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Author(s): Alexandra Spitz-Oener

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Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure

Alexandra Spitz-Oener, *Humboldt University*

Empirical work has been limited in its ability to directly study whether skill requirements in the workplace have been rising and whether these changes have been related to technological change. This article answers these questions using a unique data set from West Germany that enabled me to look at how skill requirements have changed within occupations. I show that occupations require more complex skills today than in 1979 and that the changes in skill requirements have been most pronounced in rapidly computerizing occupations. Changes in occupational content account for about 36% of the recent educational upgrading in employment.

The article was written as part of the research project, ICT, Workplace Organization, and Wages Across and Within Skill Groups, commissioned by the Landesstiftung Baden-Württemberg foundation when the auther worked in the ICT Research Group at ZEW, Mannheim. The data used in this article have been obtained from the German Zentralarchiv für Empirische Sozialforschung at the University of Köln (ZA). The data were collected by the Bundesinstitut für Berufsbildung and the Institut für Arbeitsmarkt- und Berufsforschung and documented by the ZA. Neither the producers of the data nor the ZA bears any responsibility for the analysis and interpretation of the data in this article. I particularly thank David Autor for his invaluable suggestions. I am also indebted to Daron Acemoglu, Miriam Beblo, Irene Bertschek, Sandra Black, Lex Borghans, Bernd Fitzenberger, Thomas Hempell, Francis Kramarz, Frank Levy, Elisabeth Mueller, Friedhelm Pfeiffer, Jörn-Steffen Pischke, Susanne Prantl, Bas ter Weel, and Elke Wolf for their suggestions and comments. Contact the author at alexandra.spitz-oener@wiwi.hu-berlin.de.

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I. Introduction

In recent decades, the United States and the United Kingdom have witnessed both a major increase in the supply of more educated workers and a rise in the return to education, supporting the argument that technological change has been skill biased. A puzzle that continues to motivate economic research, however, is that the wage structure in continental European economies has not changed accordingly, even though companies in these countries have had access to the same technologies as companies in the United States and the United Kingdom.[1] But, to date, no conclusive evidence has been available on how skill requirements have changed in continental Europe and how these changes are related to technological changes.

In this study, I go beyond the analysis of wages and analyze changing occupational skill requirements directly, using a unique survey-based data set from West Germany. Skill requirement measures are based on the task composition of occupations; in other words, employees who participated in the survey indicated what they actually do in their jobs. Importantly, while wages typically incorporate nonskill characteristics, such as the effects of unions and discrimination, the task composition of occupations is unlikely to be influenced by such factors.

The analysis builds on the Autor-Levy-Murnane model (2003), which proposes a nuanced version of the skill-biased technological change hypothesis. The evidence presented in this study, however, improves considerably on the evidence offered by Autor, Levy, and Murnane (2003), who infer the task content of individual occupations by linking Current Population Survey job titles to data from the Dictionary of Occupational Titles (DOT). This introduces considerable noise into the measurement of skills required for individual occupations. In particular, it precludes, to a large extent, a discussion of task changes within occupations. In contrast, the analysis in this article is based on a consistent, well-defined, direct measure of occupational task inputs. Assuming that computer technologies substitute certain tasks—those that are expressible in rules and thus programmable—and not whole occupations, task changes within occupations are the natural dimension for analyzing questions of skill-biased technological change. Thus, by focusing the analysis on within-occupational task changes, this article goes one important step further than existing literature. In addition, I use the detailed task measures to

[1] Comprehensive reviews of the skill-biased technological change literature can be found in Chennells and Van Reenen (1999), Katz and Autor (1999), and Acemoglu (2002). Krueger and Pischke (1998), Card, Kramarz, and Lemieux (1999), Acemoglu (2003), Piketty and Saez (2003), and Saez and Veall (2005), e.g., discuss the puzzle of differential inequality trends in continental European countries and the United States/United Kingdom in recent decades.

show that the German labor market has witnessed changes in skill requirements similar to those in the United States.

The results suggest that occupations involve greater complexity today than at the end of the 1970s. There has been a sharp increase in nonroutine cognitive tasks, such as doing research, planning, or selling, and a pronounced decline in manual and cognitive routine tasks, such as double-entry bookkeeping and machine feeding. Importantly, and consistent with the skill-biased technological change hypothesis, most of the task changes have occurred within occupations, and they have been most pronounced in occupations in which computer technologies have made major headway. Neither changes in the educational structure nor in the gender composition of occupations provide alternative explanations for changing skill requirements. In contrast, the above patterns also exist within occupation-education groups and within occupation-age groups. Moreover, the analysis suggests that changing occupational skill requirements explain a significant part of the educational upgrading of recent decades. In addition, the changes in the occupational structure of employment between 1979 and 1998/99 suggest that there is evidence of a "hollowing out" in the labor market.

This article is organized in six sections. In the next section, I discuss the related literature and introduce the task framework used in this study. I describe the data set and the variables in Section III. In Section IV, I present stylized facts on occupational skill requirements and educational and technological trends in West Germany since 1979. In Section V, I investigate the relationship between computer use, occupational skill requirements, and educational attainment on the basis of synthetic occupational groups. Section VI concludes.

II. Occupational Skill Requirements and the Rising Supply of Education

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 as a result of technological developments leads to skill upgrading or skill downgrading.[2] The discussion has intensified with the spread of workplace-based computer technology in recent decades. Based on recently observed shifts in the distribution of earnings in the United States, nonneutral technological change, increasing the productivity of highly skilled employees more than that of less skilled workers, has been given particular

[2] 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.

attention. In addition, the polarization of the labor force has often been discussed (see, e.g., Levy and Murnane 1992).

Empirical research has provided evidence of robust correlations between computer-based technologies and the use of highly skilled employees at various levels of aggregation, strengthening the hypothesis that recent technological change has been skill biased. These studies emphasize the higher workplace skills that computerization now requires. The opposite view has been taken by the overeducation literature that states that skill requirements have not changed significantly in recent decades and that the increased deployment of highly educated employees resulted in these employees holding occupations that were previously held by employees with lower educational levels. Empirical studies are, for example, Rumberger (1987), Verdugo and Verdugo (1989), Sicherman (1991), and Alba-Ramirez (1993). The empirical studies have been criticized for the way that they operationalize overeducation (see, e.g., Smith 1986; Halaby 1994). In addition, results of recent studies that take unobserved heterogeneity into account or use instrumental variable techniques question the positive wage effects of overeducation found in cross-sectional analyses (see, e.g., Bauer 2002). These results suggest that part of what is referred to as overeducation simply reflects the heterogeneity of individual abilities and skills within particular educational qualifications. In addition, the stylized fact of rising returns to education in spite of an increasing supply of more educated workers supports the skill-biased technological change (SBTC) hypothesis.

The analysis in the present study focuses on technological change (as opposed to deindustrialization and globalization as alternative explanations, which are discussed in the literature, for the skill upgrading in recent decades) measured by workplace computerization, because this is the only explanation that generates predictions about within-occupational task changes. Deindustrialization and globalization, by contrast, emphasize between-industry or between-occupation developments.

