Review of Income and Wealth
Series 48, Number 1, March 2002

COMPUTERIZATION AND STRUCTURAL CHANGE

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I develop three measures of structural change on the basis of U.S. data: changes in occupational composition, changes in input–output technical coefficients, and changes in capital coefficients. Using pooled cross-section, time-series data for 44 industries over the period from 1970 to 1990, I find that computer investment per worker has had a positive and significant effect on the degree of occupational change and changes in input and capital coefficients.

INTRODUCTION

Though most of the attention in the literature has focused on the connection between information technology (IT) or information and communications technology (ICT) and productivity, little work has been conducted on the linkage between IT and broader indicators of structural change (with a few exceptions noted below). The purpose of this paper is to help fill this gap.

Robert Solow was, perhaps, the first to point out the anomaly between productivity growth and computerization. Indeed, he quipped that we see computers everywhere except in the productivity statistics. As we shall see below, industries that have had the greatest investment in computers (namely, services) have had the lowest growth in conventionally measured productivity. Moreover, at least until recently, there has been little evidence of a pay-off to computer investment in terms of productivity growth.

However, another recent phenomenon of considerable visibility has been the rapid degree of industrial restructuring among U.S. corporations. As I shall argue below, standard measures of productivity growth are only one indicator of structural change. There are others such as changes in direct input and capital coefficients. Changes in occupational mix and the composition of inputs were greater in the 1980s than in the preceding two decades. This is coincident with the sharp rise in computerization. I find evidence from my sample that the degree of computerization has had a statistically significant effect on changes in industry input coefficients and other dimensions of structural change.

Section 1 introduces the accounting framework and model. Section 2 provides a summary of some of the recent literature on IT and productivity changes. Section 3 presents descriptive statistics on IT investment and indicators of structural change. Multivariate analysis is then conducted on the industry level to assess their influence (Section 4). Concluding remarks are made in the last section.

1. MODELING FRAMEWORK

Following Stiroh (2002), let f_j be the standard neoclassical production for sector j:

$$X_j = Z_j f_j(K_{j,ICT}, K_{j,0}, L_j, N_j) \tag{1}$$

where X_j is the (gross) output of sector j, L_j is the total labor input, $K_{j,ICT}$ is the input of ICT-related capital, $K_{j,0}$ is the input of other capital goods, N_j are total intermediate inputs, and Z_j is a (Hicks-neutral) total factor productivity (TFP) index that shifts the production function of sector j over time. For convenience, I have suppressed the time subscript. Moreover, capacity utilization and adjustment costs are ignored. It then follows that

$$(2) \quad d\,\mathrm{d}\ln_j = \mathrm{d}\ln Z_j + \varepsilon_{j,ICT}\, d\ln K_{j,ICT} + \varepsilon_{j,0}\, d\ln K_{j,0} + \varepsilon_{j,L}\, d\ln L_j + \varepsilon_{j,N}\, d\ln N_j$$

where ε represents the output elasticity of each input and $d \ln Z_j$ is the rate of Hicks-neutral TFP growth. If we now impose the assumption of competitive input markets and constant returns to scale, it follows that an input's factor share (α_j) will equal its output elasticity. Let us now employ the standard measure of TFP growth for sector $j(\pi_j)$:

$$(3) \quad \pi_j \equiv d\ln X_j/dt - \alpha_{j,ICT}\, d\ln K_{j,ICT}/dt - \alpha_{j,0}\, d\ln K_{j,0}/dt - \alpha_{j,L}\, d\ln L_j/dt - \alpha_{j,N}\, d\ln N_j/dt$$

It then follows that:

$$(4) \quad \pi_j = d\ln Z_j/dt$$

In particular, in the standard neoclassical model, there is no special place reserved for ICT capital in terms of its effect on TFP growth.

As Stiroh (2002) argues, there are several reasons why we might expect the standard neoclassical model to fail in the case of the introduction of a radically new technology that might be captured by ICT investment. These include the presence of productivity spillovers from ICT, problems of omitted variables, the presence of embodied technological change, measurement error in variables, and reverse causality. If for one of these reasons, the output elasticity of ICT $\varepsilon_{j,ICT}$ exceeds its measured input share $\alpha_{j,ICT}$, say by $u_{j,ICT}$, then

$$(5) \quad \pi_j = d\ln Z_j/dt + u_{j,ICT}\, d\ln K_{j,ICT}/dt$$

In other words, conventionally measured TFP growth π_j will be positively correlated with the growth in ICT capital.

However, as I indicate in the literature survey in the next section, very few studies, with the exceptions of Griliches and Siegel (1992) and ten Raa and Wolff (2000), have found a positive correlation between industry TFP growth and ICT investment. As a result, in this study, I consider other indicators of the degree of structural change in an industry. These include changes in the occupational composition of employment and changes in the input and capital composition within an industry. Productivity growth and changes in input composition usually go hand in hand. To see this, let me first introduce three new matrices:

A = 45-order matrix of technical interindustry input–output coefficients, where a_{ij} is the amount of input i used per constant dollar of output j.

The technical coefficient (A) matrices were constructed on the basis of current dollar matrices and sector-specific price deflators. Sectoral price indices for years 1958, 1963, and 1967 were provided by the Brandeis Economic Research Center and those for 1972 and 1977 from the Bureau of Economic Analysis worksheets. Deflators for 1982, 1987, 1992, and 1996 were calculated from the Bureau of Labor Statistics' Historical Output Data Series (obtained on computer diskette) on the basis of the current and constant dollar series. See the Appendix for details on sources and methods and a listing of the 45 industries.

