The separation of ownership of a firm from its control has been of interest since the seminal contribution by Berle and Means (1932). This separation is supposed to create agency costs because owners (principals) and managers (agents) have different objectives. The emphasis of much of the literature is large, publicly held US corporations.

We address the problem of separation of ownership and control empirically for a sample of small and medium-sized private companies with limited liability (GmbHs) in the German business-related service sector.[1] Although listed firms play a large role in the United States and in the UK, their importance for other countries is much smaller. Private companies with limited liability are important in many economies. In Germany, for example, GmbHs accounted for more than 33 percent of total

[§]The major part of this chapter corresponds to the paper "Managerial Ownership and Company Performance in German Small and Medium-Sized Private Enterprises", jointly written with Elisabeth Müller and forthcoming in the German Economic Review.

[1]The counterparts of German GmbHs are limited companies (Ltd) in the UK and closely-held corporations in the USA.

turnover in 2000 and their overall importance has increased steadily in the last thirty years.[2]

Economic theory identifies two opposing effects of managerial ownership – the incentive and the entrenchment effect. On the one hand, managerial ownership aligns the objectives of owners and managers. From this incentive effect we expect a positive relationship between managerial ownership and company performance. On the other hand, managers with large ownership shares have the ability to "entrench" themselves. Their large ownership share makes them immune to control by outside owners. If the entrenchment effect is larger than the incentive effect, performance decreases in managerial ownership.

GmbHs have one or more owners who enjoy limited liability. In contrast to public companies, their shares cannot be listed on a stock market. GmbHs are run by managers who can hold a stake in the firm as well. Compared to large publicly held companies, the ownership share of managers is usually relatively large. Managers with a very large ownership share have good incentives to maximize company value because they bear a large proportion of the costs of their actions themselves.[3] In general, a high managerial ownership share makes it difficult for other shareholders to control the management and gives the owner-managers the power to potentially disregard the interests of small shareholders. However, non-managing owners of private companies usually also have a high ownership share which makes it likely that they are well informed. Therefore, the possibility for managers to "entrench" themselves is restricted, even if they hold substantial ownership shares. This differentiates private from public companies. In public companies, ownership is often so dispersed that, for example, an ownership share of 5 percent can be enough for managerial entrenchment. At such low levels of ownership shares, managers have not full incentives to maximize company value.

For our analysis we combine information from a business survey with company data from Creditreform, Germany's largest credit rating agency. This gives us an

[2]See Table A1 in the appendix to this chapter for more details. For a detailed discussion of the institutional aspects of a company's legal status and the relative importance of legal forms in Germany see, for example, Harhoff and Stahl (1995) and Harhoff, Stahl and Woywode (1998).

[3]Our considerations always refer to relative ownership share because this is the information included in our data set. The absolute amount, however, may also be important with respect to the incentive effects. A 10 percent share of a Euro 50,000 company, for example, may have different incentive effects than 10 percent in a Euro 5 million company. This difference also depends on the private wealth of the owner-manager. Incentives increase if a higher share of personal net worth is invested in the company (see Mueller, 2004).

unbalanced panel of about 350 companies from 1997-2000. The survey covers the business-related service sector and is conducted by the Centre for European Economic Research (ZEW) in Mannheim, Germany. The companies are asked on a quarterly basis whether their profits have increased, stayed the same or decreased in the last three months. On the basis of these quarterly answers, we construct an annual performance measure. The credit rating agency provides us with information about managerial ownership share defined as the sum of the ownership share of all managers.

Our empirical specification explains company performance by managerial ownership share up to the third power. Additional variables are the number of managers who hold ownership shares, the number of outside owners, the number of a company's bank relationships, the size and age of the company. We find a positive relationship between managerial ownership share and company performance up to a maximum of around 40 percent of ownership.

In the context of our analysis we need to be concerned with problems of endogeneity. It is possible that managerial ownership itself is influenced by company performance. Since we use panel data, we are able to control for unobserved firm heterogeneity, for example, managerial ability. This controls for endogeneity due to time-invariant effects. Additionally, endogeneity due to time-variant effects is dealt with by lagged regressors and by using instruments.

The main contribution of this paper to the literature is the study of the relationship of managerial ownership and performance for private companies. Up to now this relationship has mainly been studied for listed companies.[4] In general it is difficult to observe the performance of private companies because data from balance sheets and profit and loss accounts is rarely available. Our findings suggest that there are important differences between public and private companies. For public companies it is mostly found that very high values of managerial ownership have a negative influence on performance due to managerial entrenchment. In contrast, we do not find an entrenchment effect for private companies.

