Productivity, Computerization, and Skill Change

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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, industries that have had the greatest investment in computers (namely, financial services) have ranked among the lowest in terms of conventionally measured productivity growth. Moreover, at least until recently, there has been little evidence of a payoff 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. This paper argues that 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 pattern coincides with the sharp rise in computerization.

Though most of 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). One purpose of this paper is to help fill this gap. Indeed, this study finds evidence from regression analysis that the degree of computerization has had a statistically significant effect on changes in industry input coefficients and other dimensions of structural change.

Another apparent anomaly arises when we consider the relationship between schooling and skills on the one hand and productivity growth on the other hand. Human capital theory predicts that rising educational attainment and skills will lead to increasing productivity. Considerable policy discussion has also focused on the importance of education and skill upgrading as an ingredient in promoting productivity growth. Yet, as this discussion will show, while overall productivity growth in the United States slowed after 1973, the growth of schooling levels and skills continued unabated. Indeed, college completion rates accelerated after 1970. In the time series data, from 1947 to 1997, there is virtually no correlation between the growth of total factor productivity on the one hand and that of skills or educational attainment on the other. Likewise, on the industry level, sectors with the highest skills—namely services—have had the lowest productivity growth.

This paper will concentrate on the relation of skills, education, and computerization to productivity growth and other indicators of technological change on the industry level. I find no evidence that the growth of educational attainment has any statistically measured effect on industry productivity growth. The growth in cognitive skills, on the other hand, is significantly related to industry productivity growth though the effect is very modest. Moreover, the degree of computerization is not significant. In contrast, computerization has had a statistically significant effect on changes in industry input coefficients.

The paper begins with a review of some of the pertinent literature on the role of skill change and computerization on productivity changes in the U.S. economy. The next two sections introduce the accounting framework and model and present descriptive statistics on postwar productivity trends. Descriptive statistics are also presented for key variables that have shaped the pattern of productivity growth over the postwar period, and multivariate analysis is conducted on the industry level to assess their influence.

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Review of Previous Literature

Human capital theory views schooling as an investment in skills and hence as a way of augmenting worker productivity (see, for example, Schultz 1960 and Becker 1975). This line of reasoning leads to growth accounting models in which productivity or output growth is derived as a function of the change in educational attainment. The early studies on this subject showed very powerful effects of educational change on economic growth. Griliches (1970) estimated that the increased educational attainment of the U.S. labor force accounted for one-third of the aggregate technical change between 1940 and 1967. Denison (1979) estimated that about one-fifth of the growth in U.S. national income per person employed (NIPPE) between 1948 and 1973 could be attributed to increases in educational levels of the labor force. Jorgenson and Fraumeni (1993) calculated that improvements in labor quality accounted for one-fourth of U.S. economic growth between 1948 and 1986.

Yet some anomalies have appeared in this line of inquiry. Denison (1983), in his analysis of the productivity slowdown in the United States between 1973 and 1981, reported that the growth in NIPPE fell by 0.2 percentage points whereas increases in educational attainment contributed 0.6 percentage points to the growth in NIPPE. Maddison (1982) reported similar results for other OECD countries for the 1970–79 period. Wolff (2001), using various series on educational attainment, found no statistically significant effect of the growth in mean years of schooling on GDP growth per capita among OECD countries over the 1950–90 period.

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 studies include Franke (1987), who found that the installation of automated teller machines was associated with a lowered real return on equity; Bailey and Gordon (1988), who examined aggregate productivity growth in the United States 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 during the 1948–86 period in the United States even though it ranked fourth among sixty-four 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 United States, 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, over the 1987–94 time period, a positive correlation between firm-level productivity growth and IT investment when accompanied by organizational changes. Lehr and Lichtenberg (1998) used data for U.S. federal government agencies for 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 for the 1977–93 period and also reported evidence that computers, particularly personal computers, contributed positively and significantly to productivity growth. Ten Raa and Wolff (2001), 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 economywide productivity growth. They also found very high productivity spillovers between the computer-producing sector and sectors using computers. In their imputation procedure, these large spillovers were attributable to the high rate of productivity growth within the computer industry.

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 0 percent for 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 United States, they found that both the use of IT in sectors purchasing computers and other forms of information technology and the production of computers appear to have made an important contribution to the speedup 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 the use of computers improved communications and resource allocation decisions and led to a 3 percent increase in capacity utilization within the industry.

One other factor that will be used in the data analysis is research and development (R&D). A large literature, beginning with Mansfield (1965), has now almost universally established a positive and significant effect of R&D expenditures on productivity growth (see Griliches 1979 and 1992 and Mohnen 1992 for reviews of the literature).

Modeling Framework

I begin with a standard neoclassical production function f_j for sector j:

$$(1)\quad X_j = Z_j f_j(K_{Cj}, K_{Ej}, K_{Sj}, L_j, N_j, R_j),$$

where X_j is the (gross) output of sector j, K_{Cj} is the input of IT-related capital, K_{Ej} is the input of other machinery and equipment capital goods, K_{Sj} is the input of plant and other structures, L_j is the total labor input, N_j is total intermediate input, R_j is the stock of R&D capital, and Z_j is a (Hicks-neutral) total factor productivity (TFP) index that shifts the production function of sector j over time.[1] For convenience, the time subscript has been suppressed. Moreover, capacity utilization and adjustment costs are ignored. It then follows that

$$(2)\quad d\ln X_j = d\ln Z_j + \varepsilon_{Cj} d\ln K_{Cj} + \varepsilon_{Ej} d\ln K_{Ej} + \varepsilon_{Sj} d\ln K_{Sj} + \varepsilon_{Lj} d\ln L_j + \varepsilon_{Nj} d\ln N_j + \varepsilon_{Rj} d\ln R_j,$$

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

$$(3)\quad \pi_j \equiv d\ln X_j/dt - \alpha_{Cj} d\ln K_{Cj}/dt - \alpha_{Ej} d\ln K_{Ej}/dt - \alpha_{Sj} d\ln K_{Sj}/dt - \alpha_{Lj} d\ln L_j/dt - \alpha_{Nj} d\ln N_j/dt.$$

It then follows that

$$(4)\quad \pi_j = d\ln Z_j/dt + \alpha_{Rj} d\ln R_j/dt.$$

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

As Stiroh (2002) argues, there are several reasons that the standard necoclassical model might be expected to fail in the case of the introduction of a radically new technology that might be captured by IT investment. These include the presence of productivity spillovers from IT, 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 IT, $\varepsilon_{Cj,}$ exceeds its measured input share, α_{Cj}, say, by u_{Cj}, then

$$(5)\quad \pi_j = d\ln Z_j/dt + \alpha_{Rj} d\ln R_j/dt + u_{Cj} d\ln K_{Cj}/dt.$$

1. This equation is a modified form of the production function used by Stiroh (2002).

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

A similar argument applies to labor productivity growth, LP, defined as

$$(6)\ LP_j \equiv d\ln X_j/dt - d\ln L_j/dt.$$

If the assumption of competitive input markets and constant returns to scale is again imposed, it follows that

$$(7)\ LP_j = d\ln Z_j/dt + \alpha_{Cj} d\ln k_{Cj}/dt + \alpha_{Ej} d\ln k_{Ej}/dt + \alpha_{Sj} d\ln k_{Sj}/dt + \alpha_{Nj} d\ln n_j/dt + \alpha_{Rj} d\ln R_j/dt,$$

Measures of structural change may provide a more direct and robust test of the effects of computerization on changes in technology than standard measures of productivity growth do.

where lowercase symbols indicate the amount of the input per worker.[2] If for the reasons cited above there is a special productivity "kick" from IT investment, then the estimated coefficient of k_{Cj}/dt should exceeds its factor input share.

However, as indicated in the literature survey in the previous section, very few studies, with the exception of Siegel and Griliches (1992), have found a direct positive correlation between industry TFP growth and IT investment. As a result, this study considers other indicators of the degree of structural change in an industry. These include changes in the occupational composition of employment and in the input and capital composition within an industry. Productivity growth and changes in input composition usually go hand in hand. To illustrate, three new matrices are introduced:

A = forty-five-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 are 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 (BEA) worksheets. Deflators for 1982, 1987, 1992, and 1996 are 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 forty-five industries.

C = forty-five-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 BEA (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 were obtained from the decennial Census of Population for the years 1950, 1960, 1970, 1980, and 1990 (see Wolff 1996 for details).

