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OCCUPATIONAL UPGRADING AND CHANGES IN CAPITAL USAGE IN U.S. MANUFACTURING INDUSTRIES, 1989–98

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Proposed explanations of the role of microprocessor technology in the shifts toward relatively highly skilled workers that have occurred within industries since the mid 1970s have implications for the types of occupations that should be most affected by computerization. In this study, I measure the effects of changes in capital usage, and of the level of high-tech capital usage in particular, on skill change caused by employment shifts among detailed occupations within industries over the 1989–98 period. The study utilizes data collected by the Bureau of Labor Statistics Occupational Employment Statistics (OES) survey, which produces data on employment and wages for over 700 occupations in non-farm establishments, by industry. These data provide an unprecedented opportunity to determine the types of occupations and skills that are most affected by changes in capital and technology usage, by making it possible to measure skill change within relatively narrowly defined occupational groups.

INTRODUCTION

The capital-skill complementarity hypothesis suggests that skilled workers are less easily substitutable with physical capital than are unskilled workers (Griliches, 1969). Recent evidence suggesting a similar relationship between increased usage of skilled labor and the use of micro-processor technology in particular have sparked attempts to make explicit the role of technology in capital-skill complementarity. These newly proposed explanations contain at least some implications concerning the effects of changes in capital usage (and high-tech capital usage) on employment and skill levels within relatively narrowly defined occupational groups.

In this study, I attempt to determine the degree to which capital deepening, and the level of high-tech capital usage in particular, appear to be factors related to the employment shifts of detailed occupations within industries over the 1989–98 period. Average skill levels have been rising within manufacturing industries as a result of employment shifts toward more highly skilled workers since at least 1958, when measures classifying workers by non-production worker/production worker status first became available from the Annual Survey of Manufacturers. These data reveal that non-production workers' share of the industry wage bill increased over the entire 1958–87 period, and exhibited an especially rapid increase over the 1979–87 period. Studies utilizing these data, including Berman, Bound, and Griliches (1994), and Goldin and Katz (1998), have further shown that shifts toward relatively highly skilled workers that occurred both early in this century and during the 1980s were positively related to measures of change in capital usage.

The present study investigates the relationship between capital usage and recent shifts toward relatively highly skilled workers utilizing data collected by the Bureau of Labor Statistics Occupational Employment Statistics (OES) survey, which produces data on employment and wages for over 700 occupations in non-farm establishments, by industry. These data provide an unprecedented opportunity to determine the types of occupations and skills that are most affected by changes in capital and technology usage, by increasing the level of industry and occupational detail at which employment shifts within industries can be measured.

The analyses reveal that shifts toward more highly skilled workers within industries continued over the 1989–98 period, with an important difference from the past. Before 1989, much of the shift toward relatively highly skilled workers could be summarized as a shift from production worker employment to non-production worker employment. Over the 1989–98 period, the employment share of non-production workers actually fell slightly; all of the shift toward more highly skilled workers occurred within the non-production worker and production worker groups.

The results further reveal a wealth of information about the detailed occupational composition of the recent employment shifts within industries that could not, in the past, be investigated using available data. The results reveal that large employment shifts toward computer scientists, computer engineers, and a variety of "product," "process," and "quality" engineers that occurred over the period have a positive, statistically significant relationship with a measure of high-tech capital usage. The results support Goldin and Katz's (1998) arguments that recent evidence of computer-skill complementarity is the result of the high machine maintenance/machine repair segment of production processes based on microprocessor technology.

The paper is organized as follows. In the following section, I discuss recent evidence of the role of high-tech capital in the increases in average skill levels that occurred in manufacturing industries over the 1980s. In Section II, I summarize some of the explanations that have been recently proposed concerning the role of particular technologies in capital-skill complementarity. In Section III, I describe the wage and employment data for detailed occupations that are now being produced by the Bureau of Labor Statistics OES survey, and I discuss the data on capital and output that are used in the study. In Section IV, I discuss the measure of skill change that makes use of these data, and which is similar to that used in recent research by Berman *et al.* (1994). In Section V, I discuss the estimation equation. Finally, in Section VI, I discuss the pattern and correlates of skill change that are suggested by the analyses, and I attempt to assess the degree to which the results are consistent with recently proposed explanations of the role of technology in capital-skill complementarity. Section VII concludes.

I. Evidence of the Role of High Tech Capital in Increased Skill Levels in Manufacturing

Average skill levels have been rising in the manufacturing sectors of developed economies for over three decades as a result of both shifts in the industrial composition of employment and, primarily, increases in the relative demand for skilled workers within industries.[1] Using plant-level data for U.S. manufacturing

[1]See Machin and Van Reenen (1998) for an analysis of OECD countries.

for the 1970s and 1980s, Dunne, Haltiwanger, and Troske (1996) have further shown that this increase in aggregate skill levels is in fact dominated by *within plant* changes.

These patterns have led many to suspect the role of skill-biased technological change in the skill upgrading over this period. Berman *et al.* (1994), Autor, Katz, and Krueger (1997), and Berndt, Morrison, and Rosenblum (1992) each found that increases in non-production workers' share of the industry wage bill over the 1980s were positively related to both changes in overall capital intensity and to various measures of high-tech capital usage. Each of these studies utilized industry-level data. Doms, Dunne, and Troske (1997, hereafter DDT) studied this issue using plant-level data containing information about the use of specific technologies. DDT found that, although the share of non-production workers within plants is positively related to the share of computers in investment, as in other studies, this measure of skill change has almost no relationship to a count measure of the number of technologies used to process materials and control machinery. DDT further found little relationship between the share of computers in investment and the average wage of either production workers or non-production workers, while the number of technologies used in the plant was positively correlated with wages for both groups. According to DDT, these findings might suggest that technology adoption over the period was concentrated among high wage plants.

II. Recent Attempts to Explain the Role of Technology in Capital-Skill Complementarity

Goldin and Katz (1998) argue that capital-skill complementarity first became an important factor during and after the 1890s, when electrification facilitated the emergence of highly capital intensive production processes. The eventual shift in some industries to batch and continuous process methods of production caused especially large increases in the demand for skilled labor in these industries, as a result of their large machine installation/machine maintenance component. Goldin and Katz (1998) argue that capital and skilled labor are always complements in the machine-installation/machine-maintenance segment of manufacturing, in which workers must be able to read and understand technical manuals, decipher blueprints, and in many cases understand electricity, chemistry, and algebra. Goldin and Katz suggest that the most recent shift toward skilled workers has resulted from the shift toward production processes based on microprocessor technology (hereafter IT), for which machine installation/machine maintenance operations are also a relatively large segment of the production process.