C = 45-order matrix of capital coefficients, where c_{ij} is the net stock of capital of type i (in 1992 dollars) used per constant dollar of output j.

The capital matrix in constant dollars was provided by the Bureau of Economic Analysis (see the Appendix for sources) and is based on price deflators for individual components of the capital stock (such as computers, industrial machinery, buildings, etc.).

M = occupation-by-industry employment coefficient matrix, where m_{ij} shows the employment of occupation i in industry j as a share of total employment in industry j.

The employment data are for 267 occupations and 64 industries and are obtained from the decennial Census of Population for years 1950, 1960, 1970, 1980, and 1990 (see Wolff, 1996, for details).

Then, since for any input I in sector j, $\alpha_{j,I} = p_I I_j / p_j X_j$, where p is the price, I can rewrite equation (3) as

$$\pi_j = -[\textstyle\sum_i p_i\, da_{ij} + \sum_i p_{i,c}\, dc_{ij} + \sum_i w_i\, db_{ij}]/p_j \tag{6}$$

where p_i is the price of intermediate input i, $p_{i,c}$ is the price of capital input i, $b_{ij} = m_{ij} L_j / X_j$ is the total employment of occupation i per unit of output in industry j, and w_i is the wage paid to workers in occupation i. In this formulation, it is clear that measured TFP growth reflects changes in the composition of intermediate inputs, capital inputs, and occupational employment. From (5) it follows that in the circumstances enumerated above, there may be a positive correlation between measures of structural change and ICT investment.

Though productivity growth and changes in input composition are algebraically related, there are several reasons why they may deviate. First, there are costs of adjustments associated with radical restructuring of technology, so that there may be a considerable time lag between the two (see David, 1991, for example). Second, while new technology is generally used to lower costs and hence increase measured output per unit of input, new technology might be used for other purposes such as product differentiation or differential pricing. Third, in the case of services in particular, output measurement problems might prevent us from correctly assessing industry productivity growth. This problem could, of course, be partly a consequence of product differentiation and price discrimination. Measures of structural change may therefore provide a more direct and robust test of the effects of computerization on changes in technology than standard measures of productivity growth. This is particularly so in the case when a radically new technology is introduced and the consequent adjustment period is lengthy.

2. Review of Previous Literature

A substantial number of studies, perhaps inspired by Solow's quip, have now examined the linkage between computerization or information technology (IT) in general and productivity gains. The evidence is mixed. Most of the earlier studies failed to find any excess returns to IT, over and above the fact that these investments are normally in the form of equipment investment. These include Franke (1989), who found that the installation of ATMs was associated with a lowered real return on equity; Bailey and Gordon (1988), who examined aggregate productivity growth in the U.S. and found no significant contribution of computerization; Loveman (1988), who reported no productivity gains from IT investment; Parsons, Gotlieb, and Denny (1993), who estimated very low returns on computer investments in Canadian banks; and Berndt and Morrison (1995), who found negative correlations between labor productivity growth and high-tech capital investment in U.S. manufacturing industries. Wolff (1991) found that the insurance industry had a negative rate of total factor productivity growth over the 1948–86 period in the U.S. even though it ranked fourth among 64 industries in terms of computer investment.

The later studies generally tend to be more positive. Both Siegel and Griliches (1992) and Steindel (1992) estimated a positive and significant relationship between computer investment and industry-level productivity growth. Oliner and Sichel (1994) reported a significant contribution of computers to aggregate U.S. output growth. Lichtenberg (1995) estimated firm-level production functions and found an excess return to IT equipment and labor. Siegel (1997), using detailed industry-level manufacturing data for the U.S., found that computers are an important source of quality change and that, once correcting output measures for quality change, computerization had a significant positive effect on productivity growth.

Brynjolfsson and Hitt (1996, 1998) found a positive correlation between firm-level productivity growth and IT investment over the 1987–94 time period when accompanied by organizational changes. Lehr and Lichtenberg (1998) used data for U.S. federal government agencies over the 1987–92 period and found a significant positive relation between productivity growth and computer intensity. Lehr and Lichtenberg (1999) investigated firm-level data among service industries over the 1977–93 period and also reported evidence that computers, particularly personal computers, contributed positively and significantly to productivity growth. ten Raa and Wolff (2000), developing a new measure of direct and indirect productivity gains, found that the computer sector was the leading sector in the U.S. economy during the 1980s as a source of economy-wide productivity growth.

Stiroh (1998) and Jorgenson and Stiroh (1999, 2000) used a growth accounting framework to assess the impact of computers on output growth. Jorgenson and Stiroh (1999) calculated that one sixth of the 2.4 percent annual growth in output can be attributed to computer outputs, compared to about zero percent over the 1948–73 period. The effect came from capital deepening rather than from enhanced productivity growth. A study by Oliner and Sichel (2000) provides strong evidence for a substantial role of IT in the recent spurt of productivity growth during the second half of the 1990s. Using aggregate time-series data for the U.S., they found that both the use of IT in sectors purchasing computers and other forms of information technology, as well as the production of computers, appear to have made an important contribution to the speed-up of productivity growth in the latter part of the 1990s. Hubbard (2001) investigated how on-board computer adoption affected capacity utilization in the U.S. trucking industry between 1992 and 1997. He found that their use improved communications and resource allocation decisions and led to a 3 percent increase in capacity utilization within the industry.