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

$$(8)\ \pi_j = -[\Sigma_i p_i da_{ij} + \Sigma_i p_{i,c} dc_{ij} + \Sigma_i w_i db_{ij}]/p_j,$$

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. Using the multiplication rule for derivatives, equation 8 can be rewritten as

$$(9)\ \pi_j = -[\Sigma_i p_i da_{ij} + \Sigma_i p_{i,c} dc_{ij} + \Sigma_i w_i \lambda_j dm_{ij} + \Sigma_i w_i m_{ij} d\lambda_j]/p_j,$$

where $\lambda_j = L_j / X_j$. From equation 5 it follows that, in the circumstances enumerated above, there may be a positive correlation between measures of coefficient changes (such as da_{ij}, dc_{ij}, and dm_{ij}) and IT investment.

Though productivity growth and changes in input composition are algebraically related, there are several reasons they may deviate. First, there are costs of adjustments associated with radical restructuring of technology, so 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 one 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 do, particularly when a radically new technology is introduced and the consequent adjustment period is lengthy.

Finally, the change in average worker skills is included in the production function. There are two possible approaches. Let the effective labor input $E = QL$, where Q is a measure of average worker quality (or skills). Then equation 1 can be rewritten as

$$(10)\quad X_j = Z_j f^*_j(K_{Cj}, K_{Ej}, K_{Sj}, E_j, N_j, R_j).$$

Again assuming competitive input markets and constant returns to scale (to the traditional factors of production) and still using equation 6 to define labor productivity growth, one obtains

$$(11)\quad LP_j = d\ln Z_j/dt + \alpha_{Cj}d\ln k_{Cj}/dt + \alpha_{Ej}d\ln k_{Ej}/dt + \alpha_{Sj}d\ln k_{Sj}/dt + \alpha_{Nj}d\ln n_j/dt + \alpha_{Lj}d\ln Q_j/dt + \alpha_{Rj}d\ln R_j/dt.$$

In this formulation, the rate of labor productivity growth should increase directly with the rate of growth of average worker quality or skills.

The second approach derives from the standard human capital earnings function. From Mincer (1974),

$$\ln w = a_0 + a_1 S,$$

where w is the wage, S is the worker's level of schooling (or skills), and a_0 and a_1 are constants. It follows that

$$(d\ln w)/dt = a_i(dS/dt).$$

By definition, the wage share in sector j is $\alpha_{Lj} = w_j L_j/X_j$. Under the assumptions of competitive input markets and constant returns to scale, $\alpha_{Lj} = \varepsilon_{Lj}$, a constant. Therefore, $X_j/L_j = w_j/\varepsilon_{Lj}$. In this case, effective labor input E is given by the equation: $\mathrm{Ln}E = Q + \ln L$. It follows from equation 6 that

$$(12)\quad LP_j = d\ln Z_j/dt + \alpha_{Cj}d\ln k_{Cj}/dt + \alpha_{Ej}d\ln k_{Ej}/dt + \alpha_{Sj}d\ln k_{Sj}/dt + \alpha_{Nj}d\ln n_j/dt + \alpha_{Lj}dQ_j/dt + \alpha_{Rj}d\ln R_j/dt.$$

In other words, the rate of labor productivity growth should be proportional to the change in the level of average worker quality or skills over the period.

Descriptive Statistics

Technological change. Table 1 shows the annual rate of TFP growth for twelve major sectors over the decades of the 1950s, 1960s, 1970s, and 1980s. The periods are chosen to correspond to the employment by occupation and industry matrices. Factor shares are based on period averages (the Tornqvist-Divisia index). The labor input is based on persons engaged in production (PEP), the number of full-time and part-time employees plus the number of self-employed persons, and the capital input is measured by fixed nonresidential net capital stock (1992 dollars).[3] (See the appendix.)

As shown in Table 1 (and Chart 1), the annual rate of TFP growth for the entire economy fell from 1.4 percent per year in the 1950s to 1 percent per year in the 1960s, plummeted to 0.4 percent per year in the 1970s (the "productivity slowdown" period), but subsequently rose to 0.8 percent in the 1980s.[4] In the goods-producing industries (including communications, transportation, and utilities), there was generally a modest slowdown in TFP productivity growth from the 1950–60 period to the 1960–70 periods, followed by a sharp decline in the

2. Technically, the assumption of constant returns to scale of the traditional factors of production is imposed, so that $\alpha_{Cj} + \alpha_{Ej} + \alpha_{Sj} + \alpha_{Nj} + \alpha_{Lj} = 1$.

3. A second index of TFP growth was also used, with full-time equivalent employees (FTE) as the measure of labor input. Results are very similar on the basis of this measure and are not reported below.

4. In November 1999, the BEA released a major revision of the U.S. national accounts. The new BEA data showed a faster rise in real GDP and hence labor productivity during the 1990s than the older data indicated. One major element of the revision is the treatment of software expenses as a capital good rather than as an intermediate purchase. However, the BEA has not released the corresponding revised capital stock data. As a result, the statistics in this paper are based on the older BEA national accounts data.

TABLE 1

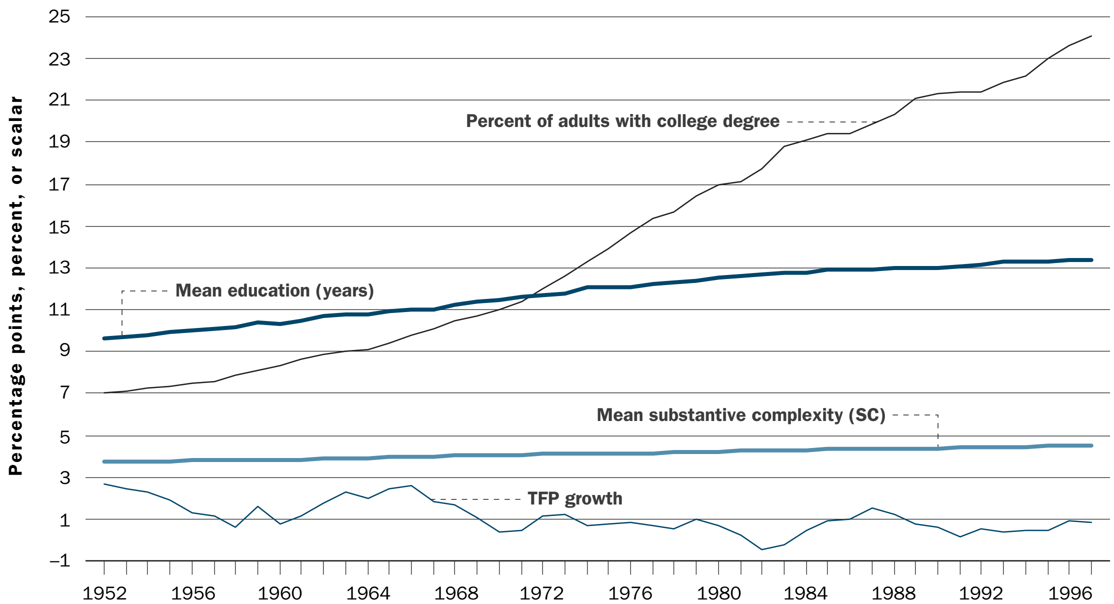
Total Factor Productivity (TFP) Growth by Major Sector, 1950–90

	1950–60	1960–70	1970–80	1980–90	1950–90
A. Goods-producing industries					
Agriculture, forestry, and fisheries	1.54	1.05	–2.33	5.52	1.45
Mining	2.22	3.19	–3.41	3.06	1.27
Construction	4.00	–2.36	–4.48	0.49	–0.59
Manufacturing, durables	1.95	1.72	2.19	3.12	2.25
Manufacturing, nondurables	0.40	1.59	1.07	2.23	1.32
Transportation	1.10	2.97	0.13	0.88	1.27
Communications	2.99	2.55	2.94	1.46	2.49
Electric, gas, and sanitary services	5.35	3.47	2.66	0.62	3.03
B. Service industries					
Wholesale and retail trade	1.08	0.60	–1.01	0.86	0.38
Finance, insurance, and real estate	1.41	0.14	0.37	–1.53	0.10
General services	0.12	–0.05	0.25	–0.35	–0.07
Government and government enterprises	0.59	–0.66	0.15	–0.03	–0.28
Total goods	2.12	1.50	0.25	2.04	1.48
Total services	0.70	0.58	0.58	0.07	0.48
Total economy (GDP)	1.39	0.96	0.38	0.77	0.88

Note: Average annual growth in percentage points.