Insight into the nature of skill requirements associated with maintenance-intensive production processes is provided by Zuboff's (1988) study of U.S. pulp mills. Zuboff argues that the effects of technology on the organization of work and on skill requirements depend both on intrinsic aspects of particular technologies as well as on the larger context of market, social, and governmental constraints posed by the external environment. According to Zuboff, continuous process technologies have considerable intrinsic power to increase skill requirements as a result of the nature of the production process. Continuous process production requires a high degree of worker responsibility in the form of ongoing judgments that must be made on the basis of implicit skills, such as the ability to detect change in the status of the process on the basis of physical cues. Partly as a result of the high level of responsibility historically accorded workers in this process, the shift-over to automation has in many cases been organized in ways that accord these workers equally challenging tasks.

Bresnahan (1999) develops the relationship between skill change and IT by distinguishing the various functional uses of computers and the types of organizational changes associated with them. Organizational computing encompasses such uses as corporate accounting systems or transactions processing systems, while scientific and technical computing includes the use of computers to measure and control production processes, and individual computing includes functions such as word processing. According to Bresnahan, the numerous previous studies that have measured IT using data on the computer use of individual workers have overlooked the largest part of computing, which is organizational computing.[2]

Bresnahan (1999), and Bresnahan, Brynjolfsson, and Hitt (1999, hereafter BBH) argue that the main impacts of organizational computing on labor demand involve dynamics of limited substitutability and the changing structure of organizations. Limited substitutability of computers for cognitive skills and interactive skills has led to both job redesign and changes in the employment shares of many types of workers. One widespread example is the decline in the employment shares of low-level clerical jobs that have resulted as clerical operations have been automated and their tasks recombined into higher skilled office jobs.

Organizational complementarity between computers and skilled workers, especially managers and professionals, has also had both of these effects. BBH describe complementarities between human judgment and the enormous storage and retrieval capacities of microprocessor technology, between decentralization of decision making and the enormous increases in information made available, and between human creative intelligence and the greatly expanded creative opportunities made possible by the technologies. According to BBH, these complementarities demand extraordinary management and technical skill, and probably will continue to do so for some time to come. Most importantly for the current study, these arguments suggest the need for a measure of skill change that provides much finer distinctions between types of skills than that used in most previous studies.[3]

The explanations of (high-tech) capital-skill complementarity discussed above have somewhat differing implications regarding the types of skills and occupations that should be most affected by computerization. Goldin and Katz's argument suggests that the shift to microprocessor technology should lead to a permanent increase in the share of occupations that are involved in the installation and maintenance of microprocessor-based operations. Presumably, these include occupations skilled in the setup and maintenance of microprocessor based

[2]These include Autor *et al.* (1997), DiNardo and Pischke (1997), Krueger (1993), and Levy and Murname (1996). As noted by Bresnahan (1999), some of these authors have interpreted their findings to suggest that a broader, organizational focus similar to that of Bresnahan *et al.* (1999) is more appropriate.

[3]Bresnahan (1999, pp. F408–9).

operations, including both hardware technicians and a variety of relatively highly skilled computer-related occupations including computer engineers, systems analysts, and computer programmers. Unfortunately, the OES data do not include the large numbers of computer maintenance-type jobs that are contracted out by firms, and that are therefore not counted as employment for the manufacturing industry actually using their labor. The current analysis will therefore provide only a partial view of the effects of capital intensity and computerization on the mix of these jobs.

BBH's arguments emphasize a broader impact of computerization, as a wide variety of skilled occupations are affected by the complementarities and increased creative potential made available by computer technology. BBH and some others have, in addition, emphasized the potential for computerization to greatly affect managerial jobs in particular.

III. Data

III.1. *Employment and Wage Data from the Occupational Employment Statistics Survey*

Data now being produced by the Bureau of Labor Statistics OES survey have made available a variety of new alternatives for measuring skill change caused by occupational shifts within 4-digit SIC industries. The OES survey is an annual mail survey measuring occupational employment and wage rates for wage and salary workers in non-farm establishments, by industry. Industry-specific survey forms/instructions request that respondents tally the employment totals of workers in each of approximately 200 detailed occupations, along with the number, by occupation, which earn wages in each of 11 wage ranges. The OES survey uses these data to produce estimates of employment, average (mean) wage, and median wage for over 750 detailed occupations by 3-digit SIC industry.

The data used for this study are OES establishment-level data for the years 1989 and 1996–98 (combined) that have been aggregated to the 4-digit SIC industry level. The data include only employment data for the year 1989, and both employment and wage data for the years 1996, 1997, and 1998.[4]

During 1989 and all years prior to 1996, the sample for any given industrial sector was collected once every three years, and the full, all-industry sample of approximately 750,000 establishments was collected over three consecutive years. The sample frame for the 1989 data used in the study included all manufacturing sector establishments that reported to the State Employment Security Agencies (SESA) for Unemployment Insurance (UI) purposes for the second quarter of 1988. UI reporting units with more than 250 employees were included in the sample with certainty, and other units received a sampling weight equal to the reciprocal of the probability of selection, adjusted for survey non-response. The response rate for the 1989 survey round was about 80 percent.[5]

[4]The OES survey began collection of wage data for all industries in 1996.

[5]For a more detailed discussion of the survey methods used in the production of the 1989 data, see Appendix A, "Survey Methods and Reliability of Estimates," in *Occupational Employment in Manufacturing Industries*, pp. 110–15, U.S. Department of Labor, Bureau of Labor Statistics, Bulletin 2376, March 1991.

Beginning in 1996, one third of a total sample of 1.2 million establishments is collected each year for all industries, resulting in full collection of the sample over a three-year period. The sample frame for the 1996 data used in this study included all manufacturing establishments that reported to the SESA during the second quarter of 1995. The sample frame for the 1997 data included all manufacturing establishments that reported during the third quarter of 1996, and the sample frame for the 1998 data included establishments that reported during the second quarter of 1997. For each of the years 1996–98, one third of all establishments employing over 250 workers were included in the sample with certainty, and other units received a sampling weight equal to the reciprocal of the probability of selection. The response rate for the 1996 survey round was about 73 percent and the response rate for both the 1997 and 1998 survey rounds was about 79 percent.

The data from the 1996, 1997, and 1998 survey rounds comprises the full OES sample. These data were weighted and combined such that the combined sample represented the universe. Combining the separate years of data involved updating the 1996 and 1997 wage data to reflect wage inflation, using update factors developed by the Bureau of Labor Statistics Employment Cost Index (ECI) program. These update factors measure the rate of change in wages from fourth quarter 1996/97 to fourth quarter 1998 for nine major occupational groups.[6]

The 1989 and 1996–98 data otherwise differ with respect to the stratification of the sample, the method of adjusting for non-response, and occupational coding. The 1996–98 samples were stratified by MSA/3-digit SIC/size class, while the 1989 sample was stratified by state/3-digit SIC/size class. The method of adjusting for non-response in the 1989 survey involved multiplying the sample-weighted employment of each 3-digit SIC/size class cell by a "non-response adjustment factor." This factor is equal to the total sample-weighted employment for the cell divided by the sample-weighted employment of the usable units obtained for the cell. The method of adjusting for non-response in the 1996–98 samples involved imputing for non-responding units using current employment data from a respondent that most closely matches the area/SIC/size class of the non-respondent. The wage data used for each imputed establishment utilized the wage distribution for each occupation, defined by area, SIC, and size class.