3. Descriptive Statistics

I use three measures of structural change in this study. The first measure is the degree to which the occupational structure shifts over time. For this, I employ an index of similarity. The similarity index for industry j between two time periods 1 and 2 is given by:

$$\text{(7)} \qquad \mathrm{SI}^{12} = \frac{\sum_i m_{ij}^1 m_{ij}^2}{[\sum_i (m_{ij}^1)^2 \sum_i (m_{ij}^2)^2]^{1/2}}$$

The index SI is the cosine between the two vectors s^{t1} and s^{t2} and varies from 0 (the two vectors are orthogonal) to 1 (the two vectors are identical). The index of occupational dissimilarity, DI, is defined as:

$$\text{(8)} \qquad \mathrm{DIOCCUP}^{12} = 1 - \mathrm{SI}^{12}$$

Descriptive statistics for DIOCCUP are shown in Table 1. The DIOCCUP index for the total economy, after rising slightly from 0.050 in the 1950–60 period to

TABLE 1
Dissimilarity Index (DIOCCUP) of the Distribution of Occupational Employment by Major Sector, 1950–90

Sector	1950–60	1960–70	1970–80	1980–90	Average 1950–90
A. Goods industries					
Agriculture, forestry, and fisheries	0.000	0.001	0.001	0.017	0.005
Mining	0.022	0.025	0.020	0.045	0.028
Construction	0.040	0.025	0.005	0.053	0.031
Manufacturing, durables	0.100	0.039	0.014	0.096	0.062
Manufacturing, nondurables	0.077	0.050	0.023	0.088	0.060
Transportation	0.030	0.024	0.014	0.048	0.029
Communications	0.032	0.061	0.043	0.128	0.066
Electric, gas, and sanitary services	0.078	0.169	0.053	0.105	0.101
B. Service industries					
Wholesale and retail trade	0.026	0.019	0.029	0.078	0.038
Finance, insurance, and real estate	0.043	0.117	0.033	0.080	0.068
General services	0.061	0.091	0.029	0.047	0.057
Government and government enterprises	0.046	0.054	0.042	0.045	0.047
Total goods	0.063	0.061	0.014	0.110	0.062
Total services	0.022	0.056	0.026	0.077	0.045
All industries	0.050	0.056	0.019	0.095	0.055

Note: Computations are based on employment by occupation aggregated for each of the major sectors.

0.056 in the 1960–70 decade, dropped to 0.019 in the 1970s but then surged to 0.095 in the 1980s, its highest level of the four decades. These results confirm anecdotal evidence about the substantial degree of industrial restructuring during the 1980s. Similar patterns are evident for the major sectors as well. In fact, seven out of the twelve major sectors experienced their most rapid degree of occupational change during the 1980s. The three sectors that experienced the greatest occupational restructuring over the four decades were utilities (0.101), FIRE (0.068), and communications (0.066). Occupational change was particularly low in agriculture (0.005), mining (0.028), transportation (0.029), and construction (0.031).

A second index reflects changes in the technical interindustry coefficients within an industry:

$$\text{DIACOEFF}^{12} = 1 - \frac{\sum_i a_{ij}^1 a_{ij}^2}{[\sum_i (a_{ij}^1)^2 \sum_i (a_{ij}^2)^2]^{1/2}} \tag{9}$$

Figures shown in Table 2 indicate that the DIACOEFF index for the total economy, after falling from 0.036 in the 1950–60 period to 0.027 in the 1960–70 decade, rose to 0.030 in the 1970s and again to 0.033 in the 1980s. Eight of the twelve major sectors also recorded an increase in the degree of change in their interindustry coefficients between the 1960s and the 1980s. The sectors with the greatest interindustry coefficient change over the four decades were communications (0.129), utilities (0.075), and mining (0.067), and those with the least were agriculture (0.007) and durable manufacturing (0.013).

A third index measures the change in capital coefficients within an industry:

$$\text{DIKCOEFF}^{12} = 1 - \frac{\sum_i c_{ij}^1 c_{ij}^2}{[\sum_i (c_{ij}^1)^2 \sum_i (c_{ij}^2)^2]^{1/2}} \tag{10}$$

TABLE 2

DISSIMILARITY INDEX DIACOEFF FOR TECHNICAL INTERINDUSTRY COEFFICIENTS BY MAJOR SECTOR, 1950–90

Sector	1950–60	1960–70	1970–80	1980–90	Average 1950–90
A. Goods industries					
Agriculture, forestry, and fisheries	0.008	0.006	0.004	0.009	0.007
Mining	0.041	0.065	0.070	0.092	0.067
Construction	0.012	0.004	0.028	0.008	0.013
Manufacturing, durables	0.013	0.007	0.009	0.014	0.011
Manufacturing, nondurables	0.022	0.012	0.027	0.025	0.021
Transportation	0.043	0.067	0.016	0.017	0.036
Communications	0.270	0.024	0.051	0.170	0.129
Electric, gas, and sanitary services	0.048	0.087	0.020	0.147	0.075
B. Service industries					
Wholesale and retail trade	0.015	0.049	0.017	0.010	0.023
Finance, insurance, and real estate	0.015	0.033	0.010	0.010	0.017
General services	0.034	0.047	0.066	0.027	0.043
Government and government enterprises	0.054	0.046	0.026	0.061	0.047
Total goods	0.020	0.017	0.024	0.029	0.023
Total services	0.057	0.046	0.043	0.045	0.048
All industries	0.036	0.027	0.030	0.033	0.031

Note: Sectoral figures are based on unweighted averages of industries within the sector.