Most studies in the SBTC literature use "traditional" skill measures to assess the skill level of employees, such as the proportion of production/nonproduction workers or blue-collar/white-collar workers.[3] These classifications use divisions according to occupational groups, which are of limited use in determining skill requirements. They document, for example, the structural shift toward increased employment of white-collar work in all major sectors of industrialized countries. Other studies rely on measures of formal education or wages (see, e.g., Autor, Katz, and Krueger 1998). Education, however, is an input factor. First, it is very likely that people with equal investment in their formal education attain

[3] See, e.g., Berman, Bound, and Griliches (1994), Berndt, Morrison, and Rosenblum (1994), and Berman, Bound, and Machin (1998).

different levels of skills. Each educational group is therefore best characterized by a distribution of skills.[4] In addition, skills that people bring to 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 in the workplace (Spenner 1983, 1990). Wages, however, may not reflect the "true" skill level of individuals either. This is not only the case in countries where wages are set centrally, such as Germany and France. It may also be the case in other countries owing, for example, to discrimination or segregation in the labor market.

The recent study by Autor et al. (2003), however, now offers a framework that enables occupational skill requirements to be analyzed directly. The major feature of this framework is that it conceptualizes work as a series of tasks; with this, one can analyze the recent changes in the task composition of occupations directly. Thus, this framework sheds light on the "black box" that typically encloses studies on SBTC, as was, for example, expressed by Bresnahan, Brynjolfsson, and Hitt (2002, 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.'"

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: nonroutine analytical tasks, such as research, planning, or evaluation activities; nonroutine interactive tasks, such as selling or coordinating and delegating work; routine cognitive tasks, such as double-entry bookkeeping and calculating; routine manual tasks, such as machine feeding or running a machine; and nonroutine manual tasks, such as housekeeping or restoring houses.

The terms *routine* and *nonroutine* characterize the relationship between the respective task measure and information technology (IT). Both manual and cognitive routine tasks are well defined in the sense that they are expressible in rules such that they are easily programmable and can be performed by computers at economically feasible costs (Levy and Murnane 1996). Hence, routine tasks are subject to substitution by computer capital. Nonroutine tasks are not well defined and programmable and, as things currently stand, cannot be accomplished by computers. However, computer capital is complementary to both analytical and interactive nonroutine cognitive tasks in the sense that computer technology increases the productivity of employees performing these tasks. The term *analytical*

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

refers to the ability of workers to think, reason, and solve problems encountered in the workplace. The term *interactive* 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 coworkers and customers.[5]

The scope for substitution is thus limited to certain tasks. This "limited substitution" relationship (Bresnahan et al. 2002) between IT and occupational tasks shifts the demand for labor toward employees with higher levels of educational attainment, who are presumed to have a comparative advantage in performing nonroutine cognitive tasks. Autor et al. (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.

Wage trends in Germany are often regarded as differing from those in other countries, even though Fitzenberger (1999) and Fitzenberger et al. (2001) provide evidence that there have been changes in the wage structure in West Germany in recent decades.[6] These changes have been small by international standards, however (see, e.g., Prasad 2004; Abraham and Houseman 1995). 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, wage dispersion among medium- and high-educated employees increased over time. The main difference between West Germany and other countries is the experience of employees with low levels of education. In contrast to wage decreases in most other countries, their wages slightly increased, and wage dispersion within this group of workers remained stable over time. Unemployment among this group of workers, however, has increased sharply since the 1980s—an observation that has led to the hypothesis that the European unemployment problem and the U.S. inequality problem are "two sides of the same coin" (Krugman 1994; Freeman 1995).[7]

[5] Case studies identified analytical and interactive skills as the "key" skills required by modern workplaces in industrialized countries (e.g., Hirschhorn 1984; Stasz 1997, 2001). For a detailed discussion of interactive skills, see Borghans, ter Weel, and Weinberg (2005).

[6] The most comprehensive analyses of wage trends exists for the United States, e.g., by Bound and Johnson (1992), Katz and Murphy (1992), Levy and Murnane (1992), and Juhn et al. (1993). Gottschalk and Smeeding (1997) provide an international comparison of earnings and income developments since the early 1980s.

[7] Criticism of this hypothesis can be found, e.g., in Nickell and Bell (1996) and Krueger and Pischke (1998). Card et al. (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.

The lack of adjustment of wages of employees with low levels of education is often explained by union wages that represent binding minimum rates for low-wage earners.[8] Other observers have proposed “social norms” as alternative explanations for the divergent developments in the wage structure in the United States and Germany (or continental European countries in general).[9]

One important advantage of the skill measure used in this study is that centralized wage-setting institutions are unlikely to influence the task composition of occupations. Unions bargain over wages, but they do not have influence on decisions concerning, for example, technology diffusion within companies. Works councils, which are mandated in Germany for companies with more than five employees, typically have an influence on questions of technological changes within companies (see, e.g., Freeman and Lazear 1995). However, recent studies investigating the relationship between the existence of works councils and firm productivity find positive or insignificant effects.[10] Overall, these results suggest that works councils do not, on average, block productivity-enhancing measures in companies. In addition, Bemmels and Reshef (1991) find that an effective means of avoiding employee resistance to technological changes is to involve them in the decision-making process; employees even tend to react positively to technological changes if these are associated with an increase in workers’ skill requirements.

III. 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 about 30,000 individuals (men and women). For details on the data set, see appendix B.

The data set is particularly suited to analyze changes in skill requirements within occupations, since these are categorized in all four waves according to the 1988 classification. The constant occupational titles thus provide the reference point for the analysis. A major improvement over

[8] Empirical studies by Fitzenberger (1999), Kaiser (2000), and Falk and Koebel (2001, 2004) 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.

[9] See, e.g., Krueger and Pischke (1998), Piketty and Saez (2003), and Saez and Veall (2005).

[10] See Addison et al. (2003) for a comprehensive review of this body of the literature.

previous work is that 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 DOT, which contains the descriptions of occupations often used by researchers in the United States for questions related to skills. 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 therein).

The credibility of the analysis in the present study would be impaired if the answers provided by survey participants with high levels of education were systematically biased toward analytical and interactive activities. This is unlikely because survey participants only indicate whether they perform certain activities and do not assign scores to the different measures. In addition, most of the analysis is performed using 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 the employees' formal education. Occupational skill requirements are measured by workers' job duties, depicted in the survey by the activities that employees have to perform at the workplace.[11] I pool these activities into five task categories: nonroutine analytical tasks, nonroutine interactive tasks, routine cognitive tasks, routine manual tasks, and nonroutine manual tasks. Table 1 illustrates the assignment of activities to the five categories. On the individual level i, the task measures ($Task_{ijt}$) are defined as

$$Task_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in cross section } t}{\text{total number of activities in category } j \text{ at time } t} \times 100, \tag{1}$$

where t = 1979, 1984/85, 1991/92, and 1998/99, and $j = 1$ (nonroutine analytic tasks), $j = 2$ (nonroutine interactive tasks), $j = 3$ (routine cognitive tasks), $j = 4$ (routine manual tasks), and $j = 5$ (nonroutine manual tasks). For example, if the analytical task category includes four activities, and employee i indicates that she performs two of them, her analytical task measure is 50.

[11] I use the terms *skill requirements* and *skill/task inputs* interchangeably throughout the article, although strictly speaking, the correct term is *skill/task inputs*. In order to speak of skill requirements, I would need information about task prices.