Jensen and Meckling (1976) distinguish between insiders, who manage the firm, and outsiders, who supply funds to the firm. Inside managers adopt investment

[4] See, for example, Jensen and Murphy (1990) and Kaplan (1994) for the US, Köke (2000) and Januszewski, Köke and Winter (2002) for Germany. Examples of the rare studies for small companies are Ang, Cole and Lin (2000), Bennedsen, Fosgerau and Wolfenzon (2000) and Harhoff and Stahl (1995). Hellmann and Puri (2002) provide evidence on venture capital financing of small and medium-sized companies.

strategies that benefit them but reduce the payment to outside suppliers of funds. This behaviour is constrained by higher managerial ownership because this increases the costs that managers have to bear (incentive effect). On the other hand, for a given ownership distribution, the higher the level of managerial ownership, the more difficult it is for outsiders to control the management. This gives the management the possibility to "entrench" themselves. Taking the incentive hypothesis and the entrenchment hypothesis into account, the relationship between management's ownership share and company performance can be non-linear. At low levels of ownership the incentive effect can be dominant, that is, there is a positive effect. However, at very high levels of ownership the entrenchment effect might be more important and the effect of ownership could be negative.[5]

This theoretical view is supported by empirical results of Morck, Shleifer and Vishny (1988) who investigate the relationship between managerial ownership of the firm's equity and Tobin's Q for large publicly held companies in the US. They find that Tobin's Q rises as managerial ownership increases from 0 percent to 5 percent, as ownership share increases further up to 25 percent it falls, and then continues to rise again as ownership share exceeds 25 percent. Other empirical studies support their results qualitatively, although they do not agree on the exact functional form of the relationship (for example, McConnell and Servaes, 1990; Mehran, 1995; Kole, 1995. In addition, the relationship between managerial ownership and company performance has been found to become insignificant after including fixed effects (Himmelberg, Hubbard and Palia, 1999). This may be due to the trade-off between utility maximization of managers and their profit orientation pointed out by Demsetz (1983). In a competitive environment managers have to pay for their on-the-job consumption by a reduction in their pecuniary managerial compensation. As a consequence, managers will not consume while on the job unless the cost of doing so is less than if they consumed at home. However, with a greater ownership share and loose market discipline the owner manager has the power to enjoy both on-the-job consumption and a high salary. In equilibrium, the structure of ownership that emerges is an endogenous result depending on monitoring costs and incentives. This theoretical view is supported by the empirical analysis by Demsetz and Lehn (1985), who find no significant linear relationship between ownership concentration and company performance, measured as the accounting profit rate.

The previously mentioned empirical studies are all concerned with large publicly

[5]See Sheifer and Vishny (1997) for a comprehensive review of the corporate governance literature discussing the relationship between ownership structure and performance.

held corporations. In contrast, Ang et al. (2000) study the relationship between a firm's ownership structure and its agency costs for a sample of small US companies. Two efficiency measures serve as proxy for agency costs: the ratio of operating expenses to annual sales and the ratio of annual sales to total assets. They find that companies with an owner-manager have lower agency costs, that agency costs decrease with the managerial ownership share, and that agency costs increase with the number of outside shareholders.

This paper is structured as follows: Section 6.2 describes the data, Section 6.3 presents the estimation results, and Section 6.4 concludes.

6.2 Data Description

6.2.1 Data Set

The data that are the basis for the estimation is derived from a business survey in the German business-related service sector carried out since 1994 by the ZEW and Creditreform, Germany's largest credit rating agency. The industries as well as their industrial classification codes are displayed in Table A2 in the appendix.

The survey is carried out quarterly. A single page questionnaire is sent to about 4000 firms, achieving a response rate of approximately 25 percent. In 1994, when the survey was launched, a stratified sample covering all companies included in the Creditreform database was taken. The stratification was done according to company size, region and sector affiliation. A sample refreshment takes place annually.[6]

The questionnaire is divided into two parts. The first part contains questions on the business development of the firms in the current quarter with respect to the previous quarter and on their expectations for the next quarter. The second part is devoted to questions of current economic or political interest. The survey is conducted as a panel.

The data derived from the survey is merged with company information from the Creditreform database. This database includes detailed information on the ownership structure of private firms with limited liability. It states the ownership

[6]The sample is stratified with respect to the ten sectors listed in Table A2 in the appendix, five size classes (two for East and three for West Germany), as well as with respect to regional affiliation (East/West Germany). The annual sample refreshment replaces companies that have not answered the survey for two years. For more details of the sample design and the data set see Kaiser, Kreuter and Niggemann (2000).

share of managers and gives the identity of outside owners. Furthermore, the number of bank relationships a firm has is displayed. Other information is the number of employees and the age of a company. These variables have been gathered on a yearly basis since 1997. This gives us an unbalanced panel data set that includes observations from 1997 to 2000. The participation pattern is as follows: 20 percent of the companies participated in all 4 years, 14 percent participated in 3 years, and 24 percent of the companies are observed twice. The empirical results are based on 918 observations referring to 356 firms. The number of observations and firms per sector is displayed in Table A3 in the appendix.