CHART 1

Annual TFP Growth, Mean Substantive Complexity, Mean Education, and Percent of Adults with a College Education, 1952–97



Note: Annual TFP growth is a five-year running average in percent per year.
Source: See Appendix.

TABLE 2

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

	1950–60	1960–70	1970–80	1980–90	Average 1950–90
A. Goods-producing 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.

1970s (with agriculture, mining, and construction recording negative productivity growth) and then a substantial recovery in the 1980s. The major exceptions are durable manufacturing and communications, whose TFP growth rate rose from the 1960s to the 1970s. TFP growth in the goods-producing industries as a whole averaged 2.1 percent per year in the 1950s, fell to 1.5 percent per year in the 1960s, and then collapsed to 0.3 percent in the 1970s before climbing back to 2 percent per year in the 1980s.

TFP growth has been much lower in the service sector than among goods-producing industries—0.48 percent per year over the 1950–90 period for the former compared to 1.48 percent per year for the latter. The pattern over time is also generally different for the service industries. TFP growth in wholesale and retail trade had a similar pattern to that in goods industries—strong in the 1950–60 period (1.1 percent per year) before falling to 0.6 percent in the 1960s, turning negative in the next decade, and then rebounding to 0.9 percent per year in the 1980s. However, in finance, insurance, and real estate (FIRE) general services, and the government sector, TFP growth dropped from the 1950s to the 1960s, recovered somewhat in the 1970s, and then slipped once again in the 1980s, turning negative in each case. Overall, annual TFP growth among all services fell monotonically between the 1950s and the 1980s, from 0.7 to 0.1 percent.

As noted above, I use three measures of structural change. 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

$$(13)\quad SI^{12} = (\Sigma_i m^1_{ij} m^2_{ij})/[\Sigma_i (m^1_{ij})^2 \Sigma_i (m^2_{ij})^2]^{1/2}.$$

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

$$(14)\quad \text{DIOCCUP}^{12} = 1 - SI^{12}.$$

Descriptive statistics for DIOCCUP are shown in Table 2. The DIOCCUP index for the total economy, after rising slightly from 0.050 in the 1950s to 0.056 in the 1960s 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 of the twelve major sectors

TABLE 3

Dissimilarity Index (DIACOEFF) for Technical Interindustry Coefficients by Major Sector, 1950–90

	1950–60	1960–70	1970–80	1980–90	Average 1950–90
A. Goods-producing 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.

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).

It is also apparent that the association between the DIOCCUP index and industry TFP growth is quite loose. Though the degree of occupational restructuring has been somewhat greater in the goods-producing industries than in services (average scores of 0.062 and 0.045, respectively, for the 1950–90 period), the difference is not nearly as marked as for TFP growth (annual rates of 1.5 percent and 0.5 percent, respectively, over the same period). Moreover, while FIRE ranks second-highest in terms of occupational change, it is the fourth-lowest in terms of TFP growth. In contrast, while agriculture ranks fourth-highest in terms of TFP growth, it ranks lowest in terms of occupational restructuring. The DIOCCUP index provides a separate and relatively independent dimension of the degree of technological change occurring in an industry.

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

$$(15)\quad \text{DIACOEFF}^{12} = 1 - (\Sigma_i a^1_{ij} a^2_{ij}) / [\Sigma_i (a^1_{ij})^2 \Sigma_i (a^2_{ij})^2]^{1/2}.$$

Figures in Table 3 indicate that the DIACOEFF index for the total economy, after falling from 0.036 in the 1950–60 period to 0.027 in the 1960s, 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 the two with the least were agriculture (0.007) and durable manufacturing (0.011).

The correlation between the DIACOEFF index and industry TFP growth is again quite small. While TFP growth was much higher in goods-producing industries than in services, DIACOEFF was higher for services than the goods sector. While agriculture, durable manufacturing, and nondurable manufacturing all ranked high in terms of TFP growth, they were the three lowest in terms of coefficient changes. The DIACOEFF index provides another independent indicator of the degree of industry technological change.

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

TABLE 4

Dissimilarity Index (DIKCOEFF) for Capital Coefficients, 1950–90

	1950–60	1960–70	1970–80	1980–90	Average 1950–90
A. Goods-producing 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.

(16) $$\text{DIKCOEFF}^{12} = 1 - (\Sigma_i c^1_{ij} c^2_{ij}) / [\Sigma_i (c^1_{ij})^2 \Sigma_i (c^2_{ij})^2]^{1/2}.$$

Table 4 shows that the DIKCOEFF index for the total economy, after declining from 0.020 in the 1950s to 0.014 in the 1960s, 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. Here, again, while TFP growth was much higher in goods than in service industries, DIKCOEFF was higher for the latter than the former. Moreover, while agriculture, durable manufacturing, and nondurable manufacturing were all among the top industries in terms of TFP growth, they were among the lowest in terms of capital coefficient changes.

Changes in skills and educational attainment. As discussed in the previous two sections, the human capital model predicts a positive relation between changes in average education or average skill levels and productivity growth. Figures on mean years of schooling by industry are derived directly from decennial Census of Population data for 1950, 1960, 1970, 1980, and 1990.

Educational attainment has been widely employed to measure the skills supplied in the workplace. However, the usefulness of schooling measures is limited by such problems as variations in the quality of schooling both over time and among areas, the use of credentials as a screening mechanism, and inflationary trends in credential and certification requirements. Indeed, evidence presented in Wolff (1996) suggests that years of schooling may not closely correspond to the technical skill requirements of the jobs.

As a result, I also make use of the fourth (1977) edition of the *Dictionary of Occupational Titles* (*DOT*) for direct measures of workplace skills. For some 12,000 job titles, it provides a variety of alternative measures of job-skill requirements based upon data collected between 1966 and 1974. It probably provides the best source of detailed measures of skill requirements covering the period 1950 to 1990. Three measures of workplace skills, described below, are developed from this source for each of 267 occupations (see Wolff 1996 for more details).

Substantive complexity (SC). Substantive complexity is a composite measure of skills derived from a factor analytic test of *DOT* variables. It was found to be correlated with general educational development, specific vocational preparation (training time requirements), data (synthesizing, coordinating, analyzing), and three worker aptitudes—intelligence (general learning and reasoning ability), verbal, and numerical.

Interactive skills (IS). Interactive skills can be measured, at least roughly, by the DOT "people" variable, which, on a scale of 0 to 8, identifies whether the job requires mentoring (0), negotiating (1), instructing (2), supervising (3), diverting (4), persuading (5), speaking-signaling (6), serving (7), or taking instructions (8). For comparability with the other measures, this variable is rescaled so that its value ranges from 0 to 10 and reversed so that mentoring is now scored 10 and taking instructions is scored 0.

The human capital model predicts a positive relation between changes in average education or average skill levels and productivity growth.

Motor skills (MS). Motor skills is another DOT factor-based variable. Also scaled from 0 to 10, this measure reflects occupational scores on motor coordination, manual dexterity, and "things"—job requirements that range from setting up machines and precision working to feeding machines and handling materials.

Composite skills (CS). I also introduce a measure of composite skill, CS, which is based on a regression of hourly wages in 1970 on SC, MS, and IS scores across the 267 occupations. The resulting formula is

$$CS = 0.454SC + 0.093MS + 0.028IS$$

SC is the dominant factor in determining relative wages in 1970, followed by MS and then IS.[5]

Average industry skill scores are computed as a weighted average of the skill scores of each occupation, with the occupational employment mix of the industry as weights. Computations are performed for 1950, 1960, 1970, 1980, and 1990 on the basis of consistent occupation by industry employment matrices for each of these years constructed from decennial census data. There are 267 occupations and 64 industries.

Chart 1 provides some evidence on trends in both cognitive skills (substantive complexity), mean education of the workforce, and the percentage of adults with a college degree or more. Cognitive skills do not appear to be closely correlated with TFP growth. The average annual change in the SC index between 1947 and 1973 was .0156 points while TFP growth averaged 1.4 percent per year and .0170 points between 1973 and 1997, when TFP grew at only 0.6 percent per year. Moreover, the growth of college graduates in the adult population was much greater in the later period, averaging 0.45 percentage points per year, than in the earlier period, averaging only 0.28 percentage points per year. Mean schooling, on the other hand, tracks TFP more closely. The average annual change in mean education was 0.096 years over the 1948–73 period and 0.053 years over the 1973–97 period.