Table 1
Assignment of Activities

Classification	Tasks
Nonroutine analytic	Researching, analyzing, evaluating and planning, making plans/constructions, designing, sketching, working out rules/prescriptions, and using and interpreting rules
Nonroutine interactive	Negotiating, lobbying, coordinating, organizing, teaching or training, selling, buying, advising customers, advertising, entertaining or presenting, and employing or managing personnel
Routine cognitive	Calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature
Routine manual	Operating or controlling machines and equipping machines
Nonroutine manual	Repairing or renovating houses/apartments/machines/vehicles, restoring art/monuments, and serving or accommodating

The data set does not include information about the time spent on different activities. In addition, while most questions remained the same over time, there were some changes in questions concerning the activities employees perform in the workplace. For consistency, I reduced the activities in each category j to those that are comparable over time.

The data set includes detailed information on the tools and machines used by the 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.

Employees are classified into three qualification groups according to their vocational education (school qualifications are not considered): (1) people with low levels of education, that is, people with no occupational training; (2) people with medium levels of education, that is, people with a vocational qualification who might have either completed an apprenticeship or graduated from a vocational college; and (3) people with high levels of education, that is, people holding a degree from a university or technical college. These variables are dummy variables, taking on the value one if the employee falls within the particular educational level.

IV. Overall Trends in Educational Supply, Occupational Skill Requirements, and the Evolution of IT at the Workplace

As in most industrialized countries, the labor force in West Germany has witnessed a sizable relative increase in the proportion of workers with high levels of education (see table 2, panel A). The proportion of the workforce holding a university degree or a qualification from a technical college increased from about 8% in 1979 to more than 16% in 1999, whereas there was a substantial decline in the proportion of employees without formal educational attainment. Workers with a medium level of

Table 2
Descriptive Figures on Educational Trends and Computer Diffusion (%)

	1979	1985/86	1991/92	1998/99
	A. Proportion of Different Educational Groups in Employment			
High level of education	8.18	10.20	13.30	16.48
Medium level of education	72.38	68.33	71.28	70.57
Low level of education	21.84	21.47	15.42	12.95
	B. Spread of Computers, Terminals, Laptops, and Electronic Data-Processing Devices			
Overall	6.06	18.11	34.52	55.38
High level of education	12.22	25.58	60.73	83.15
Medium level of education	6.31	20.00	33.77	56.52
Low level of education	3.44	10.19	16.13	32.65

NOTE.—Sample includes workers aged 18–65 who lived in West Germany and were German nationals.

education, however, who either completed an apprenticeship or have a qualification from a vocational college, still make up the largest share of the workforce.

The educational upgrading of the labor force has gone hand in hand with a considerable change in aggregate skill requirements. Table 3, panel A, 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 decreased during that period, with an average annual decline of 0.7 percentage points each. The trend in the requirements for nonroutine manual skills is less clear. The overall period, however, suggests an increase of around 0.6 percentage points annually.

One important source of variation in workplace tasks is the substantial increase in interactive tasks, particularly in the 1990s. A detailed inspection of this category shows that tasks such as advising customers, organizing, or coordinating increased in importance in the 1990s. By contrast, the increase in the interactive task measure between 1985/86 and 1991/92 was mainly due to more people being involved in selling and negotiating with others. The main source of the increase in the analytical task measure was an increase in the number of employees undertaking analyses and research, whereas activities such as using and interpreting rules remained relatively stable over time.

Table 3 also shows the aggregate trends in skill inputs for each educational group separately (panels B–D). The analytic and interactive task measures increased over time for each educational group, whereas the cognitive and manual routine task inputs declined. Figures 1–4 illustrate this development by showing the absolute changes in aggregate skill inputs between 1979 and 1998/99. Figure 1 shows the overall trends, and figures

Table 3
Trends in Aggregate Skill Inputs Overall and by Education Level (%)

	Nonroutine Analytic	Nonroutine Interactive	Routine Cognitive	Routine Manual	Nonroutine Manual
			A. Overall		
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
			B. Employees with a 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
			C. Employees with a 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
			D. Employees with a 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

Note.—Sample includes workers aged 18–65 who lived in West Germany and were German nationals.

2–4 show the development for each educational group. One difference between groups is that the decline of routine cognitive task inputs and the increase in interactive and analytical task inputs were 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.

In contrast with a supply story, this overall pattern does not suggest that high-educated employees perform more of the tasks that used to be done by medium-educated employees at the end of the 1990s. The more pronounced development toward analytic and interactive activities and away from routine cognitive activities even suggests that overall skill requirements were rising faster for high-educated employees than for the other 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 4 shows the trends in occupational task inputs for cohorts, defined by year of birth. The first birth cohort consists of individuals born before 1940; the second, those born between 1940 and 1949; the third, those born between

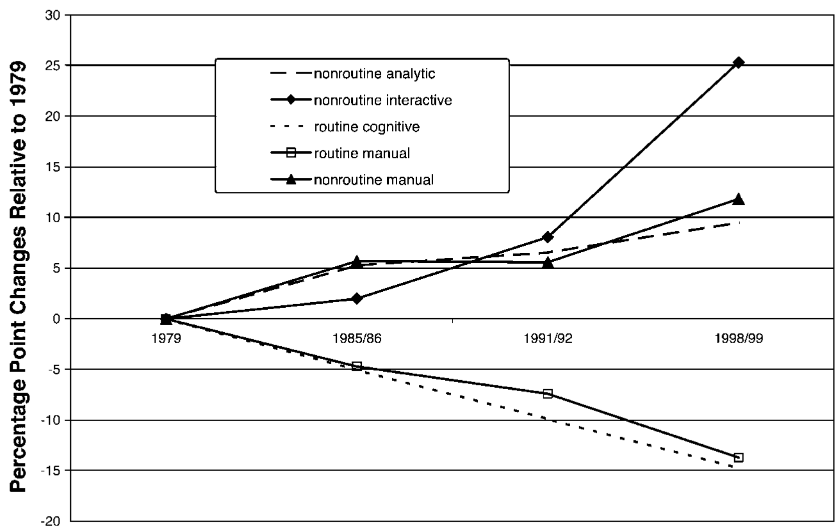

Fig. 1.—Trends in aggregate skill inputs

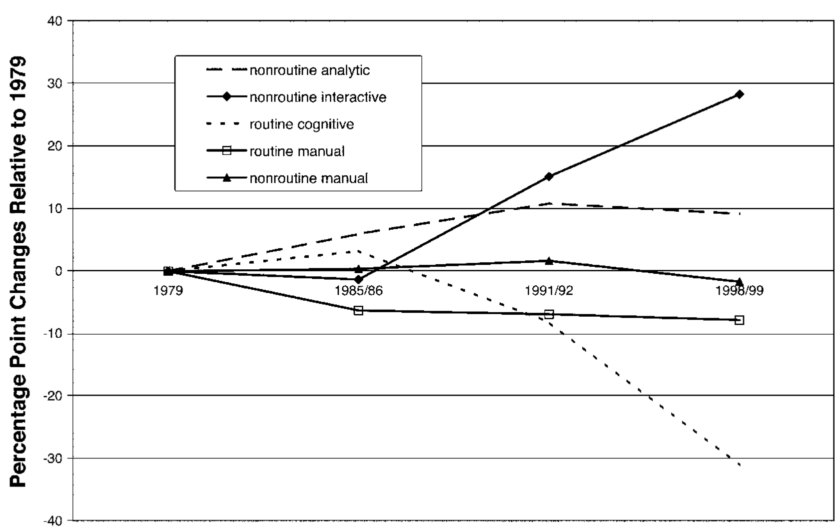

Fig. 2.—Employees with high levels of education: trends in aggregate skill inputs