Finally, several occupation titles and codes were either added, deleted, or changed over the 1989–98 period. These data were re-coded to reflect a common occupational definition in both the years 1989 and 1996–98.

III.2. *Data on Capital, Output, and the Share of Computers in Investment*

All of the data are aggregated to the 4-digit SIC level. The most important advantage of using data by detailed 4-digit SIC industry for the purpose of

[6]For a more detailed discussion of the survey methods used in the production of these data see Appendix B, "Survey Methods and Reliability of the 1997 OES Estimates," in *Occupational Employment and Wages*, pp. 107–13, U.S. Department of Labor, Bureau of Labor Statistics, Bulletin 2516, August 1999.

analyzing skill change concerns the dominant role of the production process (batch, continuous process, mass production) in determining occupational staffing patterns. The production process affects the degree of industry capital intensity, average educational levels, as well as the bureaucratic structure and choice of human resource policies. Industry aggregations to the 3-digit or 2-digit SIC levels combine at least some industries which use different production processes and which have different staffing patterns. In these cases, there is a confounding of the effects of shifts in the industrial composition of the group with the effects of shifting relative demand shares for occupations within industries in the group. Although the problem is not eliminated by using data at the 4-digit SIC level, it is at least minimized.

The capital stock and output data used in this analysis were obtained from the NBER Manufacturing Productivity Database. Data on the real value of shipments by 4-digit SIC industry, obtained from the NBER Manufacturing Productivity Database, were used as a proxy for industry output. Data by 4-digit SIC industry on the share of computers in total industry investment for the year 1992 were obtained from the U.S. Bureau of the Census. Following Berman *et al.* (1994), I use these data as a proxy for the cross sectional variation in computers as a share of the total capital stock. The mean rates of change of the capital and output variables are shown in Table 1.

TABLE 1

MEAN RATES OF CHANGE OF THE WAGE BILL, EMPLOYMENT SHARE OF NON-PRODUCTION WORKERS WITHIN 4-DIGIT SIC INDUSTRIES

	1959–73	1973–79	1979–89	1989–96
dS_N (change in non-production workers' share wage-weighted employment)	0.073	0.208	0.378	0.125
dS_E (change in non-production workers' share of employment (unweighted))	0.086	0.189	0.286	–0.014
$d\ln(K)$	4.31	3.37	2.47	1.95
$d\ln(Y)$	4.09	2.25	1.83	2.93
$d\ln(K/Y)$	0.218	1.11	0.644	–0.975

Source: Tabulations based on the Annual Survey of Manufacturing, 458 4-digit SIC industries.

Notes: Data are weighted by industry average share of total manufacturing wage bill, except dS_E, which is weighted by industry average share of total manufacturing employment.

$dS_N = 100 \times$ annual change in non-production workers' share of industry wage bill.

$dS_E = 100 \times$ annual change in non-production workers' share of industry employment.

$d\ln K = 100 \times$ annual change in log of capital stock.

$d\ln Y = 100 \times$ annual change in log of real output.

$d\ln K/Y = 100 \times$ annual change in ratio of capital stock to real output.

IV. MEASURING INDUSTRY SKILL CHANGE

IV.1. *Earlier Measures*

Detailed occupational employment and wage data have not before been available to researchers interested in measuring skill change in detailed industries. Available data have often limited the measure of skill change to the change in non-production workers' share of the industry wage bill. The data used to produce this measure are often obtained from the NBER Manufacturing Productivity Database, which contains data collected by the Annual Survey of Manufacturers for 4-digit SIC manufacturing industries for the years 1958–96. These data contain employment and payroll totals for workers classified by production worker/non-production worker status, in addition to measures of output, total factor productivity, and a variety of measures of capital spending. The NBER Manufacturing Productivity Database is maintained by Gray and Bartelsman.[7]

These data show that non-production workers' share of the wage bill has been rising since at least 1958. According to Berman, Bound, and Griliches (1994, hereafter BBG), the blue collar/white collar occupational classification of these data is also a fair approximation of educational classifications; only 17 percent of blue-collar workers had greater than a high school education in 1987, while similar numbers for clerical, sales, and managers/professionals are, respectively, 35 percent, 70 percent, and 78 percent.

Table 1 shows the average annual change in non-production workers' share of the wage bill and of employment within manufacturing industries over the 1959–96 period, along with the average annual change in the capital stock, real output, and the capital to output ratio. Non-production workers' share of both industry employment and the wage bill increased over the 1959–89 period, and this shift was most rapid over the 1979–89 period. Over the recent 1989–96 period, non-production workers' share of the industry wage bill continued to rise at a slower rate, while their share of industry employment actually fell slightly.

Given that non-production workers' share of industry employment fell slightly over the most recent period, the continued rise in their share of the average industry wage bill suggests one of two possibilities. Either the average wages of non-production occupations rose faster than the average wages of production worker occupations (after controlling for both detailed occupation and industry), or employment shifts toward relatively highly skilled workers within the non-production worker group dominated any that may have occurred within the production worker group.

The first possibility was investigated using Current Population Survey data for the manufacturing sector for the years 1989 and 1998. After controlling for detailed industry and occupation, the average wage of non-production worker occupations rose about 1.8 percent per year, while the average wage of production worker occupations rose about 2.3 percent per year.[8] Since production worker wages actually rose faster than non-production worker wages, it is clear that all of the increase in non-production workers' share of the industry wage bill resulted from a rate of occupational upgrading within the non-production worker group that exceeded that of the production worker group.

[7]See Bartelsman and Gray (1996) for a description of the dataset.

[8]CPS data for 1989 and 1998 outgoing rotation groups were used to calculate the log change in mean wages by detailed industry (1987, 3-digit Standard Industrial Classification) and occupation (1980, 3-digit Standard Occupational Classification). The mean log change of wage rates was then calculated using the appropriate CPS weights.

The recent decline of non-production workers' employment share is at least partly due to the fact that the employment share of non-production workers is counter-cyclical; rapid economic growth over the mid-1990s worked to put downward pressure on the employment share of non-production workers. Figure 1 gives a broader view of the changes over time in non-production workers' employment share, revealing an upward shift of the share of non-production worker employment that occurred primarily over the 1979–83 period and that has gone relatively unchanged until the present.