TABLE 3

DISSIMILARITY INDEX DIKCOEFF FOR CAPITAL COEFFICIENTS, 1950–90

Sector	1950–60	1960–70	1970–80	1980–90	Average 1950–90
A. Goods industries					
Agriculture, forestry, and fisheries	0.002	0.000	0.001	0.005	0.002
Mining	0.016	0.008	0.025	0.038	0.022
Construction	0.011	0.016	0.032	0.061	0.030
Manufacturing, durables	0.005	0.007	0.009	0.007	0.007
Manufacturing, nondurables	0.009	0.006	0.006	0.009	0.008
Transportation	0.002	0.009	0.011	0.008	0.007
Communications	0.015	0.028	0.045	0.087	0.044
Electric, gas, and sanitary services	0.003	0.001	0.002	0.003	0.002
B. Service industries					
Wholesale and retail trade	0.045	0.019	0.014	0.024	0.026
Finance, insurance, and real estate	0.020	0.014	0.027	0.043	0.026
General services	0.057	0.033	0.035	0.062	0.047
Total goods	0.008	0.007	0.011	0.014	0.010
Total services (except government)	0.038	0.024	0.029	0.050	0.035
Total economy (except government)	0.020	0.014	0.018	0.028	0.020

Note: Sectoral figures are based on unweighted averages of industries within the sector. Data on investment by type are not available for the government and government enterprises sectors.

Table 3 shows that the DIKCOEFF index for the total economy, after declining from 0.020 in the 1950–60 period to 0.014 in the 1960–70 decade, increased to 0.018 in the 1970s and to 0.028 in the 1980s. DIKCOEFF rose in nine of the eleven major sectors (capital stock by type is not available for the government sector) between the 1960s and the 1980s. General services and communications showed the greatest change in capital coefficients over the 1950–90 period, and agriculture and utilities the least.

Both investment in and stocks of office, computing, and accounting equipment (OCA) in 1992 dollars are provided in the Bureau of Economic Analysis' capital data (see the Appendix for sources). These figures are based on the BEA's hedonic price deflator for computers and computer-related equipment. As shown in Table 4, investment in office, computing, and accounting equipment (OCA) per person engaged in production (PEP) grew more than ninefold between the 1950s and the 1990s, from $28 (in 1992 dollars) per PEP to $263. Indeed, by 1997, it had reached $2,178 per worker. By the 1980s, the most OCA-intensive sector by far was FIRE, at $1,211 per employee, followed by utilities ($628), mining ($393), durables manufacturing ($345), and communications ($285). On the whole, the overall service sector has been investing more intensively in computer equipment than the goods sector, but this was largely due to the very heavy investments made by FIRE. The trade and general service sectors were actually below average in terms of OCA investment per PEP. Total investment in equipment, machinery, and instruments (including OCA) per PEP was more than fourteen times greater than OCA investment even in the 1980s, though by 1997 it accounted for almost exactly one-third of total equipment investment.

TABLE 4

ANNUAL INVESTMENT IN OFFICE, COMPUTING, AND ACCOUNTING EQUIPMENT (OCA) PER PERSON ENGAGED IN PRODUCTION (PEP), 1950–90 (1992$, PERIOD AVERAGES)

Sector	1950–60	1960–70	1970–80	1980–90	Ratio of 1980–90 to 1950–60
A. Goods industries					
Agriculture, forestry, and fisheries	0.1	0.3	2.1	4.9	67.4
Mining	14.3	28.6	53.3	392.9	27.5
Construction	6.8	6.9	5.8	7.7	1.1
Manufacturing, durables	24.5	21.5	30.2	119.9	4.9
Manufacturing, nondurables	49.2	54.5	98.3	345.3	7.0
Transportation	43.7	36.5	29.6	72.7	1.7
Communications	49.1	43.6	51.1	285.2	5.8
Electric, gas, and sanitary services	47.2	41.8	54.5	628.3	13.3
B. Service industries					
Wholesale and retail trade	14.0	20.3	42.5	279.8	20.0
Finance, insurance, and real estate	140.0	162.7	339.4	1211.0	8.7
General services	22.9	23.4	23.0	148.0	6.5
Total goods	26.4	27.7	42.0	162.1	6.1
Total services (except government)	30.4	37.8	70.0	329.4	10.8
Total economy (except government)	28.2	32.6	57.0	262.7	9.3

Note: Data on investment in OCA are not available for the government or government enterprises sectors.

OCA investment seems to line up well with measures of structural change. As shown in Figure 1, the sectors with two highest rates of investment in OCA per PEP over the 1950–90 period are FIRE and utilities, which also rank in the top two in terms of the average value of DIOCCUP over the same period. The sector with the lowest investment in OCA per worker is agriculture, which also ranks lowest in terms of DIOCCUP. Utilities ranks highest in terms of DIACOEFF over the 1950–90 period and second highest in terms of OCA investment per employee, while agriculture ranks lowest in both dimensions (see Figure 2). The association is not quite as tight between OCA investment and DIKCOEFF (see Figure 3). However, here again agriculture ranks lowest in both dimensions.