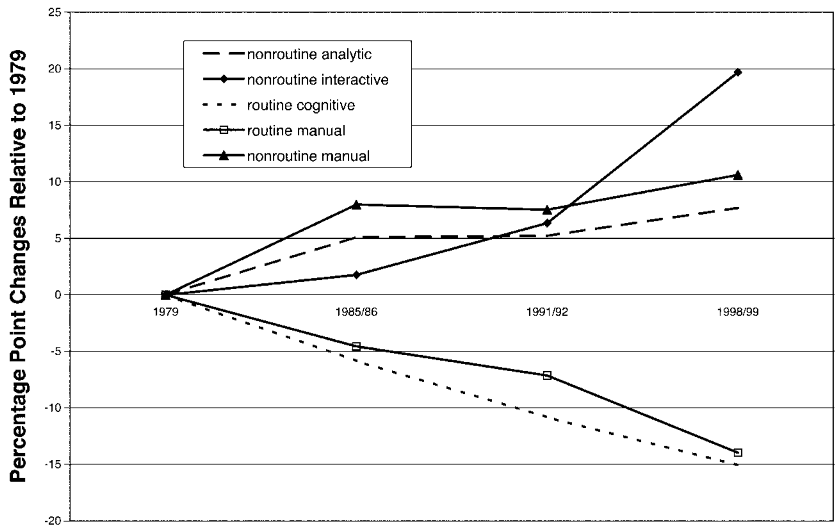

FIG. 3.—Employees with medium levels of education: trends in aggregate skill inputs

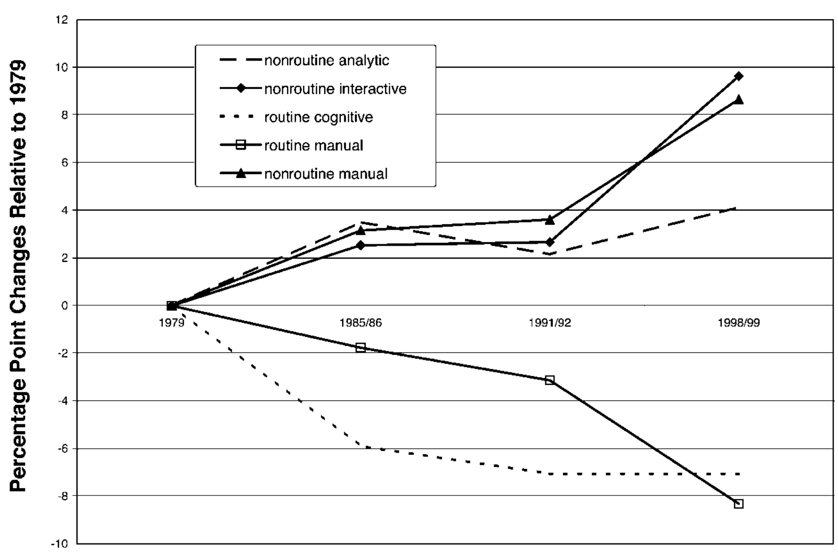

FIG. 4.—Employees with low levels of education: trends in aggregate skill inputs

Table 4
Trends in Aggregate Skill Inputs by Birth Cohorts (%)

Year of Birth	1979	1985/86	1991/92	1998/99
Nonroutine analytical task inputs:				
1975–81				7.41
1969–74			7.71	11.54
1962–68		5.58	10.16	14.63
1956–61	2.39	9.72	13.35	15.09
1950–55	5.15	11.16	12.69	13.95
1940–49	5.49	11.23	11.22	15.32
Before 1940	4.23	9.47	8.76	16.56
10 × average annualized changes 1979–1998/99:				
Within cohorts	5.90			
Within age levels	4.89			
Nonroutine interactive task inputs:				
1975–81				23.17
1969–74			9.52	30.35
1962–68		6.25	15.05	33.61
1956–61	5.72	10.13	18.36	34.37
1950–55	8.77	11.96	20.14	36.68
1940–49	9.90	11.95	17.81	37.26
Before 1940	8.48	10.65	14.15	36.98
10 × average annualized changes 1979–1998/99:				
Within cohorts	18.33			
Within age levels	16.61			
Routine cognitive task inputs:				
1975–81				22.44
1969–74			22.21	21.41
1962–68		25.06	28.86	24.01
1956–61	38.04	33.08	29.04	23.54
1950–55	42.08	35.72	29.69	20.57
1940–49	39.87	33.99	27.73	19.22
Before 1940	32.36	29.43	21.45	23.05
10 × average annualized changes 1979–1998/99:				
Within cohorts	−6.11			
Within age levels	−7.01			
Routine manual task inputs:				
1975–81				18.97
1969–74			29.80	17.23
1962–68		31.51	25.23	19.15
1956–61	41.53	27.21	24.99	17.68
1950–55	35.13	26.05	21.80	15.19
1940–49	30.52	23.91	20.87	14.71
Before 1940	25.21	24.80	22.91	17.61
10 × average annualized changes 1979–1998/99:				
Within cohorts	−10.47			
Within age levels	−8.39			
Nonroutine manual task inputs:				
1975–81				30.28
1969–74			25.23	27.78
1962–68		22.83	22.36	25.94
1956–61	15.42	20.78	20.18	25.69
1950–55	14.18	18.05	18.35	25.68
1940–49	13.39	18.91	17.31	24.45
Before 1940	14.25	19.74	19.37	23.30
10 × average annualized changes 1979–1998/99:				
Within cohorts	4.68			
Within age levels	6.57			

1950 and 1955; and so on. A birth cohort can be followed over time by moving horizontally along the same row. The same age group can be followed by moving diagonally upward (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 change as the cohort ages. The time effect describes how task inputs for a given cohort shift because of, for example, macroeconomic shocks. Changes in task inputs within an age group, by contrast, are due to cohort or time effects. Cohort effects describe differences between cohorts that may, for example, be due to changes in educational opportunities. 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 b, age a, and calender year t: $t = b + a$.

As the figures in table 4 show, the trend toward 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 results suggest that time effects appear to be more important than age or cohort effects per se in explaining changes in task inputs.

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.[12] As the results of the shift-share analysis in table 5 show, most of the aggregate changes in skill requirements result from changes in task measures within occupations.[13] The last row, which shows the results for

[12] Autor et al. (2003) provide a comprehensive analysis of the first source of variation for measuring changes in aggregate skill requirements, i.e., changes in the occupational structure of employees, but are unable to examine the second in detail.