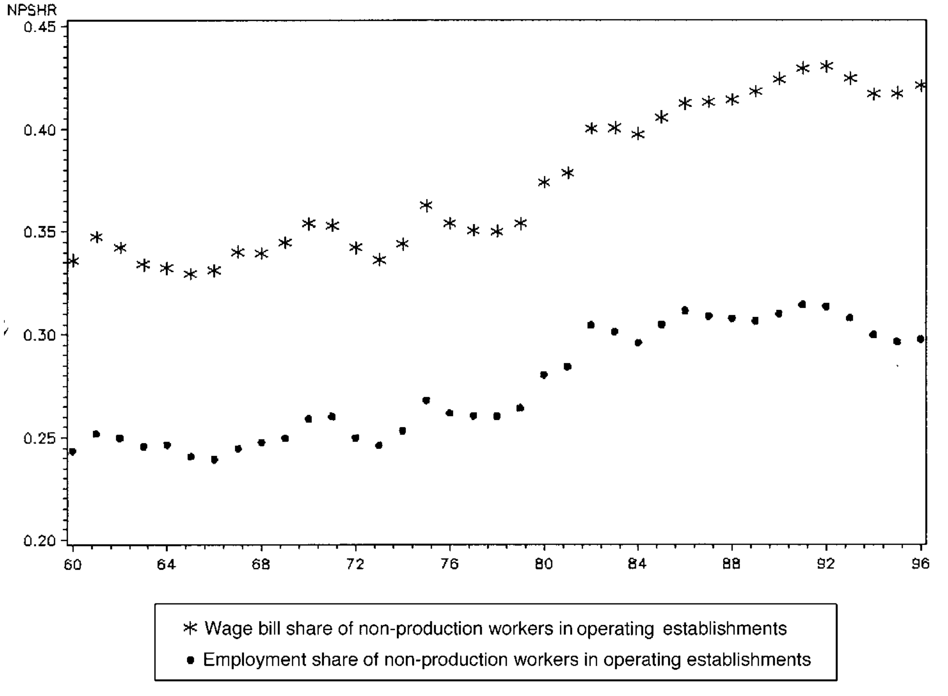

Figure 1. Non-production Workers' Share of Employment and Wage Bill

Not visible from Figure 1 is the continued shift toward more highly skilled workers that has gone on *within* the non-production worker group and, to a much less extent, the production worker group. The goal of this study is to measure and examine the correlates of this continued occupational upgrading over the most recent period.

IV.2. *Measuring Occupational Upgrading*

A measure of *occupational upgrading* (downgrading) is a measure of the effect that occupational employment shifts alone have had on the average wage of some group. It is important to clearly distinguish occupational upgrading (or downgrading) from the other factor that affects the average wage of a group. Changes in the average wage of an occupational group can be caused by (1) occupational upgrading/downgrading, (2) changes in the wages of individual occupations within the group, or (3) both. A change in the average wage of an occupational group will be equal to occupational upgrading/downgrading for the group only in cases in which the relative wages of individual occupations within the group are unchanged.

The measure of occupational upgrading used in this study is similar to that which BBG produced for the manufacturing sector as a whole using CPS data. They first produced a measure of each occupation's relative skill level using regressions, run separately for the beginning and end years of the period, of log wages on the various occupational categories. The coefficients for the beginning and end year of the period were then averaged for each occupation and applied to (multiplied by) the employment shifts of the corresponding occupational categories. The sum of these wage-weighted employment shifts gives the percentage by which occupational shifts alone would have caused average wages to rise (or fall) if the wages of individual occupations could have been held constant over the period.[9]

BBG found that the effect on the average wage in manufacturing resulting from employment shifts among ten occupational categories over the 1973–87 period was a 6.3 percent increase. Slightly over half of this increase resulted from employment shifts from the production worker group to the non-production worker group, while the balance of occupational upgrading occurred within the production and non-production worker groups. Within the non-production worker group, upward pressure on the average wage of the group was caused by an 18 percent decrease in the share of clerical workers, combined with an 11 percent increase in the share of managerial and professional workers. Within the production worker group, upward pressure on the average wage of the group was caused by a 5 percent decline in the share of operators combined with a 20 percent increase in the share of skilled craft persons over the period.[10]

The large size of the OES sample, together with the high level of both industrial and occupational detail at which the data are collected, make the OES data very well suited for use in producing the measure of occupational upgrading described above. Moreover, these characteristics of the OES data make it possible to produce this measure of occupational upgrading at the level of detailed industries, thus allowing its use as the dependent variable in regression analyses. While BBG were able to decompose their measure of occupational upgrading into within and between industry components, their data did not allow for its production at the level of detailed industries.

These considerations are important, given the bulk of research suggesting that the majority of the occupational upgrading that occurred over the 1978–89 period occurred within industries. Until now, regression studies attempting to examine the correlates of occupational upgrading within industries have had a very limited set of choices with respect to the dependent variable used.

The measure of occupational upgrading that BBG used can be produced using the OES data with a single modification. Because wage data are not available from the OES survey for the year 1989, the measure of occupational (relative)

[9]Berman *et al.* (1994) ran separate regressions for the years 1973, 1979, and 1987, and averaged the coefficients for a given period. For the 1973–87 period, for example, the coefficients for 1973 and 1987 were averaged and applied to the occupational employment shifts for that period.

[10]See Berman *et al.* (1994, p. 372).

skill level used in the measure of occupational upgrading had to be modified. The measure of occupational relative skill level that BBG used (described earlier) is a set of estimated coefficients, from the beginning and end years of the period, that measure the average relative wage of each occupation over the period. The similar measure of occupational relative skill level that is available from the OES data is the set of coefficients from a regression of log wages on detailed occupational categories, using wage data for the year 1998 only. The measure of occupational upgrading within a given industry that is produced using the OES data is:

$$W/I_{ou} = \sum_{0} \ln\,[\bar{W}_{oi}/\bar{W}_{i}]_{1998}\,[[\bar{E}_{oi}/\bar{E}_{i}]_{1998} - [\bar{E}_{oi}/\bar{E}_{i}]_{1989}]$$

where:

$\bar{W}_{oi}$ = average wage of occupation o in industry i,
$\bar{W}_{i}$ = average wage in industry i,
$\bar{E}_{oi}$ = estimated employment in occupation o in industry i,
$\bar{E}_{i}$ = estimated employment in industry i.

The index of occupational skill level used in the measure is thus specific to the year 1998. This causes the measure to overstate occupational upgrading for industries in which, on balance, occupations that were gaining share over the period were also becoming more skilled relative to other occupations over the period, and vice versa.

The measure of occupational upgrading also suffers from the criticism that the use of wages as a measure of skill level is tautological, and confounds short-term effects of market shifts and underlying skill levels. Somewhat mitigating this criticism, however, are recent studies by Levine (1992) and Groshen (1991) suggesting that data classified by occupation and industry actually control well for differences in standard human capital variables, such as are often used as a measure of skill.