Is our data set representative for private companies in the German business-related service sector? There are several possibilities for how biases could be introduced. As mentioned, the population for the questionnaire is all companies covered by Creditreform. Since Creditreform aims to include all registered companies in its database, this should not pose a problem. A second source of bias is the response pattern of the companies to the questionnaire. If the non-responses are related to the topic we want to investigate – the relationship between ownership structure and company performance – then our results will be biased. We investigate the non-response pattern exemplarily for the last wave of the year 2000. For managerial ownership share below or equal to 50 percent, we find that 35.5 percent of the contacted companies answered to the questionnaire. For managerial ownership share between 51 and 99 percent, the response rate is 34.5 percent and for managerial ownership of 100 percent, 31.4 percent of the companies answered. This response pattern suggests that there is no relationship between the willingness to answer and the ownership structure. A survivorship bias is present in our sample since we can only observe profitability for companies that still exist. In an annual sample refreshment all companies that have not responded in the six preceding waves are deleted. The last source of bias is the frequency with which Creditreform updates company information. Companies for which there are more inquiries are updated more often. Again, if the updating frequency is not related to our analysis, we face no problem.

6.2.2 Definition of Variables

The performance measure is based on the responses to the business survey. Participating companies are asked about the development of their profits, sales, prices, demand, and number of employees. They indicate whether these variables have decreased, stayed the same, or increased in the current quarter compared to the previous quarter. For the purpose of the current research the variable of most interest is the assessment of the company's profits.[7] The performance variable **(Performance)** is measured as the difference between the number of times a company has responded that its profits have increased and the number of times a company has reported that its profits have decreased. The exact formula is:

Performance:

of 'increases' per company per year − # of 'decreases' per company per year

The definitions of the variables determining performance are as follows (descriptive statistics are shown in Table 6.1):

- Ownership share of managers **(Share)** is the sum of ownership shares held by the management of the firm. It is measured between 0 and 1. Previous studies on large, public companies typically find a non-linear relationship between managerial ownership and company performance due to an incentive and entrenchment effect. Owing to the more concentrated ownership structure, however, it is not clear whether one should also expect a similar functional form for private companies.

  The share of companies that are totally owned by managers varies according to sector between 32 percent and 61 percent. The average in the whole sample is 45 percent. Excluding companies that are totally owned by managers the distribution of ownership share is approximately normal, centered around 55 percent and with relatively more observations above the mean. This distribution does not vary substantially across sectors.

- **Owner Manager** denotes the number of managers who hold ownership shares. We expect a negative sign since it is more difficult for more managers to come to an agreement. Furthermore, the incentive for a single manager is diminished since the ownership is divided between several managers.

- **Outside Owner** denotes the number of outsiders holding equity. The ownership share of each outside owner is *ceteris paribus* smaller, the higher the number outside owners. Because larger outside owners have a bigger incentive to monitor we expect a negative sign on this variable.

[7] The exact question is: in comparison to the last three months, have your profits increased, stayed the same or decreased?

- **Bank** is the number of a firm's bank relationships. Theory does not give an unambiguous prediction about the sign of this variable. On the one hand, a negative influence on performance is to be expected. If a company has more bank relationships, each bank will *ceteris paribus* have a smaller loan volume to the company and therefore less incentives to monitor. On the other hand, a positive influence on performance is also possible because firms with few bank relationships may have the problem that the banks try to hold them up. The ex-post information monopoly provides banks with a substantial bargaining power (Sharpe, 1990; Rajan, 1994). Banks, therefore, may be able to charge above-market loan rates.

- **Ln Employment** denotes the natural log of number of employees. The companies in our sample are relatively small. 78 percent of the companies have fewer than 50 employees, 14 percent have between 50 and 100 employees and only 9 percent have more than 100 employees. The direction of the relationship between profitability and size is not clear.

- **Ln Age** is the natural log of the age of the company in years. This is mainly a control variable.

Table 6.1: Descriptive Statistics

Variable	Mean	Median	Std. Dev.	Minimum	Maximum
Performance	-0.293	0	1.739	-4	4
Share	0.726	0.850	0.309	0.010	1
Owner manager	1.664	1	0.965	0	10
Outside owner	1.269	1	1.805	0	16
Bank	1.397	1	0.709	1	6
Employment	44.72	24	65.82	1	800
Age	14.98	10	12.95	2	115
West	0.602	1	0.489	0	1

6.3 Estimation Results

In this section, we present the estimation results on the relationship between company performance and ownership share of managers. Our regression equation explains company performance by managerial ownership share up to the third power, the number of managers who hold ownership shares, the number of outside owners, the number of bank relationships, the size and the age of the company. In this specification we need to be concerned about the endogeneity of managerial ownership share. Economic theory is not clear regarding the direction of causality between company performance and the size of the ownership share a manager is willing to take. It is possible that the size of the ownership shares of managers not only influences company performance but also that company performance has an influence on the size of the ownership share that managers are willing to take. Managers tend to be very well informed about the potential of a company before they decide on the share. This could lead to higher ownership share in well performing companies and lower ownership share in badly performing companies, depending on the price of the share.