[13] 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, E_{ct} is the share of employment in occupation c in total employment at time t, and γ_{cjt} is a measure of task j in occupation c at time t. An overbar denotes an average over time, i.e., $\bar{\gamma}_{cj} = (\gamma_{cjt} + \gamma_{cjt-1})/2$, and $\bar{E}_c = (E_{ct} + E_{ct-1})/2$. Value ΔT^b_{jt} reflects the change in ag-

Table 5
Shift-Share Analysis of Changes in Skill Requirements

	Overall									
	Nonroutine Analytic		Nonroutine Interactive		Routine Cognitive		Routine Manual		Nonroutine Manual	
1979–85	8.82		3.35		−8.43		−7.83		9.52	
1985–91	2.12		10.12		−8.05		−4.50		−.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	−.27	9.10	.15	3.21	−1.40	−7.03	−1.26	−6.57	.77	8.75
1985–91	.44	1.68	.10	10.02	.87	−8.92	−.00	−4.50	.34	−.55
1991–99	2.67	1.55	5.24	19.39	.06	−7.00	−6.04	−2.94	−.97	9.91
1979–99	.77	4.24	1.70	11.64	−.06	−7.70	−.98	−6.22	.12	6.11

NOTE.—Results are 10 × annual changes in task measures. Sample includes workers aged 18–65 who lived in West Germany and were German nationals. Occupations are defined according to the two-digit level of the classification of occupational titles.

the entire period, clearly illustrates this point. For example, task shifts between occupations represent around 15% of aggregate changes in the analytical task measure, whereas task changes within occupations account for around 85%. In the case of changes in interactive (routine manual) skill requirements, the values are quite similar, with around 13% (14%) attributable to the between shift, and around 87% (86%), 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 1% of aggregate changes in routine cognitive skill requirements. For this task measure, it is also informative to look at the two subperiods 1985/86–1991/92 and 1991/92–1998/99 because between-occupational results here 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 toward analytical and interactive activities induced labor demand shifts toward employees with high levels of education, who are viewed as having comparative advantages in performing nonroutine cognitive tasks. Table 3, panels B–D, shows that analytical and interactive task inputs are the highest for employees with high levels of education in each wave. The descriptive evidence thus confirms the

gregate employment of task j attributable to changes in the occupational distribution of employment, and ΔT^{w}_{jt} reflects the within-occupation task changes.

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 nonroutine 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 manual and cognitive routine activities are even higher than those for employees with low levels of education.

The educational upgrading and the changes in occupational skill requirements coincided with the spread of information technology at the workplace. Whereas mainframe computers dominated the data-processing units of large firms at the outset of the IT revolution, personal computers began to spread to business users from the late 1970s onward. Owing to the steady fall in prices, this spread has become more pronounced. Table 2, panel B, shows the percentage of computer users at work. The table shows that within 20 years, more than half of the workforce has come to use computers at work. Between 1979 and 1999, the spread of computers increased on average by more than 40% per annum. Table 2, panel B, also shows that the level of computer use increased with the educational attainment of employees. In 1979, more than 10% of employees with high levels of education already used a computer at the workplace, compared with less than 4% of employees with low levels of education and around 6% of employees with medium levels of education. This proportion had increased to more than 80% (30%, 55%) of employees with high (low, medium) levels of education in 1999. However, it is worth noting that, with an increase of around 45% per annum, the pace of computer diffusion was most pronounced among employees with low levels of education between 1979 and 1999 (compared with around 42% per annum for employees with medium levels of education and 30% for employees with high levels of education).

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 is consistent with the argument that IT increases demand for employees with high levels of education through shifting the task composition toward analytical and interactive activities.

V. Skill Requirements, Education, and Technology in the Workplace

A. Technological Change and Changes in Occupational Skill Requirements

Based on the model by Autor et al. (2003) outlined in Section II, there are two empirically testable hypotheses: (1) IT is a substitute for routine manual and routine cognitive activities, and (2) IT is complementary to

Table 6
Bivariate Regressions: Technological Change and Changes in Skill Requirements

	Nonroutine Analytic	Nonroutine Interactive	Routine Cognitive	Routine Manual
A:				
Δ computer use	.086***	.188***	−.312***	−.561***
	(.032)	(.031)	(.105)	(.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	.183	.337	.079	.131
No. of observations	237			
B:				
Lagged Δ computer use	−.022	.160***	−.796***	−.173***
	(.035)	(.031)	(.202)	(.065)
Dummy 1985/86–1991/92	1.470	−4.632***	−23.444***	6.005*
	(1.350)	(1.703)	(7.237)	(3.637)
R^2	.015	.195	.205	.053
No. of observations	156			
Weighted mean dependent variable	.425	.980	−.849	−.504

Note.—Dependent variables are annualized changes in task inputs. Robust standard errors are in parentheses; regressions are weighted by the number of individuals within an occupational group.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

analytic and interactive activities. This 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 these substitution and complementarity hypotheses. Because there are no hypotheses on the relationship between IT and changes in nonroutine manual task inputs derived from this theoretical model, I do not analyze this relationship in detail. I will come back to this issue at the end of this section, however, as the relationship might still be interesting.

Table 6, panel A, shows the first-difference relationship between workplace computerization and changes in occupational skill requirements. Each column represents a separate ordinary least squares (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, 1985/86 and 1991/92, as well as 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 tasks' changes within occupations 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 combined with greater declines in routine manual and routine cognitive task requirements. The coefficients are not only statistically significant but also are economically substantial, indicating, for example, that 50% of the changes in analytical task inputs were accounted for by computerization.[14] Similar calculations show that 47% of the changes in interactive task inputs are accounted for by computerization, and this explains 90% 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, conditioned on workplace computerization, the trend change in analytical skill requirements was negative in both periods 1985/86–1991/92 and 1991/92–1998/99 relative to the base period of 1979–1985/86, indicating that computerization more than fully accounts for the trend toward analytical task inputs in these later periods. In contrast, the trend change toward interactive skill inputs accelerated with time, even after conditioning on computerization. In the routine task 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 results when the lagged annual changes in computer use within an occupational cell are used as the 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 value, suggesting that there might be a time lag until the full impact of computerization is reflected in the occupational skill requirements. 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.

One might wonder whether changes in occupational skill requirements are implicitly captured by changes in the educational structure or changes in the gender structure of occupations. Table 7, panel A, shows the results of a richer specification that includes the respective controls. Neither of

[14] The unconditional (weighted) means of the dependent variables are shown at the bottom of table 6. 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 utilization of 2.465 percentage points, this implies that around 50% of changes in analytical tasks is accounted for by changes in IT usage.

Table 7
Changes in Skill Requirements and the Educational and Gender Distribution

	Nonroutine Analytic	Nonroutine Interactive	Routine Cognitive	Routine Manual
A:				
Δ computer use	.076***	.181***	−.311***	−.529***
	(.031)	(.033)	(.108)	(.163)
Δ proportion with high educational level	.064**	.081**	−.195*	.049
	(.033)	(.039)	(.115)	(.178)
Δ proportion with medium educational level	.006	.038	−.177*	.257
	(.025)	(.034)	(.104)	(.184)
Δ proportion of female employees	−.119***	.026	−.607***	−.068
	(.049)	(.049)	(.191)	(.175)
R^2	.222	.348	.112	.148
No. of observations	237			
B:				
Lagged Δ computer use	−.009	.153***	−.752***	−.187***
	(.032)	(.031)	(.211)	(.072)
Lagged Δ proportion with high educational level	−.056	.011	−.680***	.244***
	(.067)	(.048)	(.195)	(.094)
Lagged Δ proportion with medium educational level	−.015	−.103*	−.123	.145**
	(.036)	(.060)	(.140)	(.066)
Lagged Δ proportion of female employees	.110	.177***	−.714***	.045
	(.068)	(.054)	(.268)	(.178)
R^2	.059	.274	.275	.084
No. of observations	156			