TABLE 2

Mean Rates of Occupational Upgrading/Downgrading (1989–98)

Measures of Occupational Upgrading	Within Industries 1989–98	Between Industries 1989–98	Across all Industries 1989–98
All workers	0.009	0.0014	0.01
Non-production workers	0.026	–0.0003	0.026
Production workers	0.007	0.0045	0.012

Source: Occupational Employment Statistics survey, U.S. Bureau of Labor Statistics.

Table 2 reports the average measure of (within-industry) occupational upgrading for the manufacturing sector, for the non-production worker and production worker groups separately. Also reported in Table 2 are measures of occupational upgrading that result from employment shifts between industries, as well as total (across all industries) occupational upgrading. Between-industry occupational upgrading is equal to the sum over all industries of the average relative wage of an industry multiplied by the change in its share of total manufacturing employment over the period:

$$B/W_{ou} = \sum_{1} \ln [\bar{W}_i/\bar{W}]_{1998} [[\bar{E}_i/\bar{E}]_{1998} - [\bar{E}_i/\bar{E}]_{1989}]$$

where:

$\bar{W}_i$ = average wage of industry i,
$\bar{W}$ = average wage in manufacturing sector,
$\bar{E}_i$ = estimated employment in industry i,
$\bar{E}$ = estimated employment in manufacturing sector.

Total occupational upgrading is equal to the sum of within-industry and between-industry occupational upgrading[11]:

$$T_{ou} = B/W_{ou} + W/I_{ou}.$$

Occupational upgrading within the non-production worker and production worker groups over the 1989–98 period worked to increase the average wages of these groups by 2.6 percent and 0.7 percent respectively. (Note that the actual average wages of these groups could have risen or fallen as a result of changes in the relative wages of individual occupations within the group.) Within-industry occupational upgrading dominated the effects of between-industry shifts for the non-production worker group, while between-industry shifts contributed substantially to total occupational upgrading for the production worker group.

Table 3 shows the average within-industry employment shifts of those occupations that exhibited the largest employment shifts over the period, calculated separately for the non-production worker and production worker groups. The employment shifts most responsible for the results of the non-production worker group reported in Table 2 included increases in professional workers and decreases in clerical workers. Gaining about 2.3 percent of non-production worker employment within industries were a combination of engineering occupations and computer scientist occupations, and losing about 3 percent of non-production worker employment were clerical occupations, including secretarial and bookkeeping occupations, as well as computer operators.[12]

The employment shifts most responsible for the results of the production worker group included employment shifts within the craft worker group toward machinists and machinery maintenance mechanics and away from sheet metal workers and precision inspectors.

V. The Estimation Equation

V.1. *Recent Similar Studies*

The estimation equation is similar to the factor share equation used in recent studies by Goldin and Katz (1998) and Berman *et al.* (1994). The factor share

[11]Average within-industry occupational upgrading is a weighted average of the measure of within-industry occupational upgrading for each industry, in which the weights are each industry's average share of manufacturing employment over the period.

[12]These engineer and computer scientist groups were collected in residual occupational categories; the detailed occupational composition of these groups was approximated with reference to an auxiliary data set maintained by the OES Survey, discussed later in the paper.

TABLE 3

AVERAGE EMPLOYMENT SHARES WITHIN U.S. MANUFACTURING INDUSTRIES

		Share 1989	Share 1998	Change	1998 Wage
Non-production workers		**0.341**	**0.329**	**–0.012**	**21.07**
	Managers	0.20	0.20	0.0	32.61
	General managers	0.073	0.075	0.002	36.54
	Professionals	0.29	0.32	0.03	23.16
25199	Computer scientists and related workers	0.001	0.011	0.01	21.57
22199	Engineers (residual category)	0.018	0.028	0.01	29.37
22127	Computer engineers	0.005	0.008	0.003	29.08
25102	Systems analysts	0.01	0.009	–0.001	16.77
22126	Electrical engineers	0.018	0.017	–0.001	28.62
22505	Electrical eng. tech.	0.014	0.012	–0.002	18.13
	Sales workers	0.094	0.097	0.003	20.89
49005	Sales rep., scientific	0.012	0.015	0.003	24.07
49008	Sales rep., except retail and scientific	0.042	0.036	–0.006	21.93
	Clerical workers	0.359	0.328	–0.031	12.52
58028	Shipping, receiving clerks	0.046	0.049	0.003	11.05
55323	Order clerks	0.013	0.015	0.002	11.91
55305	Receptionists	0.006	0.009	0.003	9.91
56011	Computer operators	0.006	0.003	–0.003	14.66
55338	Bookkeeping, accounting clerks	0.039	0.033	–0.006	12.46
55108	Secretaries	0.052	0.035	–0.017	13.17
	Service workers	0.055	0.049	–0.006	10.56
67005	Janitors	0.034	0.03	–0.004	9.84
63047	Guards	0.009	0.006	–0.003	11.12
Subtotal		**100%**	**100%**		
Production workers		**0.659**	**0.671**	**0.012**	**12.46**
	Agricultural workers	0.006	0.006	0.000	11.74
	Craft workers	0.291	0.289	–0.002	15.39
85110	Machinery main. mech.	0.015	0.018	0.003	16.05
89108	Machinists	0.025	0.026	0.001	14.63
89132	Sheet metal workers	0.001	0.007	–0.003	13.92
83002	Precision inspectors	0.015	0.012	–0.003	14.30
	Operators	0.703	0.705	0.002	11.31
92998	Machine op. (residual category)	0.018	0.027	0.009	12.66
93956	Assemblers	0.082	0.082	0.000	10.86
92974	Pack. and fill mach. op.	0.021	0.023	0.002	10.97
91117	Mach. tool cut op.	0.012	0.007	–0.005	13.29
92717	Sewing machine op.	0.027	0.025	–0.002	7.21
Subtotal		**100%**	**100%**		

Note: Industries are weighted by the industry's average share of manufacturing employment over the period for all calculations.

equation of a quasi-fixed cost function, derived by Brown and Christensen (1981), results from the minimization of cost with respect to one group of inputs conditional on the level of output and the inputs considered to be fixed. Log differentiating the variable cost function with respect to the price of each variable factor yields the factor share equation whose arguments are the prices of variable factors and the levels of output and fixed inputs. A translog cost function and constant returns to scale are normally assumed. The first-differenced factor share equation is specified:

$$dS_n = \beta_0 + \beta_1 \, d\ln(W_{nj}/W_{pj}) + \beta_2 \, d\ln(K/Y) + \beta_3 \, d\ln(Y) + \varepsilon$$

where:

dS_n represents the change in the wage bill share of non-production workers.
$d\ln(W_{nj}/W_{pj})$ represents the change in the natural log of the relative wage of the occupational group.
$d\ln(K/Y)$ represents the change in the natural log of the ratio of capital spending to real output.
$d\ln(Y)$ represents the change in the natural log of real output.