There is also very little cross-industry association between skill levels and productivity growth. As Table 5 shows, cognitive skill levels (SC) were, on average, higher in the service sector than the goods sector. In the 1980s, employees in FIRE had the highest average SC score (5.25), followed by general services (4.85), communications (4.74), and the government sector (4.61). On the other hand, the growth in mean SC was somewhat higher in goods industries (0.53 points) than in services (0.43 points) between 1950 and 1990.

The pattern is very similar for the mean education of the workforce. Average schooling was higher in services than in the goods sector and was led by general services (13.7 in 1980–90), followed by FIRE (13.5), government (13.4), and communications (13.3). The change in mean education over the four decades was also larger in the goods sector (3.4 years) than in the service sector (2.6 years).

Investment in OCA. My measure of IT capital is the stock of office, computing, and accounting equipment (OCA) in 1992 dollars, which is provided in the BEA's 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 6 (and Chart 2), investment in 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 has, but this pattern was largely due to the very heavy investments made by FIRE. The trade and general service sectors were actually below average in

TABLE 5

Average Skill Level by Period and Major Sector, 1950–90

	1950–60	1960–70	1970–80	1980–90	Change 1950–90
		1. Mean years of education (in years)			
A. Goods-producing industries					
Agriculture, forestry, and fisheries	8.05	9.06	10.45	11.45	4.02
Mining	9.19	10.41	11.56	12.45	4.21
Construction	9.53	10.25	11.21	12.04	3.11
Manufacturing, durables	10.28	11.00	11.67	12.39	2.90
Manufacturing, nondurables	9.75	10.48	11.34	12.13	3.05
Transportation	9.78	10.55	11.44	12.27	3.21
Communications	11.42	11.98	12.62	13.31	2.52
Electric, gas, and sanitary services	10.69	11.19	11.78	12.68	2.79
B. Service industries					
Wholesale and retail trade	10.62	11.18	11.89	12.51	2.33
Finance, insurance, and real estate	11.82	12.40	12.95	13.53	2.29
General services	11.56	12.34	13.08	13.66	2.72
Government and government enterprises	11.50	12.02	12.69	13.37	2.42
Total goods	9.59	10.51	11.43	12.23	3.43
Total services	11.20	11.88	12.62	13.23	2.60
Total economy	10.36	11.25	12.13	12.86	3.23
		2. Mean substantive complexity			
A. Goods-producing industries					
Agriculture, forestry, and fisheries	3.67	3.64	3.61	3.64	0.01
Mining	3.35	3.71	3.98	4.13	1.02
Construction	3.67	4.02	4.16	4.22	0.80
Manufacturing, durables	3.50	3.71	3.84	3.96	0.65
Manufacturing, nondurables	2.98	3.12	3.34	3.49	0.58
Transportation	3.16	3.25	3.35	3.32	0.11
Communications	4.02	4.26	4.51	4.74	0.93
Electric, gas, and sanitary services	3.85	3.87	4.07	4.33	0.56
B. Service industries					
Wholesale and retail trade	3.91	3.84	3.88	3.98	0.04
Finance, insurance, and real estate	4.63	4.96	5.13	5.25	0.90
General services	4.32	4.46	4.73	4.85	0.52
Government and government enterprises	4.24	4.30	4.46	4.61	0.42
Total goods	3.41	3.57	3.73	3.83	0.53
Total services	4.18	4.26	4.44	4.57	0.43
Total economy	3.78	3.94	4.15	4.30	0.62

Note: Figures are weighted averages of individual industries within each major sector.

5. The regression results for 1970 hourly wages (HOURWAGE) are as follows: HOURWAGE = 1.145 + 0.454SC + 0.093MS + 0.028IS, N = 267, R^2 = 0.535(4.78) (12.1) (2.37) (0.70), with t-ratios shown in parentheses. See the *DOT*, chapter 3, section 2, for more discussion and analysis and for corresponding regression results for other years.

TABLE 6

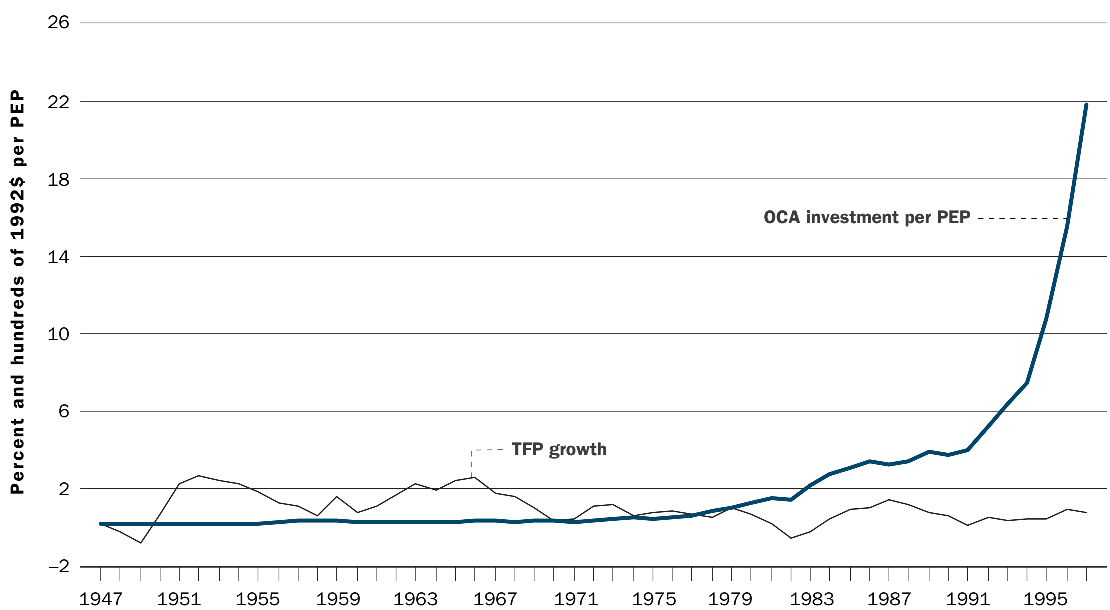
Annual Investment in Office, Computing, and Accounting Equipment (OCA) per Persons Engaged in Production (PEP), 1950–90 (1992$, Period Averages)

	1950–60	1960–70	1970–80	1980–90	Ratio of 1980–90 to 1950–60
A. Goods-producing 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 and government enterprises sectors.

CHART 2

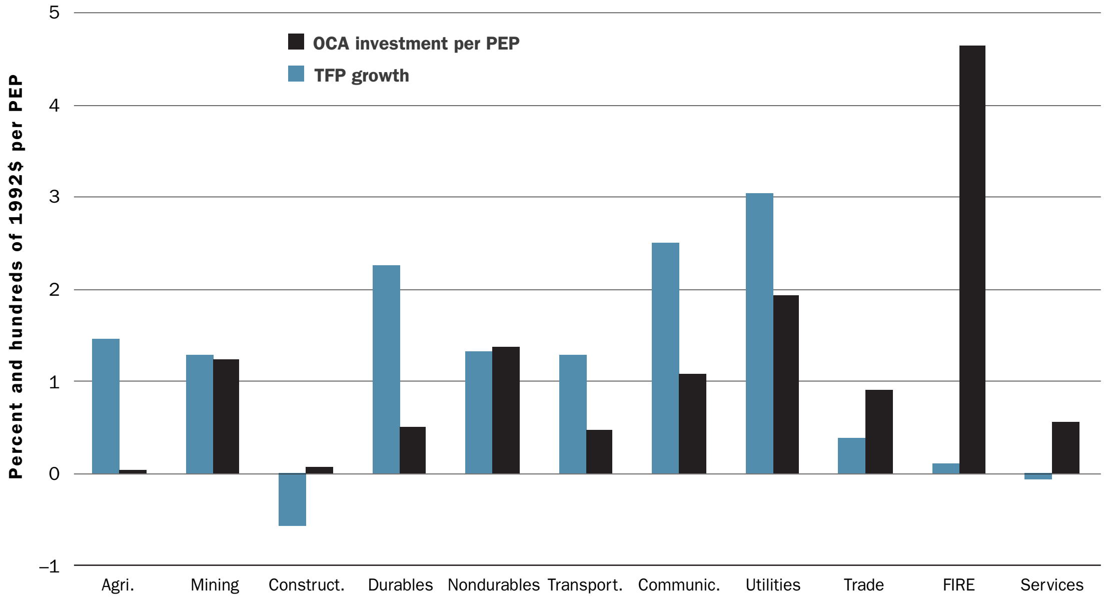
Annual TFP Growth and OCA Investment per Worker, 1947–97



Note: Annual TFP growth is a five-year running average in percent per year. OCA investment is in hundreds of 1992 dollars per PEP.
Source: See Appendix.