The data set at hand allows us the use of several approaches to cope with endogeneity. Due to the panel structure of the data set, we are able to control for unobserved firm-specific effects, for example, managerial ability, by estimating fixed-effects models. The use of fixed-effects specifications helps to control for endogeneity as long as the effect is time-invariant, because in this case it will be captured by the fixed effect.[8] In a first approach shown in Table 6.2, we use the lag of the managerial ownership share to account for the time-variant endogeneity. If the major concern of the endogeneity issue is market timing, for example, then using lags will help. It is conceivable that managers increase their ownership share on private information that company performance will improve.

In a second approach shown in Table 6.3, we use instrumental variables (Two-Stage-Least-Squares: 2SLS) estimation. The instrumental variable approach also controls for endogeneity due to the time-variant component of the error term.

[8]We also estimated random-effects models. In a comparison with the fixed-effects method, the random-effects method is rejected by the Hausman test. The test is on the null hypothesis that the firm-specific effects are uncorrelated with the regressors. For example, the Hausman test of the lagged specification in Table 6.2, column (2), has a p-value of 0.012.

Controlling for Endogeneity using Lags

Table 6.2 shows the estimation results for the lagged specifications. This strategy of temporal ordering helps if the major source for the endogeneity problem is reverse causality.

In the lagged specification, we need to be concerned about autocorrelation in the disturbance terms. Consider the model:

$$Y_{it} = \alpha + x_{i,t-1}\beta + \epsilon_{it} \tag{6.1}$$

with $i = 1, ..., N$ indicating company dimension and $t = 1, ..., T$ time dimension. For the ease of exposition, this model abstracts from any contemporaneous right-hand side variables. This specification leads to inconsistent results in the presence of a first-order autoregressive scheme: $\epsilon_{it} = \rho\epsilon_{i,t-1} + \eta_{it}; |\rho| < 1$ since $x_{i,t-1}$ and $\epsilon_{i,t-1}$ would be correlated. We tested the hypothesis that serial correlation is absent in our panel using the method proposed by Wooldridge (2002, p. 282f.). This hypothesis is not rejected, the test statistic is highly insignificant (p-value=0.95).

Column (1) in Table 6.2 shows the results of the most parsimonious specification that does not include any fixed effects. This basic specification indicates a cubic relationship between company performance and managerial ownership share.[9] In order to take time-invariant unobserved heterogeneity into account, we extent this specification by including various fixed effects. Column (2) shows the results when firm fixed effects are included, column (3) additionally takes year fixed effects into account and column (4) also includes year/industry interaction dummies. By including firm fixed effects, we control for any permanent differences across companies in unmeasured determinants of company performance. Within this framework the coefficients on the covariates share (lag), share squared (lag) and share cubed (lag) capture the partial relationship between deviations of these variables from company means and deviations of performance from company means. The year dummies control for the effects of changes over time in unmeasured determinants which are common to all companies, and the year/industry interaction dummies consider differences across industries in the effect of changes over time in unmeasured determinants in company performance.

[9]Because it is a priori not clear what functional form is appropriate for managerial ownership, we started with a polynomial including share up to the fourth power. Since the fourth power was not significant, we used a polynomial up to the third power. Here we found the third power to be significant and therefore stayed with this functional form.

Table 6.2: MANAGERIAL OWNERSHIP AND COMPANY PERFORMANCE – LAGGED SPECIFICATIONS

Dep. Variable: Performance					
	(1)	(2)	(3)	(4)	(5)
Share (lag)	5.45**	15.13***	15.74***	16.66***	26.53***
	(2.49)	(5.20)	(5.24)	(5.67)	(8.19)
Share squared (lag)	-10.42**	-22.56**	-23.57**	-25.53**	-48.04***
	(5.31)	(10.99)	(10.92)	(11.49)	(16.31)
Share cubed (lag)	5.60*	10.98	11.51*	12.74*	26.31***
	(3.18)	(6.75)	(6.67)	(6.93)	(9.61)
Owner manager (lag)	0.09	-0.60***	-0.62***	-0.59***	-0.44*
	(0.07)	(0.20)	(0.21)	(0.21)	(0.26)
Outside owner	-0.01	0.19**	0.20**	0.18**	0.04
	(0.04)	(0.09)	(0.09)	(0.09)	(0.10)
Bank	-0.06	-0.16	-0.25*	-0.28**	-0.02
	(0.10)	(0.12)	(0.13)	(0.14)	(0.13)
Ln employment	0.08	-0.34	-0.30	-0.16	-0.41
	(0.06)	(0.22)	(0.22)	(0.25)	(0.33)
Ln age	0.05	-0.95	-2.45*	-3.29**	-1.68
	(0.10)	(0.64)	(1.39)	(1.47)	(1.31)
Performance (lag)					0.14**
					(0.06)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Year fixed effects	No	No	Yes	Yes	Yes
Year industry interaction	No	No	No	Yes	Yes
No. of obs. (companies):	918 (356)	918 (356)	918 (356)	918 (356)	580 (361)
R^2	0.01	0.64	0.64	0.66	
Sargan (p-value)					0.23
Errors (p-value)					
AR(1)					0.00
AR(2)					n.a.