NOTE.—Dependent variables are annualized changes in task inputs. Control variables are time dummies. Robust standard errors are in parentheses. Regressions are weighted by the number of individuals within an occupational group.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

the additional regressors alter the qualitative relationship between computerization and changes in occupational skill requirements found in the bivariate regressions, and even the size of the coefficients is relatively insensitive to the additional controls. Only in the analytical task equation does the coefficient drop by just over 10%. 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 bad 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. Occupations, however, with greater increases in the proportion of

Table 8
Technological Change and Changes in Skill Requirements by Educational Level

	Nonroutine Analytic	Nonroutine Interactive	Routine Cognitive	Routine Manual
Employees with a high level of education:				
Δ computer use	.027	.058	−.253**	−.052
	(.065)	(.060)	(.120)	(.077)
Dummy 1985/86–1991/92	−.356	17.304***	−10.983	.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	.084	.171	.084	.010
No. of observations	121			
Employees with a medium level of education:				
Δ computer use	.069*	.127***	−.131	−.521***
	(.040)	(.029)	(.114)	(.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	.186	.299	.067	.113
No. of observations	234			
Employees with a low level of education:				
Δ computer use	.128***	.151***	−.196*	−.309***
	(.042)	(.044)	(.120)	(.129)
Dummy 1985/86–1991/92	−3.685***	.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	.149	.148	.161	.056
No. of observations	226			

NOTE.—Dependent variables are annualized changes in task inputs. Robust standard errors are in parentheses. Regressions are weighted by the number of individuals within an occupational group.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

female employees witnessed relatively larger declines in routine cognitive skill requirements.

Panel B shows the results when lagged annual changes, instead of contemporaneous changes, are included as regressors in the analysis. The results for the relationship between computerization and changes in occupational skill requirements are similar to those reported in table 6, panel B. For changes in analytical skill requirements, contemporaneous changes in all variables seem to pick up more of the relevant information. Unlike comparison with the variable for workplace computerization, a comparison of the results for education and gender variables with those in panel A reveals that they are not insensitive to the change in specification.

Table 8 shows the relationship between workplace computerization and changes in occupational skill requirements for each educational group separately. For each occupation-education group, the results are consistent with the hypothesis of a complementary relationship between computer technology and analytical and interactive activities, while computer technology and manual and cognitive routine tasks appear to be substitutes. 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.[15] I see two potential explanations for this finding. First, 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, 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 performing the different activities. This time dimension might be more important for employees who had always performed a high number of activities. 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.

I also analyzed the relationship between workplace computerization and changes in occupational skill requirements for each birth cohort introduced in table 4. The (unreported) results continue to 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 reflection of cohort effects.

Up to this point, I have completely neglected the relationship between nonroutine manual tasks and the introduction of computer technologies in the workplace because the theoretical model does not make predictions about this relationship. However, it might still be interesting to analyze this relationship, even without a prior hypothesis. The result of a regression similar to those reported in table 6, panel A, shows a positive but insignificant (coefficient = 0.126; SE = 0.086) relationship between workplace computerization and changes in nonroutine manual tasks. This result is robust to the inclusion of additional controls (analogous to the regressions presented in table 7, panel A) and for each educational group separately (analogous to table 8).

[15] Autor et al. (2003) report similar findings on the industry level.

B. Contribution of Changes in Occupational Skill Requirements to the Educational Upgrading

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

$$ED_{ict} = \alpha_{0it} + \sum_{j=1}^{4} S_{jct}\alpha_{ijt} + v_{ict}, \tag{2}$$

with t = 1979, 1985/86, 1991/92, and 1998/99; i = high or medium; c = occupation; and $j = 1$ (nonroutine analytic tasks), $j = 2$ (nonroutine interactive tasks), $j = 3$ (routine cognitive tasks), and $j = 4$ (routine manual tasks). The value ED_{ict} is the proportion of employees with educational level i in occupation c at time t. The term S_{jct} is the measure of task j in occupation c at time t. The α_{ijt} coefficients estimated in the regression provide an estimate of the demand for employees with high (medium) levels of education as a function of occupational skill requirements. This is what Autor et al. (2003) call a "fixed coefficient" model because, by assuming the α_{ijt} coefficients 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 have risen, for example, this model will lead to an underestimation of shifts toward analytical and interactive tasks and thus to an underestimation of the educational upgrading of the workforce.

The estimated coefficients α_{ijt} of equation (2) are used to predict changes in demand for employees with high and medium levels of education as

$$\Delta\widehat{ED}_{ict} = \sum_{j=1}^{4} \Delta S_{jc\tau}\hat{\alpha}_{ij(t-1)}, \tag{3}$$

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

The results of estimating equation (2) separately for employees with high and medium levels of education and for each wave are shown in table A1 in appendix A. Panel A presents the results for the proportion of employees with high levels of education. 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 educational levels. In 1979, for example, a 1 percentage point increase in analytical skill requirements results in a 1.3 percentage point increase in the demand for employees with a 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. Panel B shows the results for the proportion of employees with a 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, however, does suggest 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 9 shows the estimated annual demand changes for employees with high and medium levels of education relative to employees with low levels of education for the subperiods 1979–1985/86, 1985/86–1991/92, and 1991/92–1998/99 and for 1979–1998/99. I estimated demand changes using the CES framework that calculates the implied shift in high (medium)/low educated relative demand consistent with observed shifts in relative employment and earnings.[16] The procedure requires me to assume an elasticity of substitution, σ, and to calculate relative wage developments. The figures in panel A are calculated with $\sigma = 1.4$, the consensus value of the elasticity of substitution between college- and high school–equivalent workers in the United States.[17] Table A2 in appendix A shows the changes in high (medium)/low educated log relative wages used for the calculation.

The pace of educational upgrading has been relatively stable since 1979, with average annual increases of 6.1 log points in demand for employees with high levels of education relative to employees with low levels of education. The respective figures for employees with medium levels of education fluctuated more. Over the whole period, however, this resulted in an average annual increase of 2.5 log 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, such as the recessions that West Germany experienced at the beginning of the 1980s and around 1992/93, might affect the outcomes in these subperiods, and the unification boom just at the beginning of the 1990s might also be important with this respect.

[16] Autor et al. (1998, 2003) describe the CES model in detail. The basic assumption is that the economy operates on the demand curve so that factors are paid their marginal products.

[17] Estimates of the elasticity of substitution between high- and low-educated workers and medium- and low-educated workers in Germany have not converged to a consensus, but they are in general smaller than 1. For comparison, I show the results for calculations using the value of 1.4. Unreported estimates show, however, that alternative values (e.g., $\sigma = 0$, or $\sigma = 2$) do not change the main conclusions drawn from table 9.