4. REGRESSION ANALYSIS

The dependent variables are the various measures of structural change. The independent variables include OCA investment per worker, R&D expenditures as a percent of net sales, and R&D embodied in inputs. For the latter, two sources of knowledge spillovers are used here—purchases of intermediate inputs and purchases of capital goods made by one industry from other industries in the economy. Define the following, where all vectors and matrices are 45-order and in current dollars, unless otherwise indicated, and the matrix diagonals are set to zero to prevent double-counting of R&D expenditures (see the Appendix for sources and methods):

X = vector of total output by sector.

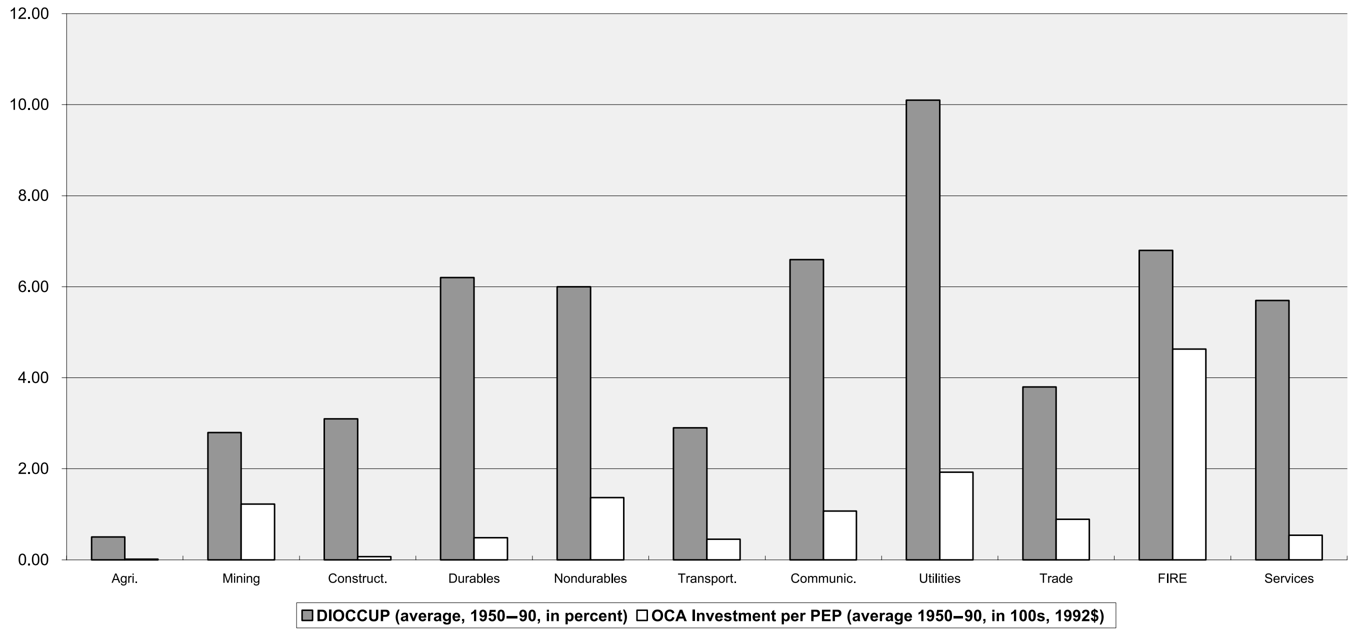

Figure 1. DIOCCUP and OCA Investment per PEP

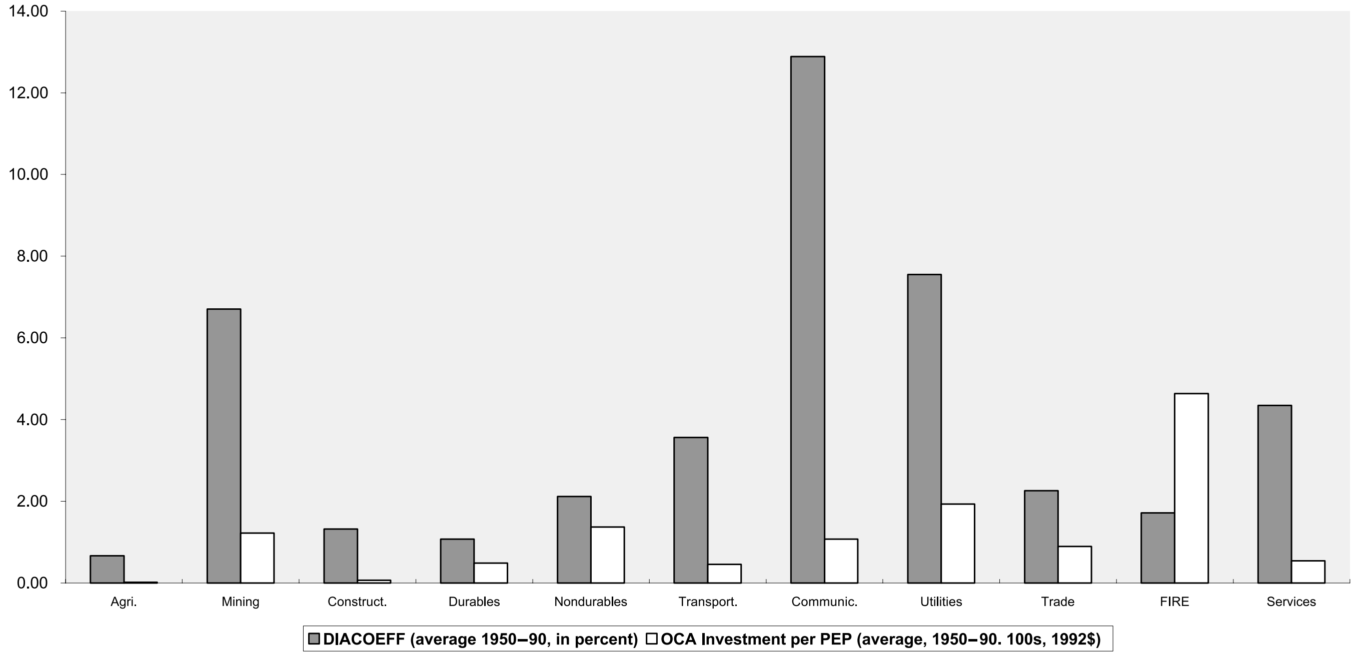

Figure 2. DIACOEFF and OCA Investment per PEP

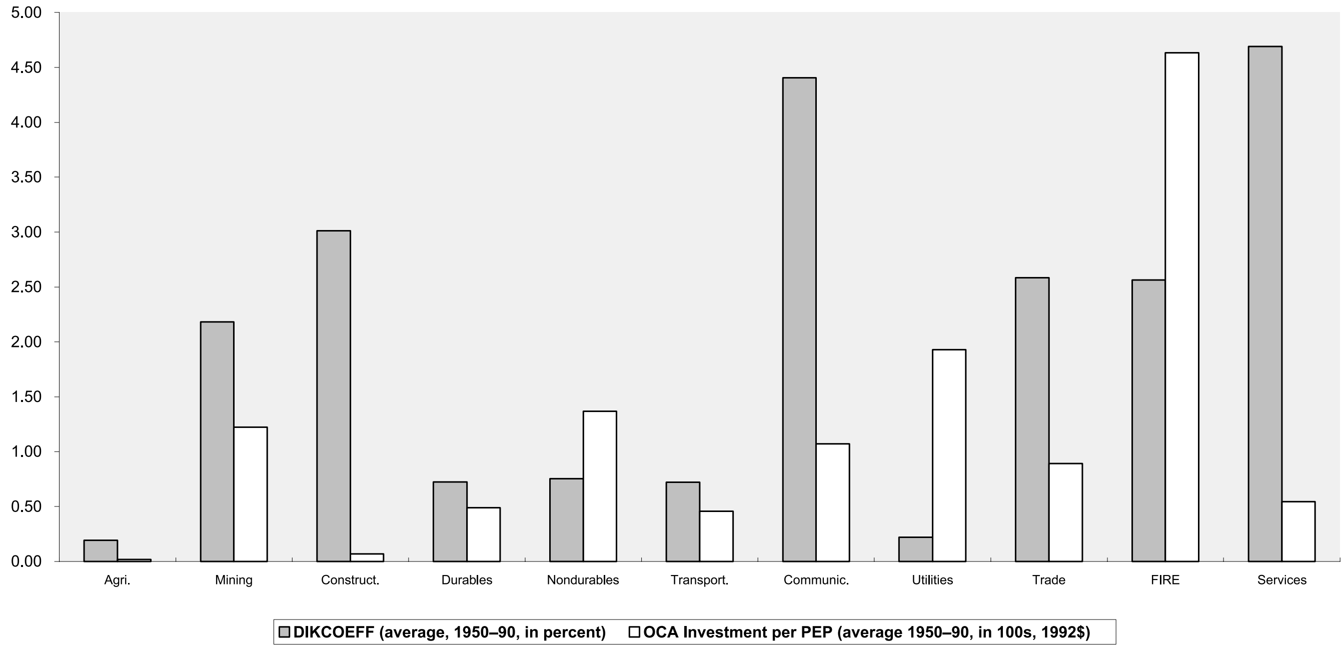

Figure 3. DIKCOEFF and OCA Investment per PEP

R = vector of R&D expenditures by sector.
U = matrix of interindustry input–output coefficients in current dollars, where u_{ij} is the amount of input i used per dollar of output j.
F = square matrix of investment coefficients, where f_{ij} shows purchases of capital goods made by industry j from industry i per (current) dollar of net output of industry j.

It is assumed that the amount of information gained from supplier i's R&D is proportional to its importance in sector j's input structure (that is, the magnitude of a_{ij}) and to sector i's R&D intensity:

(11) $$\text{RDEMB}_j = \sum_i u_{ij} R_i / X_j .$$

For this and subsequent measures, average values over the period are used in the actual construction of the variables. Another source of borrowed R&D is new investment (see Terleckyj, 1974). I assume that the information gain is proportional to the annual investment flow (the time derivative of the capital stock) per dollar of output:

(12) $$\text{RDEMBINV}_j = \sum_i f_{ij} R_i / X_j .$$

The statistical technique is based on pooled cross-section time-series regressions on industries and for the decades that correspond with the decennial Census data. The sample consists of 44 industries and two time periods (1970–80 and 1980–90).[1] The basic estimating equation is:

(13) $$\text{STRCHNG}_{jt} = b_0 + b_1\,\text{RDSALES}_{jt} + b_2\,\text{OCAINVPEP}_{jt} + b_3\,\text{RDEMB}_{jt} + b_4\,\text{RDEMBINV}_{jt} + \varepsilon_{jt}$$

where STRCHNG_{jt} is a measure of structural change, RDSALES_j is the ratio of R&D expenditures to net sales in sector j, OCAINVPEP is OCA investment per PEP, and ε_{jt} is a stochastic error term. In other specifications, the growth of OCA per worker (OCAPEPGR) is used in place of OCAINVPEP. It is assumed that the ε_{jt} are independently distributed but may not be identically distributed. The regression results reported below use the White procedure for a heteroscedasticity-consistent covariance matrix. A dummy variable identifying the 13 service industries (excluding the government sector) is also included to partially control for measurement problems in service sector output.