CHART 3

TFP Growth and OCA Investment per Worker, 1950–90



Note: Annual TFP growth is a five-year running average in percent per year. OCA investment is in hundreds of 1992 dollars per PEP.
Source: See Appendix.

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.

On the surface, at least, there does not appear to be much relation between OCA intensity and TFP growth. While investment in OCA per worker rose almost continuously over the postwar period, TFP growth tracked downward, at least until the early 1980s (see Chart 2). Moreover, the sector with the highest amount of OCA investment per worker, FIRE, averaged close to zero in terms of TFP growth over the postwar period (see Chart 3).

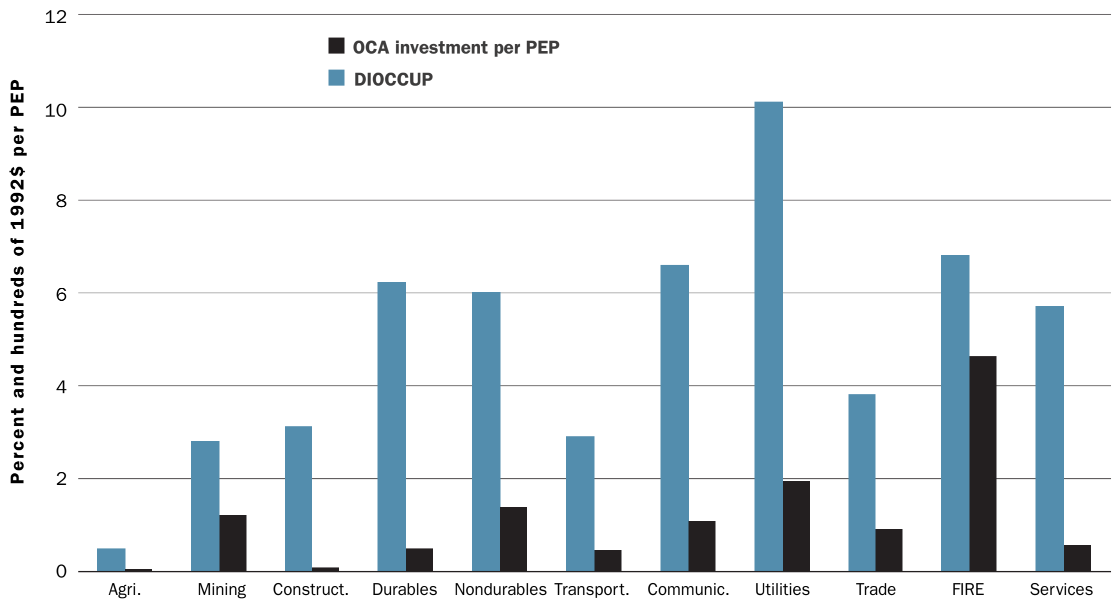
On the other hand, OCA investment seems to line up well with measures of structural change. As shown in Chart 4, the sectors with two highest rates of investment in OCA per PEP over the 1950–90 period are FIRE and utilities, which also rank in the top two in terms of the average value of DIOCCUP over 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 Chart 5). The association is not quite as tight between OCA investment and DIKCOEFF (see Chart 6). However, here again agriculture ranks lowest in both dimensions.

R&D. As shown in Chart 7, the ratio of R&D expenditures to total GDP has remained relatively constant over time, at least in comparison to the wide fluctuations in TFP growth. It averaged 2 percent in the 1960s, fell to 1.5 percent in the 1970s, recovered to 1.9 percent in the 1980s, and remained at this level in the 1990–97 period. The pattern is very similar for individual industries, with the notable exceptions of industrial machinery (including OCA) and instruments, which show a continuous rise over the three periods. The ratio of R&D to sales was considerably higher—by almost a factor of three—in durable manufacturing than in nondurables. In the 1980–90 period, it ranged from a low of 0.4 percent in food products to a high of 18.3 percent in other transportation (including aircraft). The other major R&D-intensive industries, in rank order, are instruments, electric and electronic equipment, industrial machinery, chemicals, and motor vehicles.

An alternative indicator of R&D activity is the number of full-time-equivalent scientists and engineers engaged in R&D per 1,000 full-time-equivalent employees. Like the ratio of R&D expenditures to GDP, this series shows a drop between the 1960s and

CHART 4

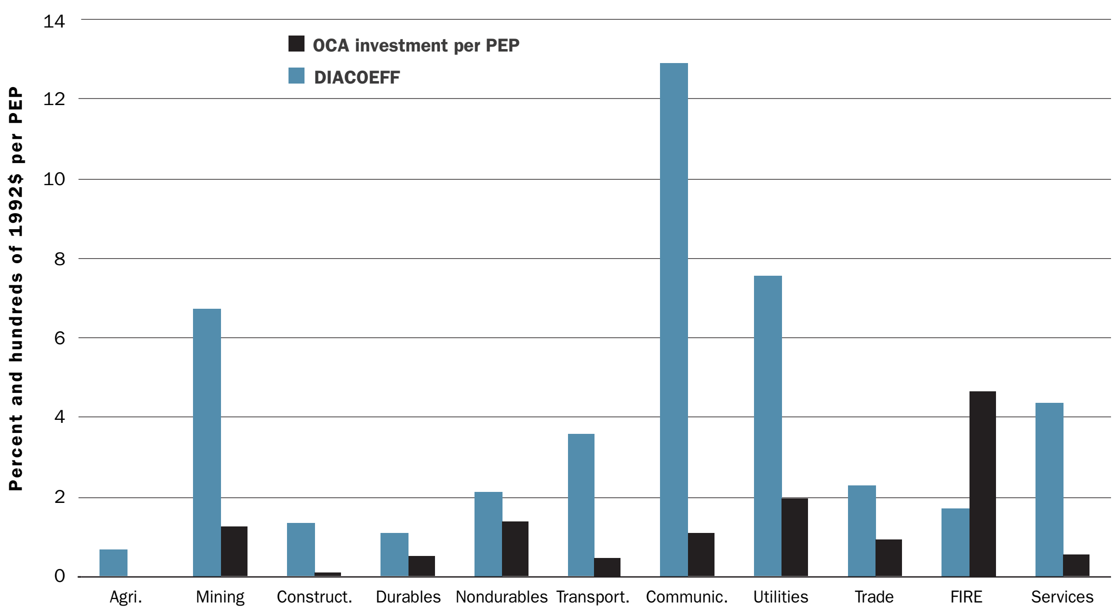
DIOCCUP and OCA Investment per Worker, 1950–90



Note: DIOCCUP is an average for the period in percent. OCA investment is in hundreds of 1992 dollars per PEP.
Source: See Appendix.

CHART 5

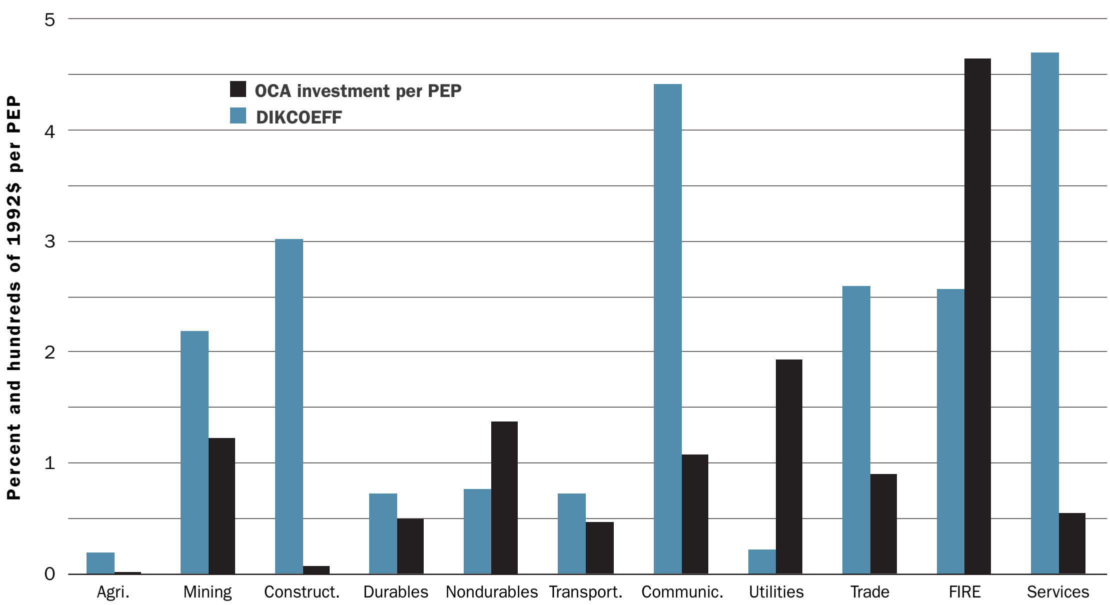
DIACOEFF and OCA Investment per Worker, 1950–90



Note: DIACOEFF is an average for the period in percent. OCA investment is in hundreds of 1992 dollars per PEP.
Source: See Appendix.