Table 9
Shifts in High-Educated-Equivalent and Medium-Educated-Equivalent Labor Demand Implied by Changes in Occupational Skill Requirement

	1979–1985/86	1985/86–1991/92	1991/92–1998/99	1979–1998/99
	A. Estimated Log Demand Shifts for Employees with High (Medium)/Low Levels of Education (100 × Annual Log Changes; $\sigma = 1.4$)			
High/low level of education	5.587	6.728	5.986	6.095
Medium/low level of education	−.774	5.326	2.755	2.452
	B. 10 × Observed Annual Changes in Within-Occupation Skill Requirements			
Nonroutine analytic	9.037	1.716	1.774	4.242
Nonroutine 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 Demand for Employees with High (Medium) Levels of Education Explained by Observed Changes in Within-Occupation Skill Requirements (%)			
High level of education	31.458	25.555	42.933	35.969
Medium level of education	77.828	−8.291	−20.946	−24.987
	D. Predicted Annual Changes in Occupational Skill Requirements Implied by Computerization (10 × Annual Changes)			
Nonroutine analytic	8.901	2.991	.519	4.129
Nonroutine interactive	4.243	9.572	15.013	9.664
Routine cognitive	−5.547	−9.001	6.519	−2.375
Routine manual	2.171	−.134	−4.503	−.964
	E. Predicted Proportion of Changes in Demand for Employees with High/Medium Levels of Education Explained by Predicted Changes in Occupational Skill Requirements Implied by Computerization (%)			
High level of education	30.967	25.603	35.438	30.638
Medium level of education	58.882	−7.046	−16.895	−17.831

Note.—Panel A: log relative demand shifts are calculated following Autor et al. (1998, 1176ff.) using a constant elasticity of substitution (CES) aggregate production function with two inputs and an elasticity of substitution, σ. Demand shifts for high/low educated labor and medium/low educated labor are calculated separately. In both cases $\sigma = 1.4$ is assumed. Table A2 in app. A shows the changes in high (medium)/low educated log relative wages also used for the calculation.

Two different measures of $\Delta S_{jc\tau}$ are used to calculate $\Delta\widehat{ED}_{ict}$ of equation (3): first, observed changes in occupational skill requirements and, second, the predicted changes in occupational skill requirements implied by computerization. In the calculations that follow, I will only use the α_{ij} coefficients of the year 1979. The relationship between task inputs and education in 1979 is closest to the precomputer era. Desktop computing, for example, only became widespread in the 1980s and 1990s.

Table 9, panel B, shows the observed changes in occupational skill requirements. Requirements for analytical and interactive skills within occupations grew between 1979 and 1998/99, with the pace of increases in interactive inputs accelerating steadily. The figures show a steady decline in occupational requirements for routine cognitive skills and also for routine manual skills.

Inserting the observed changes in occupational skill requirements, together with the $\hat{\alpha}$ coefficients of table A1 (first column), into equation (3) shows that the observed changes in occupational skill requirements account for about 36% of the changes in demand, favoring employees with high levels of education between 1979 and 1998/99 (table 9, panel C).

With respect to changes in demand for employees with medium levels of education, observed changes in occupational skill requirements point in the opposite direction. While demand for medium-educated relative to low-educated labor has increased between 1979 and 1998/99, observed task changes predicted a decreasing demand.

Panel D shows the results of the predicted changes in occupational skill requirements that are implied by computerization. These figures are based on the regression specification shown in table 6, panel A. The overall picture complies with the figures in table 9, 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 was most pronounced in the 1990s, where the predicted figures show a shift toward routine cognitive tasks.

Panel E shows the proportion of demand changes favoring employees with high and medium levels of education explained by predicted changes in occupational skill requirements implied by computerization. Between 1979 and 1998/99, occupational task changes induced by computerization accounted for 30% of the overall skill upgrading. This figure peaks at 35% (bottoms out at 25%) in the last (second) subperiod. For employees with a medium level of education, predicted figures again point in the opposite direction of demand changes.

Given that these changes in skill requirements only relate to those within occupations, these figures show the substantial economic impact of changes in skill requirements on the educational upgrading of the workforce. This analysis also reveals the role that workplace computerization plays in reshaping the occupational production process. The changes in occupational skill requirements implied by computerization account for 85% of the proportion of educational upgrading that is explained by observed task shifts.

C. A Note on Polarization

The question that has been neglected in the analysis so far is whether there has been a polarization of work in recent decades (see, e.g., Levy and Murnane 1992). The argument is that the substitution of, for example, routine cognitive tasks by computer technologies affects occupations, such as bookkeepers and bank employees, that are traditionally held by employees with medium levels of education. Nonroutine manual activities, by contrast, that at present cannot be accomplished by computers, are frequently found in occupations that are often held by employees with low levels of education, such as waiters. In this respect, the Autor-Levy-Murnane task framework diverges from the prediction of the traditional skill-biased technological change hypothesis of an increasing demand for skilled jobs relative to unskilled jobs.

In order to investigate this question, I constructed a scalar index of occupational skill requirements. This skill index is the predicted value derived from the regression presented in table A2 in appendix A (panel A, for 1979). The only difference is that I additionally included the nonroutine manual task category in the specification. This category has not been previously analyzed in detail because the task framework does not make predictions about the relationship between nonroutine manual tasks and computer technologies. However, this category now plays an important role with regard to the issue of polarization. As already stated, many occupations at the bottom of the skill distribution, such as waiters or domestic staff, involve nonroutine manual tasks. This means that it is precisely the lag in the relationship between computer technologies and this task category that suggests the possibility of employment polarization.[18]

Based on the 1979 value for this skill index, I classified occupations into 10 groups. Occupations with values in the lowest decile of the skill index of 1979 form the first group, occupations with values in the second decile form the second group, and so on.[19] This classification serves as

[18] Goos and Manning (2003) provide, based on this reasoning, evidence for increased job polarization in the United Kingdom.

[19] I also classified occupations according to mean hourly wages, a measure of the quality of occupations typically used in studies for the United States and United Kingdom. This alternative measure changes the classification of occupations, particularly in the lowest deciles, whereas the allocation of occupations in the highest deciles changes only marginally. There are a number of occupations that rank in the lowest deciles, based on the skill index, but that belong to deciles

Table 10
Distribution of Task Inputs by Deciles

Decile	Analytic Skills	Interactive Skills	Routine Cognitive	Routine Manual	Nonroutine Manual
First	.39	2.67	11.65	44.20	30.77
Second	.55	2.72	8.93	30.12	26.55
Third	1.58	3.71	23.32	36.73	12.91
Fourth	1.92	3.78	20.57	26.10	17.07
Fifth	.67	2.66	10.76	13.86	18.69
Sixth	.88	2.30	14.20	14.04	8.16
Seventh	1.63	6.39	31.04	17.71	15.39
Eighth	5.65	9.10	37.08	22.33	7.84
Ninth	11.82	13.98	44.42	22.54	9.35
Tenth	17.73	26.92	42.11	12.03	2.82

the baseline occupational distribution, representing occupational skill requirements closest to the precomputer era. Table 10 shows the distribution of task inputs in 1979 by deciles. The measure for nonroutine manual task inputs is highest in the first two deciles, while the measures for analytical and interactive task inputs increase (nearly monotonically) with each decile. Interestingly, all deciles have relatively high values in routine task inputs, but routine manual activities are more frequent in lower deciles, and routine cognitive activities are more frequent in upper deciles.

The question of whether there has been a "hollowing out" of middle-class occupations concerns the employment trends among these groups of occupations; therefore, I calculated the distribution of employment among different groups of occupations over time. Figure 5 shows the employment changes in occupational groups between 1979 and 1998/99. This figure shows that employment has grown by nearly 3 percentage points in the tenth decile and by about 2.5 percentage points in the ninth decile of the skill index between 1979 and 1998/99. Examples of occupations grouped in these two categories are engineers, consultants, tax accountants, merchandisers, dealers, and scientists. In addition, figure 5 shows that employment has also grown in occupations belonging to the first decile of the skill index, although the rate (about 1 percentage point) was less pronounced than in the top-two deciles of the skill distribution. Examples of occupations in the first decile are waiters, blacksmiths, domestic staff, hoteliers, and casters. By contrast, employment decline has been most pronounced in occupations in the third decile of the skill distribution, which includes occupations such as office clerks, machine operators, and galvanizers. Thus, this tentative analysis suggests that the

in the middle of the distribution, based on average wages. Examples are ceramicists, blacksmiths, and casters. Wages in these occupations are typically set in union pay agreements, which explains their high wage levels relative to skill requirements.