Results of the regression analysis are shown in Table 5, where the dependent variables are measures of structural change. The first of these variables is the change in occupational composition (DIOCCUP). By far the most significant variable is the rate of growth of OCA per worker. Its coefficient is positive and significant at the 1 percent level in all regressions. The results also show that R&D intensity is not a significant explanatory factor in accounting for changes in occupational composition. Nor are the variables measuring embodied R&D. The dummy variable for services is not significant.

[1]The 1950–60 and 1960–70 periods are not included in the regression analysis because OCA investment was very small during these time periods. The government sector, moreover, cannot be included because of a lack of data on OCA investment.

TABLE 5

Cross-Industry Regressions of Indicators of Structural Change on Computer Investment

Independent Variables	Dependent Variable					
	DIOCCUP	DIOCCUP	DIACOEFF	DIACOEFF	DIKCOEFF	DIKCOEFF
Constant	0.023# (1.89)	0.023# (1.77)	0.001 (0.13)	–0.02* (2.24)	0.016** (2.98)	0.008 (1.02)
R&D expenditures/ sales	0.167 (0.73)	0.203 (0.87)	0.136 (0.59)	0.309 (1.57)	0.206 (1.17)	0.129 (0.71)
Growth of OCA per PEP	0.225** (3.18)	0.210** (2.96)				
Investment in OCA per PEP			0.043** (5.24)	0.024** (2.98)		
Initial level of OCA per PEP					0.032# (1.81)	0.031# (1.66)
R&D embodied in inputs		(0.237) (1.10)		0.649** (3.70)		0.199 (1.21)
R&D embodied in investment		1.202 (1.23)		(4.240)** (4.64)		0.901 (1.21)
Dummy variable for services			0.017 (1.51)	0.030** (2.97)	0.020* (2.34)	0.026** (2.83)
R^2	0.119	0.145	0.250	0.479	0.135	0.165
Adjusted R^2	0.098	0.194	0.223	0.448	0.104	0.114
Standard error	0.0469	0.0467	0.0429	0.0361	0.0339	0.0370
Sample size	88	88	88	88	88	88
Industries	All	All	All	All	All	All

Notes: The sample consists of pooled cross-section time-series data, with observations on each of 44 industries (excluding the government sector) in 1970–80 and 1980–90. The coefficients are estimated using the White procedure for a heteroschedasticity-consistent covariance matrix. The absolute value of the *t*-statistic is shown in parentheses below the coefficient estimate.
DIOCCUP: dissimilarity index for occupational coefficients.
DIACOEFF: dissimilarity index for technical interindustry coefficients.
DIKCOEFF: dissimilarity index for capital coefficients.
#Significant at the 10% level; *significant at the 5% level; **significant at the 1% level.

The second variable is DIACOEFF, a measure of the degree of change in interindustry technical coefficients. In this case, too, computerization is significant at the 1 percent level with the predicted positive coefficient. The best fit is provided by investment in OCA per worker. The coefficient of R&D intensity is positive but not statistically significant, while the coefficients of R&D embodied in both intermediate inputs and investment goods are both positive and significant at the 1 percent level. The coefficient of the dummy variable for services is significant at the 1 percent level when embodied R&D is included in the regression but in this case has a positive sign.

The third index of structural change is DIKCOEFF, a measure of how much the composition of capital has changed over the period. In this case, it is not possible to use investment in OCA as an independent variable, since, by construction, it will be correlated with changes in the capital coefficients. Instead, I use the initial level of OCA per worker. The computerization variable has the predicted positive sign and is significant, though only at the 10 percent level. The coefficients of R&D intensity and embodied R&D are all insignificant. However, the dummy variable for services is positive and significant at the 1 or 5 percent level.

In sum, computerization is found to be strongly linked to occupational restructuring and changes in material usage and weakly linked to changes in the composition of capital. With regard to the first result, it might be appropriate to say a few words about the construction of industry OCA by the Bureau of Economic Analysis. The allocation of investment in OCA is based partly on the occupational composition of an industry. As a result, a spurious correlation may be introduced between industry-level OCA investment and the skill mix of an industry. However, there is no indication that this allocation procedure should affect the *change* in occupational composition and hence introduce a spurious correlation between OCA investment and the DIOCCUP variable. Moreover, the time-series evidence shows a marked acceleration in the degree of occupational change between the 1970s and 1980s, when OCA investment rose substantially. Regressions of the change in occupational composition (DIOCCUP) on both the growth of equipment per worker and the growth of total capital per worker fail to yield significant coefficients. As a result, we can surmise that this finding is on solid ground.