CHART 6

DIKCOEFF and OCA Investment per Worker, 1950–90



Note: DIKCOEFF is an average for the period in percent. OCA investment is in hundreds of 1992 dollars per PEP.
Source: See Appendix.

1970s, from 5.4 to 4.8, and a recovery in the 1980s to 6.4 (see Chart 7). However, it shows a further increase to 7.3 in the 1990–96 period. This indicator also gives a very similar industry ranking. The leading industries in the 1980s, in rank order, are other transportation, chemicals, electric and electronic equipment, industrial machinery, instruments, and motor vehicles.

R&D expenditures does a much better job in lining up with TFP growth than either OCA or equipment investment. Both R&D intensity and TFP growth fell from the 1960s to the 1970s and then recovered in the 1980s. Moreover, there is a strong cross-industry correlation between TFP growth and R&D intensity—for example, both R&D intensity and TFP growth are higher in durable manufacturing than in nondurable manufacturing.

Regression Analysis

In the first regression, the dependent variable is the rate of industry TFP growth. The independent variables are R&D expenditures as a percent of net sales and the growth in the stock of OCA capital. 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 forty-five industries and three time periods (1960–70, 1970–80, and 1980–90).[6] The estimating equation is

$$(17)\quad TFPGRTH_j = \beta_0 + \beta_1 RDSALES_j + \beta_2 OCAGRTH_j + vj,$$

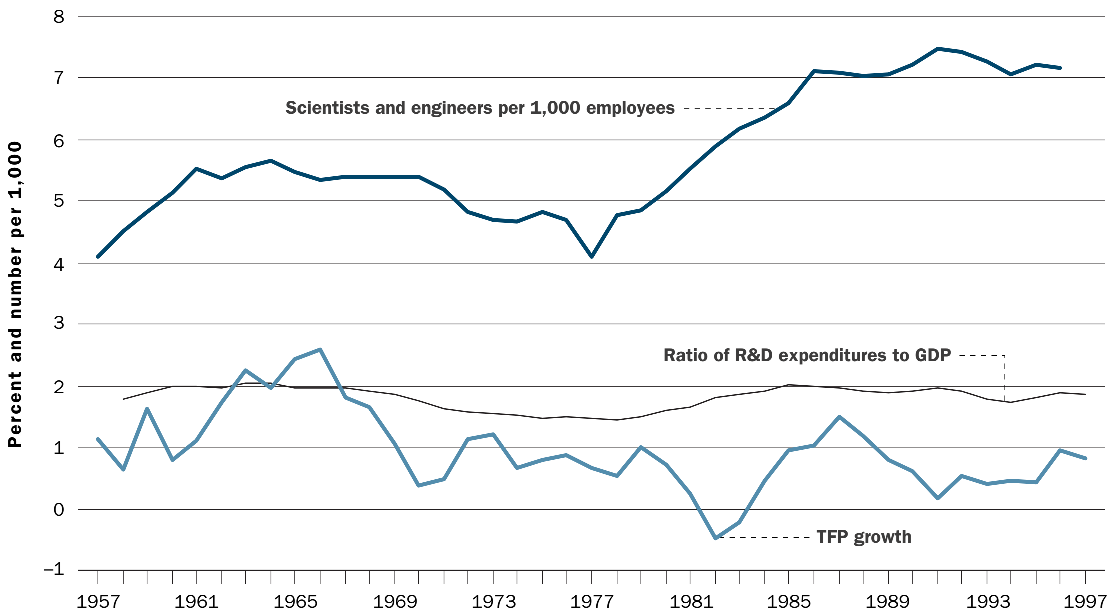
where $TFPGRTH_j$ is the rate of TFP growth in sector j, $RDSALES_j$ is the ratio of R&D expenditures to net sales in sector j, OCAGRTH is the rate of growth of the stock of OCA capital, v_j is a stochastic error term, and the time subscript has been suppressed for notational convenience. It is assumed that the v_{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.

From equation 4 it follows that the constant β_0 is the pure rate of (Hicks-neutral) technological progress. From Griliches (1980) and Mansfield (1980), the coefficient of RDSALES is interpreted as the rate of return of R&D under the assumption

6. The 1950–60 period cannot be included in the regression analysis because the R&D series begins fully only in 1958.

CHART 7

DIKCOEFF and OCA Investment per Worker, 1950–90



Note: DIKCOEFF is an average for the period in percent. OCA investment is in hundreds of 1992 dollars per PEP.
Source: See Appendix.

that the (average) rate of return to R&D is equalized across sectors.[7] Time dummies for the periods 1970–80 and 1980–90 are introduced to allow for period-specific effects on productivity growth not attributable to R&D or OCA investment. A dummy variable identifying the ten service industries is also included to partially control for measurement problems in service sector output.

Basic Regression Results

Regression results for the full sample are shown in columns 1 and 2 of Table 7. The constant term ranges from 0.015 to 0.016. These estimates are comparable to previous estimates of the Hicks-neutral rate of technological change (see Griliches 1979, for example). The coefficient of the ratio of R&D expenditures to net sales is significant at the 5 percent level. The estimated rate of return to R&D ranges from 0.20 to 0.21. These estimates are about average compared to previous work on the subject (see Mohnen 1992, for example, for a review of previous studies).[8]

The coefficient of the growth of OCA is negative but not statistically significant. The same result holds for two alternative measures of IT, the growth in the stock of computers and the stock of OCA plus communications equipment (OCACM). As noted above, these specifications really measure the excess returns to computer investment over and above that to capital in general since TFP growth already controls for the growth of total capital stock per worker. The coefficient of the dummy variable for service industries is significant at the 1 percent level; its value is –0.017. The coefficient of the dummy variable for the 1970–80 period is negative (significant in one of the two cases), and that for the 1980–90 period is positive (but not significant).

Because of difficulties in measuring output in many service industries, regressions were also performed separately for the thirty-one goods-producing industries (see the appendix table).[9] The coefficient values and significance levels of the constant term, R&D intensity, the dummy variable for services, and the two time period dummy variables are strikingly similar to those for the all-industry regressions (see specifications 3 and 4 of Table 7). The coefficient of the growth in computer stock remains negative but insignificant (specification 4).[10]

The next two regressions, focus on the "computer age," the period from 1970 onward. Does the effect of computerization on productivity growth now show up for this restricted sample? The answer is still negative, as shown in specifications 5 and 6 of Table 7. The coefficients of the other two computerization variables, the rate of growth in the stock of computers and that of OCACM are also insignificant

TABLE 7

Cross-Industry Regressions of Industry TFP Growth (TFPGRTH) on R&D Intensity and OCA Investment

Independent variables	Specification (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.015**	0.016**	0.014*	0.014**	0.011	0.020	0.010	0.005
	(3.45)	(3.59)	(2.59)	(2.63)	(1.38)	(1.53)	(1.24)	(0.35)
Ratio of R&D expenditures to sales	0.203*	0.212*	0.199#	0.205#	0.338*	0.348#	0.171*	0.131#
	(2.17)	(2.24)	(1.89)	(1.93)	(2.28)	(2.00)	(2.26)	(1.86)
Annual growth in OCA		–0.039		–0.024	–0.053	–0.102	–0.060	–0.016
		(1.36)		(0.62)	(1.27)	(1.21)	(1.29)	(0.19)
Dummy variable for services	–0.017**	–0.017**			–0.018*		–0.032**	–0.023*
	(3.47)	(3.34)			(2.47)		(3.08)	(2.10)
Dummy variable for 1970–80	–0.010#	–0.006	–0.012#	–0.009				
	(1.89)	(0.95)	(1.74)	(1.05)				
Dummy variable for 1980–90 (or 1987–97)	0.003	0.007	0.009	0.011	0.012#	0.008	0.005	
	(0.59)	(1.13)	(1.22)	(1.37)	(1.95)	(0.80)	(0.81)	
R^2	0.195	0.205	0.127	0.131	0.216	0.145	0.232	0.187
Adjusted R^2	0.171	0.174	0.098	0.092	0.178	0.078	0.201	0.129
Standard error	0.0249	0.0251	0.0280	0.0281	0.0286	0.0289	0.0267	0.0292
Sample size	132	132	93	93	88	42	88	44
Sample	All	All	Goods	Goods	All	Goods	All	All
Period	1960–90	1960–90	1960–90	1960–90	1970–90	1970–90	1977–97	1987–97