Berman *et al.* (1994) estimated the equation above (minus the relative wage terms) using data from the Annual Survey of Manufacturers for the 1977–87 period and found a positive, statistically significant relationship between changes in the share of non-production workers and changes in both real output and the capital to output ratio. They further found that the fraction of investment devoted to computers as of 1987 accounted for over 40 percent of the increase in the wage bill share of non-production workers over this period.[13]

Goldin and Katz (1998) also estimated the equation above using data from the Census of Manufacturers for the years 1909 and 1919, years during which electrification was facilitating a shift in many industries toward capital intensive production methods. Goldin and Katz found a positive, statistically significant relationship between changes in the share of non-production workers and both changes in the capital to output ratio and changes within industries in the percentage of total horse power that was run by purchased electricity.

As mentioned in the previous section, the employment share of non-production workers ceased to rise further over the 1989–98 period. The equation above was nonetheless estimated for the recent period, using OES and Annual Survey of Manufacturers data for the years 1989–96. These analyses, not included here, have statistically insignificant coefficients on all independent variables, as expected.

V.2. *The Estimation Equation*

All of the considerable occupational upgrading that occurred over the recent period occurred within the non-production worker and, to a much less extent, the production worker groups. The current analysis estimates the above equation using as the dependent variable two alternative measures of skill change that are sensitive to occupational upgrading within the non-production worker and production worker groups. The first of these is the measure of occupational upgrading discussed in the previous section, produced separately for each 4-digit SIC, for groups composed of all workers, non-production workers, and production workers. The estimation equation for the case of the all worker group is[14]:

[13]See Berman *et al.* (1994, p. 388).
[14]For the case of the non-production worker and production worker groups, *i* in the equation represents occupational group in the industry.

$$\sum_{0} \ln [\bar{W}_{oi}/\bar{W}_i][\Delta[\bar{E}_{oi}/\bar{E}_i] = \beta_0 + \beta_1\, d\ln (K/Y) + \beta_2\, d\ln (Y) + \varepsilon$$

where:

$\bar{W}_{oi}/\bar{W}_i$ represents the average relative wage of occupation *o* in industry *i* during 1998,
$\Delta[\bar{E}_{oi}/\bar{E}_i]$ represents the change in the average industry employment share of occupation *o* in industry *i* over the 1989–98 period.

The specification follows Berman *et al.* (1994) and excludes the relative wage terms in an effort to avoid division biases resulting from the presence of wage measures in both the dependent and independent variables.

The dependent variable used in the second set of regressions is the change in the industry employment share of selected non-production worker occupations, including occupations that exhibited the largest employment shifts over the period, and IT-related occupations. The estimation equation is:

$$\Delta[\bar{E}_{oi}/\bar{E}_i] = \beta_0 + \beta_1\, d\ln (K/Y) + \beta_2\, d\ln (Y) + \varepsilon$$

where:

$\Delta[\bar{E}_{oi}/\bar{E}_i]$ represents the change in the employment share of occupation *o* in industry *i* over the 1989–98 period.

Turning next to the remaining characteristics of the specification that apply to both sets of analyses, capital-skill complementarity implies that $\beta_1 > 0$. The equation was estimated twice for each occupational group; the second analysis included a measure of high-tech capital usage. The measure of high-tech capital used is the 1992 share of computers in industry total investment. Berman *et al.* (1994) argue that this measure should proxy for the cross sectional variation in the share of computers in the capital stock, "on the assumption that what varies across industries is the adaptability of different technologies to computerization."[15] Allen (1996) shows, in fact, that high-technology usage indicators are not only highly correlated over the 1979–89 period, but that the 1979 share of computers in the capital stock was strongly related to changes in wage differentials over the 1979–89 period.[16] Computer-skill complementarity implies that the coefficient on this variable is greater than zero. All regressions were weighted by the industry's average share of manufacturing employment over the period.

A number of researchers have raised the possibility that a positive relationship between the use of highly skilled workers and IT may reflect only the higher "technological opportunity" of particular establishments and industries, rather than a causal relationship between IT use and the use of highly skilled workers. Industries that benefit the most from incorporating new technologies may increase

[15]Berman *et al.* (1994, p. 388). Haskel and Hedden (1999) argue that the rapid replacement rate of IT also suggests that the share of computers in investment is an adequate proxy for the cross sectional variation of computers as a share of the capital stock.

[16]Allen also found that changes in R&D were related to changes in the wage structure over this period, but that changes in total factor productivity (TFP) appeared to be unrelated to changes in wage differentials.

their demand for highly skilled workers upon adopting IT for reasons unrelated to the particular characteristics of IT, but rather for reasons that pertain in the case of adopting any new technology.

This concern is avoided in the current study for two reasons. First, it pertains primarily to studies in which occupations are delineated by production worker/non-production worker status only, and in which the detailed occupational pattern of the shifts is therefore not available to help distinguish the types of skills that have increased in demand. As discussed earlier, proposed explanations for IT-skill complementarity contain implications for the relationship between changes in capital usage and changes in the employment shares of a variety of detailed occupations. Second, Haskel and Heden (1999) found insignificant fixed effects in a model controlling for possible establishment-specific "technological opportunity" that used panel data for U.K. manufacturing establishments.

VI. Results

Table 4 reports the results of the first set of regressions, in which the dependent variable used is the measure of occupational upgrading for groups composed of all workers, non-production workers, and production workers. The results for the all-occupation group reveal a positive, statistically significant relationship between occupational upgrading and the share of computers in investment, although the explanatory power of this analysis and all others in the set is rather

TABLE 4

The Impact of Computers on Occupational Upgrading (1989–98)

Dependent Variable: Measure of Occupational Upgrading for Group	$d\ln(K/Y)$	$d\ln(Y)$	Share of Computers in Investment (1992)	Constant		
All occupations	−0.0005	−0.0007	—	0.011***	$F = 1.09$	$R^2 = 0.005$
Mean = 0.009	(0.001)	(0.0008)		(0.003)	Prob $F = 0.33$	$\sigma = 0.001$
	−0.0003	−0.0007*	0.05*	0.007*	$F = 3.4$	$R^2 = 0.022$
	(0.001)	(0.0009)	(0.028)	(0.003)	Prob $F = 0.017$	$\sigma = 0.002$
Non-production workers	0.0004	0.0009	—	0.023***	$F = 1.92$	$R^2 = 0.008$
Mean = 0.026	(0.0009)	(0.0009)		(0.004)	Prob $F = 0.15$	$\sigma = 0.002$
	0.0006	0.001	0.041	0.02***	$F = 2.56$	$R^2 = 0.017$
	(0.0009)	(0.0009)	(0.027)	(0.005)	Prob $F = 0.05$	$\sigma = 0.002$
Production workers	0.0005	0.0008**	—	0.005**	$F = 2.98$	$R^2 = 0.012$
Mean = 0.007	(0.006)	(0.0004)		(0.002)	Prob $F = 0.05$	$\sigma = 0.007$
	0.0005	0.0007*	0.001	0.005**	$F = 1.93$	$R^2 = 0.013$
	(0.0006)	(0.0004)	(0.017)	(0.002)	Prob $F = 0.12$	$\sigma = 0.001$

Source: Occupational Employment Statistics survey, U.S. Bureau of Labor Statistics.