Note: ***, **, *-indicates significance on the 1, 5 and 10 percent level. Robust standard errors are in parentheses. Column (1) shows the results of an OLS estimation, in column (2)-(4) various fixed effects are successively included into the specification. Column (5) shows Arellano-Bond GMM estimation results.

The inclusion of the fixed effects does not change the qualitative results of the relationship between company performance and managerial ownership but the precision of the coefficients improves considerably owing to the inclusion of additional controls.

The functional form of the relationship between managerial ownership share and company performance is very similar for specifications (1) to (4). The functional form plotted in Figure 6.1 is based on the results of the specification including the most controls, shown in column (4). The positive incentive effect for low values of managerial ownership share is quite pronounced, whereas there is no clear evidence for a negative entrenchment effect for high values of managerial ownership share. We further investigate the relationship by plotting the slope of the function (Figure 6.2). From the confidence intervals it can be seen for which areas of managerial ownership share the marginal effect is significantly different from zero. The incentive effect has a significant impact on performance up to 40 percent, whereas the marginal effect is never significant for the range of values where the performance function has a negative slope. We therefore conclude that there is no entrenchment effect for our sample of private companies. Ownership in private companies is much more concentrated than in public companies. Ownership shares that would allow entrenchment are often so high that managers already have good incentives to maximize company value.

Companies perform better when fewer managers with ownership stakes are involved. If there are several managers it becomes more difficult to agree on the company strategy and, furthermore, the incentive provided by the managerial ownership share is smaller for each single manager.

With regard to the effect of outside owners we find that performance is increasing in the number of outside owners. This finding is consistent with the absence of a significant entrenchment effect, however, it is in contrast to some part of the corporate governance literature. This literature indicates the importance of monitoring activities, best performed by concentrated ownership. In contrast, widespread ownership leads to the free rider problem since there are only weak incentives for individual investors to seek information about the managers' work. We, in turn, do not find that owners with a large share would be more effective in monitoring. For the interpretation of this result it is also important to consider that family ownership is widespread in small and medium-sized companies. It is very likely that family members who are not part of the management are not so well informed about the business. If those family members have a high ownership share, they can easily influence business decisions, which may be harmful.[10]

Monitoring by banks has a positive effect. The more bank relationships a com-

[10] This rather pessimistic view about the business acumen of family members is supported by other empirical analyses, see, for example, Morck, Strangeland and Yeung (2000).

pany has, the worse its performance. This is compatible with the argument that banks with a high loan volume to one company will spend more resources on monitoring than banks with a small loan volume. But it also confirms the view that companies with a poor performance need to seek loans from several banks because no bank wants to make a big commitment. It is not possible to differentiate between these two arguments.[11]

Firm size in terms of the natural logarithm of the number of employees does not have a significant effect on company performance. Younger companies do, however, show a better performance than older companies.

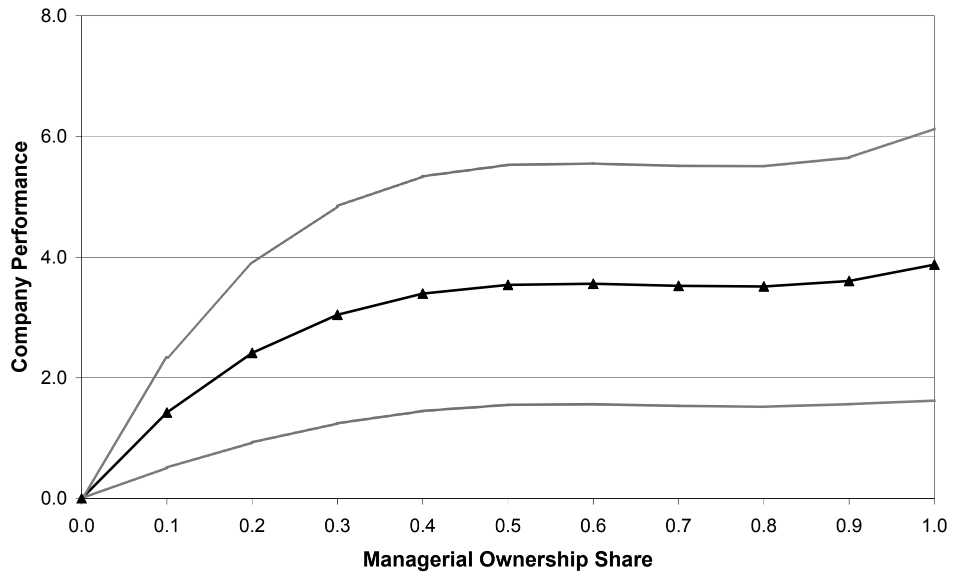
Although we regress the change in profits on the level of managerial ownership share our results do not imply that better companies will grow faster than weaker companies for ever. Nickell, Nicolitsas and Dryden (1997) find that competitive pressure has a positive influence on productivity growth. Companies that grow faster build up market share over time, but then they often lose their power to innovate and hence their productivity declines.