5. Conclusion and Interpretation of Results

I find that computerization is strongly and positively associated with two dimensions of structural change. These are occupational restructuring and changes in the composition of intermediate inputs. The evidence is a bit weaker for its effects on changes in the composition of industry capital stock. The bottom line is that the diffusion of IT has "shaken up" the U.S. economy, beginning in the 1970s. However, it is a technological revolution that appears to show up more strongly in measures of structural change rather than in terms of productivity, if the previous literature is a good guide on the latter issue. In particular, the strongest results of the effects of OCA on productivity growth are found for the late 1990s in the U.S. My results seem to indicate that OCA has had strong effects on changes in occupational composition and input structure dating from the early 1970s.

These two sets of results might reflect the high adjustment costs associated with the introduction of new technology. The paradigmatic shift from electro-mechanical automation to information technologies might require major changes in the organizational structure of companies before the new technology can be realized in the form of measured productivity gains (see, David, 1991, for greater elaboration of this argument). Some confirmation of this hypothesis is provided by Brynjolfsson and Hitt (1998), for example, who find that computerization has a positive effect on firm-level productivity only as long as there are concomitant changes in firm.

These results on computerization are also consistent with an alternative interpretation of its role in modern industry. The argument is that a substantial amount of new technology (particularly information technology) may be used for product differentiation rather than productivity enhancement. Computers allow for greater diversification of products, which, in turn, also allows for greater price discrimination (e.g. airline pricing systems) and the ability to extract a large portion of consumer surplus. Greater product diversity might increase firm profits, though not necessarily its productivity. Some evidence on the production differentiation effects of computers is provided by Chakraborty and Kazarosian (1999) for the U.S. trucking industry (for example, speed of delivery versus average load).

Appendix

(1) NIPA employee compensation: Figures are from the National Income and Product Accounts (NIPA), available on the Internet. Employee compensation includes wages and salaries and employee benefits.

(2) NIPA employment data: Full-time equivalent employees (FTE) equals the number of employees on full-time schedules plus the number of employees on part-time schedules converted to a full-time basis. FTE is computed as the product of the total number of employees and the ratio of average weekly hours per employee for all employees to average weekly hours per employee on full-time schedules. Persons engaged in production (PEP) equals the number of full-time equivalent employees plus the number of self-employed persons. Unpaid family workers are not included.

(3) Capital stock figures are based on chain-type quantity indexes for net stock of fixed capital in 1992$, year-end estimates. Source: U.S. Bureau of Economic Analysis, CD-ROM NCN-0229, "Fixed Reproducible Tangible Wealth of the United States, 1925–97."

(4) Research and development expenditures performed by industry include company, federal, and other sources of funds. Company-financed R&D performed outside the company is excluded. Industry series on R&D and full-time equivalent scientists and engineers engaged in R&D per full-time equivalent employee run from 1957 to 1997. Source: National Science Foundation, Internet. For technical details, see National Science Foundation, *Research and Development in Industry* (National Science Foundation, Arlington, VA), NSF96-304, 1996.

(5) The original input–output data are 85-sector U.S. input–output tables for years 1947, 1958, 1963, 1967, 1972, 1977, 1982, 1987, 1992, and 1996 (see, for example, Lawson, 1997, for details on the sectoring). The 1947, 1958, and 1963 tables are available only in single-table format. The 1967, 1972, 1977, 1982, 1987, 1992, and 1996 data are available in separate make and use tables. These tables have been aggregated to 45 sectors for conformity with the other data sources. The 1950, 1960, 1970, 1980, and 1990 input–output tables are interpolated from the benchmark U.S. input–output tables.

TABLE A1

45-Sector Industry Classification

Industry Number	1987 SIC Codes
1. Agriculture, forestry, and fishing	01–09
2. Metal mining	10
3. Coal mining	11,12
4. Oil and gas extraction	13
5. Mining of nonmetallic minerals, except fuels	14
6. Construction	15–17
7. Food and kindred products	20
8. Tobacco products	21
9. Textile mill products	22
10. Apparel and other textile products	23
11. Lumber and wood products	24
12. Furniture and fixtures	25
13. Paper and allied products	26
14. Printing and publishing	27
15. Chemicals and allied products	28
16. Petroleum and coal products	29
17. Rubber and miscellaneous plastic products	30
18. Leather and leather products	31
19. Stone, clay, and glass products	32
20. Primary metal products	33
21. Fabricated metal products, including ordnance	34
22. Industrial machinery and equipment, excl. electrical	35
23. Electric and electronic equipment	36
24. Motor vehicles and equipment	371
25. Other transportation equipment	37 [except 371]
26. Instruments and related products	38
27. Miscellaneous manufactures	39
28. Transportation	40–42, 44–47
29. Telephone and telegraph	481, 482, 484, 489
30. Radio and TV broadcasting	483
31. Electric, gas, and sanitary services	49
32. Wholesale trade	50–51
33. Retail trade	52–59
34. Banking; credit and investment companies	60–62, 67
35. Insurance	63–64
36. Real estate	65–66
37. Hotels, motels, and lodging places	70
38. Personal services	72
39. Business and repair services except auto	73, 76
40. Auto services and repair	75
41. Amusement and recreation services	78–79
42. Health services, including hospitals	80
43. Educational services	82
44. Legal and other professional services and nonprofit organizations	81, 83, 84, 86, 87, 89
45. Public administration	–

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