Notes: $N = 458$ in analyses omitting the computer share of investment variable, $N = 448$ in analyses containing the computer share variable.

Heteroscedasticity-consistent standard errors in parentheses.

$^{***}p = 0.01$, $^{**}p = 0.05$, $^{*}p = 0.10$.

low. The results for the non-production worker group contain a marginally insignificant coefficient on the computer share variable, while that for the production worker group is insignificant.

Table 5 reports the results of the second set of regressions, in which the dependent variable used is the change in the employment share of those detailed and semi-detailed non-production worker occupations that either exhibited the largest employment shifts over the period, or that consist of IT-related occupations.

Two occupational groups that gained the largest shares of average industry employment over the period consist of certain computer science and engineering professional occupations that were grouped into "residual" categories either by the OES survey or for the purposes of the current analysis. These residual occupational categories account for employment in occupations that did not appear on the survey form received by the respondent. In these cases in which the respondent wishes to record employment in an occupation that does not fit any of the occupations described in the survey form materials, the respondent is instructed to "write in" an appropriate occupation title and description. The OES survey records this employment in a semi-detailed residual occupational category. A rough approximation of the detailed occupational makeup of these residual occupations is obtained by examining a database maintained by the OES survey that contains the occupation titles that were provided by the respondents.

The computer scientist residual group is comprised primarily of database administrators and computer support specialists; these were placed in a residual category for the purposes of the current analysis because they did not appear on the OES survey form until after 1989. According to the Occupational Outlook Handbook, produced biannually by the Bureau of Labor Statistics, database administrators "coordinate physical changes to computer databases and code, test, and implement the database applying knowledge of database management systems." Computer support specialists "provide technical assistance and training to computer system users."[17]

The computer scientist residual group gained about 0.4 percent of average industry employment over the 1989–98 period, most of which occurred after 1992. This group had a positive, statistically significant coefficient on the share of computers in investment variable, and the coefficient is much larger than for any other occupational group examined. The group also had a positive, statistically significant relationship with the growth rate of industry output, and a negative, statistically significant relationship with the change in the ratio of capital to output. Over half of the total variation in the average within-industry employment change of these workers is explained by the independent variables. The results for the 1992–98 period, not shown in the table, are similar to those for the 1989–98 period; all remaining analyses will similarly be reported only for the 1989–98 period unless the 1992–98 period results are dissimilar.

A variety of residual engineering occupations also gained about 0.4 percent of average industry employment over the period and, like the computer scientist group, most of this employment growth occurred after 1992. This group contains large shares of occupations that respondents termed "environmental," "quality,"

[17]Occupational Outlook Handbook, 2000–2001 Edition, U.S. Department of Labor, Bureau of Labor Statistics, January 2000, Bulletin 2520, p. 109.

TABLE 5

Skill Change Within 4-Digit SIC Industries (Dependent Variable: Change in Share of Industry Employment, 1989–98 and 1992–98. Detailed and Semi-Detailed Occupations)

Dependent Variable: Change in the Share of Industry Employment	Period	Dependent Variable Mean	$d\ln(K/Y)$	$d\ln(Y)$	Share of Computers in Investment (1992)	Constant		
Computer scientists and related workers	1989–98	Dep. mean	−0.0003	0.0003***		0.002***	$F = 76.66$	$R^2 = 0.25$
(residual category)		= 0.004	(0.0003)	(0.00003)		(0.0004)	Prob $F = 0.0001$	σ = 0.0003
			−0.0003***	0.0003***	0.039***	−0.0006	$F = 170.9$	$R^2 = 0.54$
			(0.00006)	(0.00009)	(0.01)	(0.0007)	Prob $F = 0.0001$	σ = 0.0002
Engineers (residual category)	1989–98	Dep. mean	−0.0001***	0.0002		0.003***	$F = 3.56$	$R^2 = 0.15$
		= 0.004	(0.0003)	(0.00006)		(0.001)	Prob $F = 0.029$	σ = 0.0005
		Dep. mean	−0.0001***	0.0002	0.003	0.003***	$F = 2.52$	$R^2 = 0.017$
		= 0.004	(0.0003)	(0.00006)	(0.014)	(0.001)	Prob $F = 0.06$	σ = 0.0005
	1992–98	Dep mean	−0.0004	0.0004***		0.0002	$F = 51.54$	$R^2 = 0.18$
		= 0.003	(0.0003)	(0.00008)		(0.001)	Prob $F = 0.0001$	σ = 0.0006
		Dep. mean	−0.0003***	0.0004***	0.024*	−0.002*	$F = 47.84$	$R^2 = 0.24$
		= 0.003	(0.00008)	(0.00006)	(0.014)	(0.001)	Prob $F = 0.0001$	σ = 0.0005
Computer engineers	1989–98	Dep. mean	−0.0005***	−0.0001**		0.002**	$F = 6.84$	$R^2 = 0.03$
		= 0.002	(0.00008)	(0.00005)		(0.001)	Prob $F = 0.001$	σ = 0.0005
		Dep. mean	−0.0003***	−0.0001**	0.037***	−0.001**	$F = 44.37$	$R^2 = 0.23$
		= 0.002	(0.00004)	(0.00004)	(0.013)	(0.0004)	Prob $F = 0.0001$	σ = 0.0003
	1992–98	Dep. mean	0.0	−0.0004**		0.001	$F = 22.91$	$R^2 = 0.09$
		= −0.0001	(0.00007)	(0.00004)		(0.0007)	Prob $F = 0.0001$	σ = 0.0004
		Dep. mean	0.0	−0.0003**	0.008	0.0004	$F = 21.16$	$R^2 = 0.12$
		= −0.0001	(0.00007)	(0.00003)	(0.012)	(0.0009)	Prob $F = 0.0001$	σ = 0.004