We also investigate the dynamic structure of the specification applying an Arellano-Bond GMM estimator. The results are shown in the last column of Table 6.2. We used the one-step method because it is generally recommended for inference (see, for example, Blundell and Bond, 1998). The two-step model is more efficient, but the standard errors tend to be downward biased in small samples. The Sargan test statistic, shown at the bottom of column (5), is insignificant indicating that the instruments are valid. The Arellano-Bond test for first-order serial correlation in disturbances is highly significant, which was to be expected since the variables are used in first differences. The Arellano-Bond test for second-order autocorrelation can not be calculated in our panel because the number of years is too small.

Lagged company performance has a positive significant influence on current performance, indicating persistence. However, with a value of 0.14 the coefficient is relatively small. This additional specification does not alter our previous findings regarding company performance and managerial ownership, but the significance of the additional controls declines.

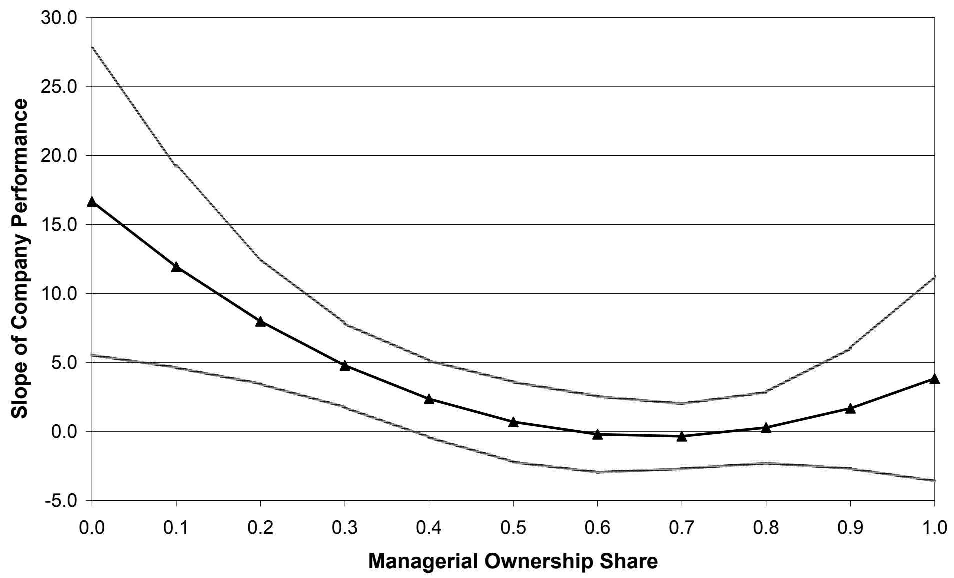
[11]This result is in line with previous empirical findings by Petersen and Rajan (1994), who find that firms that borrow from multiple banks are charged a significantly higher interest rate. In addition, concentrating on few bank relationships has a positive effect on the availability of loans.

Figure 6.1: The Influence of Managerial Ownership Share on Performance



Note: 95 percent confidence intervals are indicated. This graph is based on specification (4) shown in Table 6.2.

Figure 6.2: Slope of the Performance Function



Note: 95 percent confidence intervals are indicated. This graph is based on specification (4) shown in Table 6.2.

Controlling for Endogeneity Using Instrumental Variables

In this subsection, we use instruments to control for the potential endogeneity of managerial ownership share. Instrumental variables (IV) estimation is a general solution to the problem of an endogenous variable. The previous proceeding focused on one particular aspect of endogeneity – reverse causality, that is that higher profitability may lead to more ownership. But the problem is much more general. The concern is that some unobserved factor may lead to increases in both ownership and performance. An example of such unobserved factors is changes in corporate governance, including more pressure from outsiders or the arrival of a new manager. The purpose of the IV approach is to account for this general problem. In addition, in contrast to the fixed-effects method, which takes account of time-invariant unobserved heterogeneity, the IV methods also helps if the unobserved component is time-varying. We use the contemporaneous value of share in the regression, but instrument it with its lag.[12] The first lag of managerial ownership share up to the fifth power is used as instruments. The regression results are shown in Table 6.3. The specifications include all controls described above.

Analogously to Table 6.2, the first column shows the parsimonious specification without any fixed effects. Column (2)-(4) add consecutively firm fixed effects, year fixed effects, and year/industry interaction dummies.

The results of the specification in column (1) are in line with the previous findings concerning managerial ownership share, but the other controls are not significant anymore. Once we include the various fixed effects, we do not find a significant relationship between managerial ownership share and company performance. Figure 6.3 shows the profile of the estimation. The plot is based on the the specification including the most controls (column 4), as in Figure 6.1. The confidence intervals are wide, indicating that share, share squared and share cubed are jointly insignificant. In addition, the marginal effects are always insignificant (Figure 6.4).