Note: Significance levels: #, 10%; *, 5%; **, 1%. The full sample consists of pooled cross-section time-series data, with observations on each of 44 industries in 1960–70, 1970–80, and 1980–90 or in 1977–87 and 1987–97 (sector 45, public administration, is excluded because of a lack of appropriate capital stock data). The goods sample consists of 31 industries (industries 1 to 31 in the Appendix table). The coefficients are estimated using the White procedure for a heteroscedasticity-consistent covariance matrix. The absolute value of the t-statistic is in parentheses below the coefficient. See the Appendix for sources and methods.

(results not shown). R&D intensity remains significant in these regressions, and the estimated return to R&D is higher, between 34 and 35 percent. The same results for computerization (and R&D investment) are found when the sample is further restricted to the 1980–90 period.

Specification 7 in Table 7 is based on a pooled sample of observations for the 1977–87 and 1987–97 periods, while specification 8 is restricted to the 1987–97 period. As before, the coefficient of the growth of OCA per worker is negative but not significant. Likewise, the coefficients of the rate of growth in the stock of OCACM per employee and the rate of growth of computers per employee are insignificant (results not shown). In these regressions, the coefficient of R&D intensity remains significant but is somewhat lower (a range of 0.13 to 0.17) while the coefficient of the service dummy variable also stays significant but is higher in absolute value (a range of –0.23 to –0.032).

Regression results with worker skills. Table 8 shows the regression results for the various measures of worker skills and for the two alternative formulations. Following equations 11 and 12, I use labor productivity growth as the dependent variable. The first specification does not include skill

7. The proof is that RDSALES = dR/X. From equations 2 and 4 it follows that $\pi = \varepsilon_R(dR/R) = \varepsilon_R(dR/X)(X/R) = (\varepsilon_R X/R)(dR/X)$. Therefore, $\beta_1 = (\varepsilon_R X/R) = (dX/X)(X/R)/(dR/R) = dX/dR$. The term dX/dR is the marginal productivity of R&D capital, which is equivalent to the rate of return to R&D.
8. The coefficient of the number of full-time-equivalent scientists and engineers engaged in R&D per employee is also significant in every case, typically at the 1 percent level. The tables present results using R&D expenditures because it is more conventional.
9. Since output measurement problems are less likely to affect transportation, communications, and utilities, they are classified as goods-producing industries here.
10. Results are again similar when the sample of industries is further restricted to the twenty manufacturing industries (results not shown).

TABLE 8

Cross-Industry Regressions of Industry Labor Productivity Growth on R&D Intensity, Capital Investment, and Skill Change, 1960–90

Independent variables	Specification (1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.017**	0.033	0.031**	0.030*	0.038*	0.017**	0.014#
	(2.96)	(1.47)	(3.23)	(3.39)	(2.00)	(2.81)	(1.74)
Ratio of R&D expenditures to sales	0.164#	0.182#	0.174#	0.184#	0.178#	0.174#	0.170#
	(1.73)	(1.86)	(1.84)	(1.95)	(1.86)	(1.77)	(1.77)
Growth in OCA per worker	–0.006						
	(0.20)						
Growth in total capital less OCA per worker	0.262*						
	(2.50)						
Growth in total capital per worker		0.235*	0.237*	0.239*	0.252*	0.244*	0.251*
		(2.27)	(2.31)	(2.34)	(2.45)	(2.31)	(2.43)
Growth in substantive complexity (SC)		0.181	0.125#				
		(1.19)	(1.78)				
Growth in interactive skills (IS)		–0.055					
		(0.44)					
Growth in motor skills (MS)		–0.015					
		(0.09)					
Growth in composite skills (CS)				0.202#			
				(1.89)			
Growth in mean education					0.110		
					(1.14)		
Change in substantive complexity (SC)						0.224	
						(0.90)	
Change in interactive skills (IS)						–0.346	
						(1.04)	
Change in motor skills (MS)						0.006	
						(0.02)	
Change in mean education							0.056
							(0.66)
Dummy variable for services	–0.014**	–0.013#	–0.011*	–0.011*	–0.012*	–0.015**	–0.013*
	(2.66)	(1.93)	(2.14)	(2.05)	(2.13)	(2.92)	(2.47)
Dummy variable for 1970–80	–0.009#	–0.009	–0.009	–0.009*	–0.012*	–0.009	–0.012*
	(1.47)	(1.60)	(1.65)	(1.59)	(2.12)	(1.59)	(1.98)
Dummy variable for 1980–90	0.005	0.006	0.006	0.006	0.009	0.008	0.004
	(0.82)	(0.96)	(1.00)	(1.08)	(0.99)	(1.23)	(0.77)
R^2	0.217	0.236	0.234	0.237	0.223	0.226	0.218
Adjusted R^2	0.179	0.186	0.197	0.200	0.186	0.176	0.180
Standard error	0.0252	0.0251	0.0249	0.0249	0.0251	0.0253	0.0252
Sample size	132	132	132	132	132	132	132

Note: Significance levels: #, 10%; *, 5%; **, 1%.The sample consists of pooled cross-section time-series data, with observations on each of 44 industries in 1960–70, 1970–80, and 1980–90 (sector 45, public administration, is excluded because of a lack of appropriate capital stock data).The coefficients are estimated using the White procedure for a heteroscedasticity-consistent covariance matrix. The absolute value of the *t*-statistic is in parentheses below the coefficient. See the Appendix for sources and methods.

change but splits total capital into OCA and other capital. The coefficient of the growth of OCA per worker is virtually zero, and the t-statistic is close to zero. This result provides further corroboration of a lack of a special effect of OCA investment on productivity growth.

In the second specification, I include the annual change of the three measures of workplace skill: substantive complexity (SC), interactive skills (IS), and motor skills (MS). I also include the growth of total capital per worker. None of the skill variables is statistically significant in this regression. The coefficients of the growth of IS and MS are, in fact, negative. However, when the growth in cognitive skills is included by itself, its coefficient becomes marginally significant (at the 10 percent level). Its elasticity is 0.13. The growth in the composite skill index (CS) is also significant at the 10 percent level (with a higher t-ratio) and its elasticity is 0.20 (specification 4). The best fit (highest adjusted R^2) occurs with the use of the CS variable. The coefficient of the growth in mean schooling is also positive, with an elasticity of 0.11, but not statistically significant (specification 5).

Estimated coefficients for the change in mean skills and mean schooling are not as significant as those for the corresponding growth rates (specifications 6 and 7). None of the coefficients is even close to significance. These results suggest that the labor productivity growth is more closely related to the growth in worker schools rather than to their absolute change. This set of results remains robust among alternative samples—goods-producing industries only and for the 1970–90 period.[11]

In the set of regressions shown in Table 8, R&D intensity is significant at the 10 percent level and its estimated value is somewhat lower than in the corresponding TFP regressions (Table 7). The coefficient of the dummy variable for services is also slightly lower (in absolute value) than in the TFP regressions. The coefficient of the growth of total capital per worker is in the range of 0.24 to 0.25, somewhat lower than its income share, and is significant at the 5 percent level in all cases.

As discussed in the introduction, Brynjolfsson and Hitt (1996, 1998) found a positive correlation between firm-level productivity growth and IT investment when the introduction of IT was accompanied by organizational changes. This finding suggests that interaction effects may exist between OCA investment and changes in occupational composition. This was investigated by adding an interaction term between the growth of OCA per worker and DIOCCUP to the labor productivity regression equation derived from equation 11. The regression was estimated for the full sample of industries over both the 1960–90 and the 1970–90 periods and for goods industries only over the two sets of periods. The coefficient of the interaction term is statistically insignificant in all cases and actually negative in about half the cases.[12]

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.