Systems analysts	1989–98	Dep. mean	–0.0001	0.0		–0.001**	F = 0.79	R^2 = 0.004
		= –0.001	(0.00004)	(0.00009)		(0.0004)	Prob F = 0.45	σ = 0.0002
			–0.0001	0.0	–0.011	–0.0001	F = 7.29	R^2 = 0.047
			(0.00004)	(0.0)	(0.005)	(0.0004)	Prob F = 0.0001	σ = 0.0002
Electrical engineers	1989–98	Dep. mean	0.0	0.0		–0.002**	F = 5.95	R^2 = 0.045
		= –0.0008	(0.00007)	(0.00004)		(0.001)	Prob F = 0.003	σ = 0.0004
			0.0001	0.0001	–0.0001	–0.001	F = 2.68	R^2 = 0.018
			(0.00007)	(0.00003)	(0.008)	(0.001)	Prob F = 0.047	σ = 0.0003
Electrical engineering technicians	1989–98	Dep. mean	0.0005	–0.0004***		0.0001	F = 191.98	R^2 = 0.46
		= –0.002	(0.00008)	(0.00004)		(0.0004)	Prob F = 0.0001	σ = 0.0003
			0.0005	–0.0004***	–0.015*	0.001	F = 143.79	R^2 = 0.49
			(0.00006)	(0.00005)	(0.008)	(0.001)	Prob F = 0.0001	σ = 0.0003
	1992–98	Dep. mean	–0.00006	–0.0006***		0.001	F = 139.87	R^2 = 0.38
		= –0.001	(0.00004)	(0.00007)		(0.0006)	Prob F = 0.0001	σ = 0.0003
			–0.00007	–0.0006***	–0.001	0.001	F = 105.49	R^2 = 0.42
			(0.00004)	(0.00006)	(0.005)	(0.0005)	Prob F = 0.0001	σ = 0.0002
Secretaries	1989–98	Dep. mean	–0.0008***	–0.0008***		–0.005	F = 28.66	R^2 = 0.11
		= –0.006	(0.0003)	(0.00008)		(0.0003)	Prob F = 0.0001	σ = 0.0003
			–0.0008***	–0.0008***	–0.018***	–0.003	F = 32.77	R^2 = 0.18
			(0.0003)	(0.00008)	(0.006)	(0.0004)	Prob F = 0.0001	σ = 0.0003

Source: Occupational Employment Statistics survey, U.S. Bureau of Labor Statistics.
Notes: Heteroscedasticity-consistent standard errors in parentheses.
***p = 0.01, **p = 0.05, *p = 0.10.
N = 458 (448) in regressions omitting (containing) the computer share variable.

"process," or "product" engineers. Although the Occupational Outlook Handbook does not contain definitions for these detailed occupations, engineers in general "apply the theories and principles of science and mathematics to research and develop economical solutions to technical problems".[18] The regression results for this group were similar to those for the computer scientist group, with the important exception that a significant degree of explanatory power of the analysis exists only for the 1992–98 period. For the post-92 period there exists a negative, statistically significant coefficient on the growth rate of the capital to output ratio, and a positive, statistically significant coefficient on the growth rate of industry output and on the computer share of investment variable.

Computer engineers gained about 0.2 percent of average industry employment over the 1989–98 period, all of which occurred before 1992, as seen by the dependent variable mean of –0.0002 for the 1992–98 period. Computer engineers "design hardware, software, networks, and processes."[19] The results for the 1989–98 period reveal that almost all of the considerable explanatory power of the analysis ($R^2 = 0.23$) is accounted for by the computer share of investment variable, which has a positive, statistically significant coefficient, as would be expected.

The remaining occupations included in the analysis lost employment share. The independent variables had little explanatory power in the case of systems analysts and engineers, although there exists a negative, statistically significant relationship between changes in the share of systems analysts and both the computer share variable and changes in the capital to output ratio.

Electrical engineering technicians lost 0.2 percent of average industry employment over the 1989–98 period, spread relatively evenly over the period. These workers "solve technical problems in research and development, manufacturing, sales, construction, inspection, and maintenance."[20] All of the analyses have uniformly high explanatory power. Changes in the share of these workers had a negative, statistically significant relationship with the rate of growth of industry output. Over the 1989–98 period only, changes in the share of these workers had a positive, statistically significant relationship with the rate of growth of the capital to output ratio and a negative, statistically significant relationship with the computer share variable.

Finally, secretarial occupations lost about 0.6 percent of average industry employment over the 1989–98 period. This group includes all types of secretaries, including, among others, legal and medical secretaries. Changes in the share of secretaries had a negative, statistically significant relationship with the growth rate of industry output and a negative, statistically significant relationship with the share of computers in investment.

VII. Discussion and Conclusions

The results for the computer engineer and engineer residual occupations are most interesting with respect to the distinct differences in the results across time

[18]Occupational Outlook Handbook, 2000–2001 Edition, U.S. Department of Labor, Bureau of Labor Statistics, January 2000, Bulletin 2520, p. 85.

[19]Occupational Outlook Handbook, 2000–2001 Edition, U.S. Department of Labor, Bureau of Labor Statistics, January 2000, Bulletin 2520, p. 109.

[20]Occupational Outlook Handbook, 2000–2001 Edition, U.S. Department of Labor, Bureau of Labor Statistics, January 2000, Bulletin 2520, p. 96.

periods. The results appear to reflect a logical time progression in the focus of work activity geared toward the implementation and maintenance of computer technology. Before 1992, computer engineers were employed in large numbers to design the hardware, software, networks, and processes that form microprocessor-based systems for the control and automation of manufacturing, business, and management processes. This was followed by a large increase in the employment of engineers, termed by respondents "product," "process," and "quality" engineers, whose job it was to design and perfect manufacturing equipment tailored to the specific technical requirements of individual manufacturing processes in an automated environment.

Spread more evenly over the entire period was a large increase in the employment shares of database administrators and computer support specialists.

Each of these three employment shifts has resulted in what appears to be a long term increase in the group's employment share, and each of the shifts appears to be associated with the use of microprocessor-based equipment and processes. These results support Goldin and Katz's (1998) arguments suggesting that the recent shift toward skilled workers has occurred for reasons similar to those which applied after 1890, during the shift of some industries toward continuous process and batch process methods of production. In each case, the shift toward skilled workers was a logical result of a shift toward technology that has a relatively large machine maintenance and repair component.

The results are slightly puzzling with respect to the negative coefficients on the rate of change in the capital to output ratio for several of the occupations. A positive coefficient on this variable indicates capital-skill complementarity. The negative coefficient that was obtained on this variable for the computer engineers, engineers residual, and computer scientist residual occupations is also obtained for the 1992–98 time period, suggesting that the economic conditions specific to 1989 were not the determining factor in this outcome. These results may stem from the fact that 1998 was a period of robust growth, while the years 1973, 1979, and 1989 roughly coincided with peaks in the business cycle, and 1992 came on the heels of a downturn in economic activity.

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