The imprecise measurement of the effects could be due to a weak correlation between the endogenous regressor and the instruments. In order to judge instrument quality, we calculated Shea's partial R squared (Shea, 1997). It is a measure for instrument relevance for regressions with several endogenous regressors. Its values are quite low for the share variables. They are in the order of 0.02 to 0.03. We

[12]This proceeding is only valid in the absence of autocorrelation in residuals. The absence of autocorrelation is not rejected by a test of serial correlation, as outlined in the previous part of this section.

interpret these values as an indication of weak instruments. Under these circumstances, the IV method does not allow us to reliably identify the relevant effects. In addition, the bias of IV estimates can be higher than the bias of OLS estimates, when instruments are weak. We therefore prefer our lagged specification.

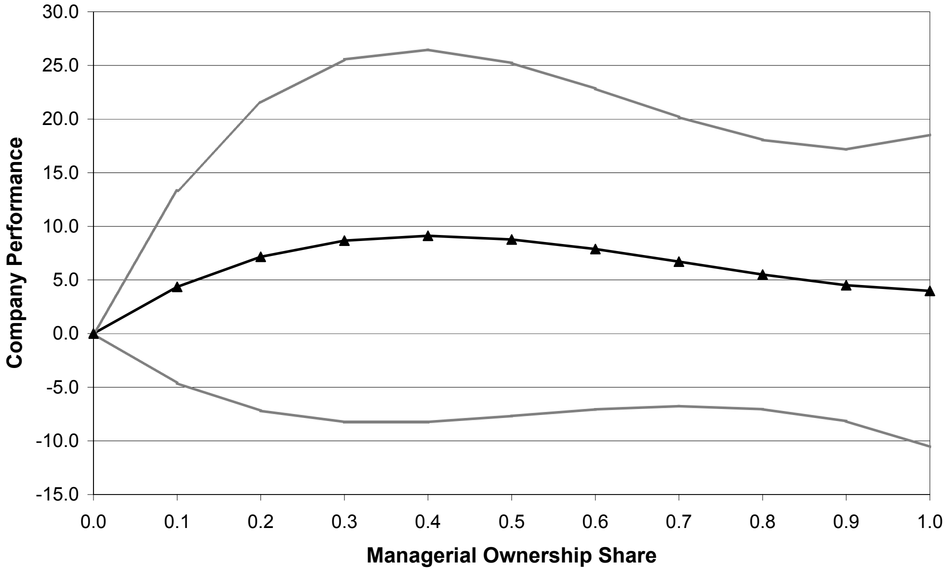
The signs of the other regressors remain the same in the instrumental variables regression, but are less precisely measured.

Table 6.3: Managerial Ownership and Company Performance – Specifications Using Instrumental Variables

Dep. Variable: Performance				
	(1)	(2)	(3)	(4)
Share	6.16**	46.13	43.95	42.15
	(2.86)	(68.46)	(68.39)	(56.20)
Share squared	-11.75**	-96.95	-93.25	-90.36
	(6.09)	(132.82)	(132.55)	(111.52)
Share cubed	6.32*	55.18	53.30	52.18
	(3.65)	(73.44)	(73.23)	(62.48)
Owner manager	0.09	-0.73*	-0.73*	-0.80**
	(0.07)	(0.43)	(0.42)	(0.40)
Outside owner	-0.003	0.25	0.24	0.22
	(0.04)	(0.34)	(0.34)	(0.29)
Bank	-0.06	-0.20	-0.21*	-0.22*
	(0.10)	(0.13)	(0.13)	(0.12)
Ln employment	0.09	-0.52*	-0.52*	-0.49**
	(0.06)	(0.27)	(0.13)	(0.24)
Ln age	0.05	-0.62	-1.06	-1.29
	(0.10)	(0.80)	(1.02)	(0.93)
Firm fixed effects	No	Yes	Yes	Yes
Year fixed effects	No	No	Yes	Yes
Year industry interaction	No	No	No	Yes
No. of obs. (companies):	918 (356)	918 (356)	918 (356)	918 (356)
R^2	0.01	0.59	0.60	0.61
Shea Partial R^2				
Share	0.79	0.019	0.019	0.024
Share squared	0.78	0.019	0.019	0.024
Share cubed	0.78	0.021	0.021	0.026
Owner manager	0.89	0.186	0.187	0.204