Other indicators of technological activity. In the last set of regressions, shown in Table 9, measures of structural change are used as dependent variables. As before, 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 forty-four industries and two time periods (1970–80 and 1980–90).[13] The basic estimating equation is of the same form as equation 17, with R&D intensity and the growth of OCA stock as independent variables. Dummy variables are also included for the service sector and the 1970–80 period. Moreover, following equation 11, I also use the growth of OCA per worker and OCA investment per worker as independent variables in place of the growth of total OCA stock.

The first of the dependent variables is the change in occupational composition (DIOCCUP). In contrast to the TFP regressions, the coefficient of investment in OCA per worker is positive and significant at the

11. Results remain almost unchanged when an alternative measure of labor productivity growth, based on full-time-equivalent employees (FTE) instead of persons engaged in production, is used as the dependent variable.

12. Regressions were also estimated with interaction terms between the growth of OCA per worker and the growth or change in SC < CS and mean education. None of these interaction terms was found to be statistically significant.

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

TABLE 9

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

Independent variables	Dependent variable DIOCCUP	DIOCCUP	DIACOEFF	DIACOEFF	DIKCOEFF	DIKCOEFF
Constant	0.048**	0.055**	0.001	–0.02*	0.016**	0.008
	7.29	(8.00)	(0.13)	(2.24)	(2.98)	(1.02)
Ratio of R&D expenditures to sales	0.251	0.214	0.136	0.309	0.206	0.129
	(1.10)	(0.97)	(0.59)	(1.57)	(1.17)	(0.71)
Investment in OCA per worker	0.060**	0.048*	0.043**	0.024**		
	(3.07)	(2.23)	(5.24)	(2.98)		
Initial level of OCA per worker					0.032#	0.031#
					(1.81)	(1.66)
Dummy variable for services		0.008		0.017		0.026**
		(0.08)		(1.51)		(2.83)
Dummy variable for 1970–980		–0.021*		-0.001		–0.007
		(2.30)		(0.12)		(0.89)
R^2	0.112	0.145	0.250	0.271	0.135	0.165
Adjusted R^2	0.091	0.104	0.223	0.227	0.104	0.114
Standard error	0.0470	0.0457	0.0429	0.0410	0.0339	0.0341
Sample size	88	88	88	88	88	88
Industries	All	All	All	All	All	All

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

1 percent level in the regression without the service and time period dummy variables and positive and significant at the 5 percent level when the dummy variables are included. The coefficients of the alternative computerization measures, the growth in OCA per employee, investment in OCACM per worker, and the rate of growth in the stock of OCACM per employee are also significant at the 1 or 5 percent level (results not shown). However, the best fit is provided by investment in OCA per worker. The results also show that R&D intensity is not a significant explanatory factor in accounting for changes in occupational composition, nor is the dummy variable for services. However, the time period dummy variable is significant at the 5 percent level.[14]

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, as is the coefficient of the dummy variable for services. The coefficient of the time dummy variable is virtually zero.

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 coefficient of R&D is positive but insignificant. However, the dummy variable for services is positive and significant at the 1 percent level. The coefficient of the dummy variable for 1970–80 is negative but not significant.

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. For the first result, it might be appropriate to look at the construction of industry OCA by the BEA. 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. The cross-industry correlation between OCA per worker and the mean SC level is 0.48 in 1970, 0.39 in 1980, and 0.56 in 1990 while that between OCA per worker and the mean schooling level of an industry is 0.46 in 1970, 0.29 in 1980, and 0.37 in 1990.

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.

Conclusion and Interpretation of Results

Three sets of findings emerge from the regression analysis. First, the regression results provide some modest evidence that skill growth is positively linked with productivity growth. The coefficients of the growth in both cognitive skills (SC) and the composite skill (CS) index are marginally significant (at the 10 percent level). The effects are not large—elasticities of 0.125 and 0.202, respectively. Between 1947 and 1997, cognitive skills have grown at an average annual rate of 0.41 percent, and composite skills by 0.33 percent. The growth of cognitive skills over this period would have added 0.05 percentage points to the growth of annual labor productivity, while the growth of composite skills would have added 0.07 percentage points. On the other hand, the coefficient of the growth of the mean education of the workforce, while positive, is not statistically significant. Its estimated elasticity is 0.110. Since mean education grew, on average, by 0.69 percent per year over the 1947–97 period, its growth would have added 0.07 percentage points to annual labor productivity growth.

These findings appear to be inconsistent with growth accounting models, which have attributed a substantial portion of the growth in U.S. productivity to increases in schooling levels. The conflict stems from methodological differences in the two techniques. Growth accounting simply assigns to schooling (or measures of labor quality) a (positive) role in productivity growth based on the share of labor in total income. In contrast, in regression analysis an estimation procedure is used to determine whether a variable such as education is a significant factor in productivity growth.

The findings on the role of education in productivity growth also appear to be at variance with the standard human capital model. There are several possible reasons. First, the causal relation between productivity and schooling may be the reverse of what is normally assumed. In particular, as per capita income rises within a country, schooling opportunities increase, and more and more students may seek a college education (see Griliches 1996 for a discussion of the endogeneity of education). Second, the skills acquired in formal education, particularly at the university level, may not be relevant to the workplace. Rather, higher education may perform a screening function, and a university degree may serve employers mainly as a signal of potential productive ability (see Arrow 1973 or Spence 1973). As enrollment rates rise, screening or educational credentials may gain in importance, and a higher proportion of university graduates may become overeducated relative to the actual skills required in the workplace.

A third possibility is that university education may be associated with rent-seeking activities rather than lead directly to productive ones. This pattern may be true for many professional workers, such as lawyers, accountants, advertising personnel, and brokers. A fourth possible explanation is the increasing absorption of university graduates by "cost disease" sectors characterized by low productivity growth, such as health, teaching, law, and business (see Baumol, Blackman, and Wolff 1989). These are essentially labor activities and, as such, are not subject to the types of automation and mechanization that occur in manufacturing and other goods-producing industries. Moreover, these industries may be subject to output measurement problems, particularly in regard to quality change.

Second, there is no evidence that computer investment is positively linked to TFP growth. In other words, there is no residual correlation between computer investment and TFP growth over and above the inclusion of OCA as normal capital equipment in the TFP calculation. This result holds not only for the 1960–90 period but also for the 1970–90, 1980–90, 1977–97, and 1987–97 periods. The result also holds among exclusively goods-producing industries and among exclusively manufacturing industries. This finding is not inconsistent with recent work on the subject. Oliner and Sichel

14. It is not possible to use changes in skill levels or education as independent variables since, by definition, they would be associated with shifts in occupational composition.

(2000), for example, found a strong effect of computers on productivity growth only beginning in the mid-1990s, which is beyond my period of analysis.

Third, in contrast, computerization is strongly and positively associated with other dimensions of structural change. These include 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 appears to have shaken up the U.S. economy, beginning in the 1970s. However, it is a technological revolution that shows 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 United States. 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 electromechanical 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). The results of 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 (for example, airline pricing systems) and the ability to extract a large portion of consumer surplus. Greater product diversity might increase a firm's 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

Data Sources and Methods

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

Educational attainment: (a) Median years of schooling, adult population; (b) percent of adults with four years of high school or more; and (c) percent of adults with four years of college or more. Source: U.S. Bureau of the Census, *Current Population Reports Reports* <www.census.gov/hhes/income/histinc/incperdet.html>. "Adults" refers to persons twenty-five years of age and over in the noninstitutional population (excluding members of the armed forces living in barracks). (d) Mean (or median) schooling of workers by industry for 1950, 1960, 1970, 1980, and 1990 is derived from the decennial U.S. Census of Population Public Use Samples for the corresponding years.

Input-output data: The original input-output data are eighty-five-sector U.S. input-output tables for 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 forty-five 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.

NIPA employee compensation: Figures are from the National Income and Product Accounts (NIPA) <www.bea.gov/bea/dn/nipaweb/>. Employee compensation includes wages and salaries and employee benefits.

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.

Research and development expenditures: R&D 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 <www.nsf.gov/sbe/srs/nsf02312/>. For technical details, see National Science Foundation, *Research and Development in Industry* (Arlington, Va.: National Science Foundation) NSF96-304, 1996.

TABLE

45-Sector Industry Classification Scheme

Industry	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, exc. electrical	35
23. Electric and electronic equipment	36
24. Motor vehicles and equipment	371
25. Other transportation equipment	37 [exc. 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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