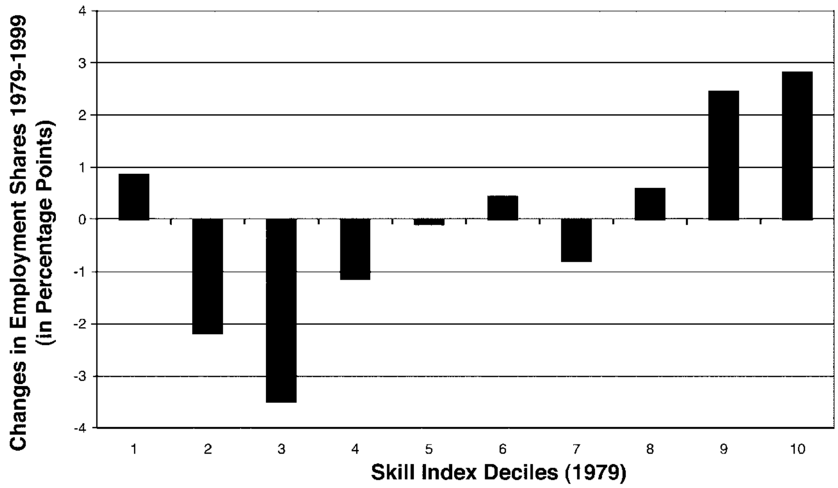

FIG. 5.—Changes in employment shares by occupational skill index deciles

employment trends are consistent with a process of employment polarization.[20]

VI. Conclusion

West Germany (together with other continental European countries) has attracted attention because of the stability of its wage structure, raising the question of whether or not West Germany has experienced similar changes in skill demand to those in the United States and the United Kingdom in recent decades. This article advances the debate by looking beyond wages and by offering a detailed characterization of changing occupational skill requirements in West Germany between 1979 and 1998/99. In addition, I provide detailed evidence on the nuanced version of the skill-biased technological change hypothesis introduced in the literature by Autor et al. (2003).

The results suggest that occupations today involve greater complexity than they did 2 decades ago. In recent decades, occupations have experienced a shift toward 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

[20] An exception is the seventh decile; despite ranking relatively high in the skill index distribution in 1979, occupations in this category have witnessed a decline in employment. Bearing in mind the occupations and task inputs in this group, however, this evidence is not surprising, given that cognitive and manual routine activities are frequent in this decile. Examples of such occupations are bank clerks and insurance clerks.

groups, and within occupation-age groups. In addition, the results indicate that these changes have been intensified by the diffusion of computer technologies in the workplace. This is due to the fact that computers substitute for workers performing manual and cognitive routine tasks but complement workers in performing analytical and interactive activities.

In addition, I used direct skill measures—which are unlikely to be influenced by factors such as unions, which typically distort the relationship between wages and skills—to show that West Germany (and probably other continental European countries as well) has witnessed changes in skill requirements similar to those in the United States in recent decades. This evidence moves the debate over the differential wage developments in continental European countries and the United States/United Kingdom forward, and the question that now arises is why similar changes in skill requirements in all of these countries have not led to similar changes in the structure of wages.

Appendix A

Table A1
OLS Results: Educational Requirements within Occupational Groups as a Function of Task Inputs

	1979	1985/86	1991/92	1998/99
	A. Dependent Variable: Proportion of Employees with a High Level of Education			
Nonroutine analytic	1.321***	1.639***	1.102***	1.267***
	(.337)	(.416)	(.217)	(.279)
Nonroutine interactive	1.332***	.129	1.464***	.706***
	(.307)	(.566)	(.232)	(.186)
Routine cognitive	−.061	−.301*	−.576***	−.039
	(.110)	(.159)	(.131)	(.223)
Routine manual	−.206	−.476***	−.021	.086
	(.120)	(.157)	(.077)	(.232)
R^2	.468	.388	.673	.583
No. of observations	83	83	80	80
	B. Dependent Variable: Proportion of Employees with a Medium Level of Education			
Nonroutine analytic	−.436	−1.007*	−.622*	−1.110***
	(.466)	(.534)	(.328)	(.364)
Nonroutine interactive	−.241	−.047	−.980***	−.087
	(.424)	(.726)	(.351)	(.343)
Routine cognitive	.019	.631***	.642***	.290
	(.152)	(.205)	(.198)	(.291)
Routine manual	.209	1.013***	.171	−.194
	(.167)	(.202)	(.116)	(.303)
R^2	.065	.272	.251	.249
No. of observations	83	83	80	80

NOTE.—Robust standard errors are in parentheses; each regression includes an intercept term.
* Significant at the 10% level.
*** Significant at the 1% level.

Table A2
The High (Medium)/Low Educated Wage Premium and Changes in Log Relative Wages

	A. High (Medium)/Low Educated Wage Premium			
	1979	1985/86	1991/92	1998/99
Log high/low wage	.262	.274	.284	.286
Log medium/low wage	.056	.053	.101	.091
	B. Changes in High (Medium)/Low Educated Log Relative Wages (100 × Annual Log Changes)			
	1979–1985/86	1985/86–1991/92	1991/92–1998/99	1979–1998/99
High/low log relative wages	.120	.160	.038	.128
Medium/low log relative wages	−.046	.808	−.150	.185

Note.—Panel A: log high (medium)/low educated wage differentials estimated with cross-sectional log hourly wage regressions. Specifications include dummies for educational groups (high and medium), a quartic in experience, a female dummy, a part-time dummy, and occupational and sector dummies. Hourly wages are constructed using information on monthly earnings that are included in the survey grouped into 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.

Appendix B

Data

The Qualification and Career Survey is a survey of employees carried out by the BIBB and IAB. It includes four cross sections launched in 1979, 1985/86, 1991/92, and 1998/99, each covering about 30,000 individuals (men and women). The data cover a wide range of industries, both services and manufacturing, listed in the classifications below.

Manufacturing, including 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 Jewelry
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

The target population is not uniform across the four waves. Because of 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 were 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.

The descriptive evidence in Section IV is based on individual-level data. The regressions in Section V are performed on the occupational level. In the data set, employees are classified according to their occupation. The categorization corresponds to that of the German Federal Employment Bureau in 1988. I use the two-digit level of classification, which includes about 80 different occupations. For the analysis in Section V, I aggregate the micro level data of the four cross sections into occupational cells and use group means for the analysis.

Theoretically, there should be 332 observations in the stacked data set (83 occupations observed in four waves). It turns out that 94.5% of the occupations are observed in all waves, whereas 1.5% of the occupations are observed only once, 1.2% are observed twice, and 2.8% are observed three times. One might wonder whether there are occupations that disappear over time and others that are newly created, particularly because a number of information technology occupations have been created by the German Federal Institute for Vocational Training in recent years. 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 were one of the newly founded information technology occupations. Overall, the occupations that were observed less than four times seem to be a random draw. In particular, the pattern of their appearance is clearly not driven by the question of interest.

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