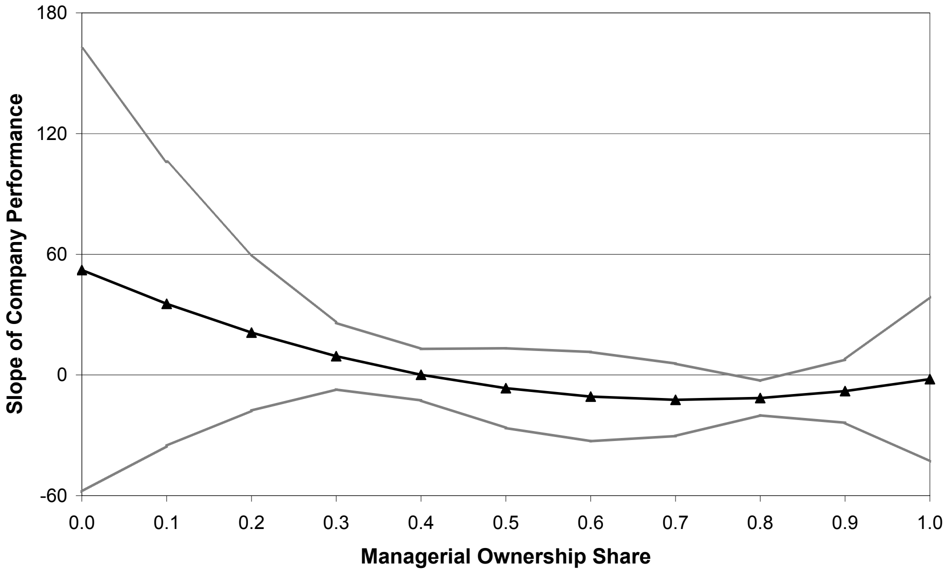
Note: ***, **, *-indicates significance on the 1, 5 and 10 percent level. Robust standard errors are in parentheses. Column (1) shows the results of a 2SLS estimation without fixed effects, in column (2)-(4) various fixed effects are successively included into the specification.

Figure 6.3: THE INFLUENCE OF MANAGERIAL OWNERSHIP SHARE ON PERFORMANCE - IV SPECIFICATION



Note: 95 percent confidence intervals are indicated. This graph is based on specification (4) shown in Table 6.3.

Figure 6.4: SLOPE OF THE PERFORMANCE FUNCTION - IV SPECIFICATION



Note: 95 percent confidence intervals are indicated. This graph is based on specification (4) shown in Table 6.3.

6.4 Conclusions

In this paper, we investigate the relationship between the ownership share of managers and company performance for small and medium-sized private companies. Up to now, most studies on managerial ownership have concentrated on companies that are listed on the stock market. However, the distortions caused by the separation of ownership and control may also affect private companies with limited liability. Since this company type is the most important legal form in Germany, it is crucial to have a good understanding of the basic corporate governance mechanisms for these companies as well.

We use an unbalanced panel data set of private companies with limited liability in the German business-related service sector. The main conclusion from our analysis is that ownership does influence company performance. We find that managerial ownership up to around 40 percent has a positive effect on company performance owing to the incentive effect. However, we do not find a significant entrenchment effect. This result is in contrast to previous findings for public companies that found evidence for the entrenchment effect. The discrepancy in results can be interpreted in terms of structural differences between private and public companies. The ownership share of managers in private companies is generally quite high. At levels at which they could become entrenched with respect to outside owners, they already bear a large proportion of the costs. The incentive to maximize firm value therefore dominates entrenchment considerations.

6.5 Appendix

Table A1:Turnover Accounted for by Companies With Different Legal Form (in percent of overall turnover)

Type of legal form	1972	1986	1990	1998	2000
Sole proprietor	23.8	15.4	14.9	13.3	12.3
OHG	-	6.8	6.8	6.1	6.1
KG	-	24.0	23.9	22.4	22.5
GmbH	17.1	25.5	29.1	32.0	33.6
AG	19.1	21.2	20.2	21.5	20.3
Other	7.9	7.2	5.1	4.7	5.3

Note: A sole proprietor is a single entrepreneur with unlimited liability. The OHG is a private company that has several owners with unlimited liability. The KG has at least one owner with unlimited liability and at least one owner with limited liability. GmbH's have one or more owners with limited liability. AG's are companies that are allowed to issue shares. They may or may not be listed on a stock market. Other includes state-owned enterprises and cooperatives. This information is taken from Statistisches Bundesamt, 1972 to 2000.

Table A2:The Business-Related Service Sector

Sector	WZ 93
Computer Services	72100, 72201-02, 72301-04, 72601-02, 72400
Tax Consultancy & Accounting	74123, 74127, 74121-22
Management Consultancy	74131-32, 74141-42
Architecture	74201-04
Technical Advice & Planning	74205-09, 74301-04
Advertising	74844, 74401-02
Vehicle Rental	71100, 71210
Machine Rental	45500, 71320, 71330
Cargo Handling & Storage	63121, 63403, 63401
Waste and Sewage Disposal	90001-07

Note: The WZ93 industrial classification code is a classification system developed by the German Federal Statistical Office in accordance with the European NACE Rev. 1 standard that classifies economic units according to their sector of concentration.

Table A3:Distribution of Observations and Number of Companies

Sector	No. of Observations	No. of Companies
Computer Services	111	44
Tax Consultancy & Accounting	76	29
Management Consultancy	81	31
Architecture	133	52
Technical Advice & Planning	186	69
Advertising	61	27
Vehicle Rental	73	29
Machine Rental	66	25
Cargo Handling & Storage	66	25
Waste and Sewage Disposal	65	25
Total	918	356

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Eidesstattliche Erklärung

Hiermit erkläre ich, dass ich die vorliegende Arbeit mit dem Titel "Changing Workplaces in the Knowledge-Based Economy - Evidence from Micro Data" selbständig angefertigt habe und die benutzten Hilfsmittel vollständig und deutlich angegeben habe.

Mannheim, den 22.10.2004

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