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Technical Change and the Demand for Skills by U.S. Industries

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Abstract. Previous studies have explained the demand for skills, usually measured by schooling attainment, by either factor price substitution, capital-skill complementarity, or technology-skill complementarity. We explore this demand with direct job-based measures of cognitive (CS), interactive (IS), and motor (MS) skills in a single model that includes all three sets of possible determinants. The results raise doubts about the adequacy of schooling as a measure of skill and TFP growth as an index of technical change. We find little support for capital-skill complementarity; capital-intensity and its growth are significantly inversely related to CS and MS levels and growth. Technical change is unambiguously linked to increasing CS, rising professional/technical shares, and declining operative/laborer shares. The effects on MS and IS are mixed, but young capital increases craft shares, and computer-intensity decreases supervisory and clerical/service shares.

A good match between the demand for skills and their supply is a prerequisite for any well-functioning economy. This is no simple matter, particularly in the current period of rapid changes in the technology and organization of production, since new skills and capabilities usually require both considerable time to develop and costly personal and institutional adjustments. The widely perceived inadequacy of education and job training in the U.S. has become an increasing source of concern for policy makers, but before better training processes can be designed, a necessary first step is to anticipate future demands for skills in the workplace. Whether this can be done very well depends in part on our ability to describe and explain recent trends in skill composition.

Previous econometric studies of interindustry differences in skills and skill growth have focused on the effects of factor prices and capital-intensity on indices of schooling attainment. The results of these tests have been interpreted to provide strong support for the

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standard factor substitution model and the capital-skill complementarity hypothesis (Hamermesh, 1986), but these studies rarely considered the effects of technical change and other structural characteristics on the demand for skills. In another strand of the literature (Nelson and Phelps, 1966; Schultz, 1975), better educated workers are assumed better adapted to deal with the changes in work organization and job tasks that accompany technical change. The results of several recent studies (Bartel and Lichtenberg, 1987; Mincer and Higuchi, 1989; Gill, 1989) have provided empirical support for this link between the demand for education and new technology. But this line of research has relied heavily on TFP growth to measure technical change and has not attempted to control for relative factor prices or a variety of potentially important industry characteristics.

But perhaps more significantly, a weaknesss common to both sets of studies has been the presumption that educational attainment is synonymous with skill requirements in the workplace. As the case study literature attests, most jobs require a multitude of different skills for adequate task performance, ranging from eye-hand coordination and strength to analytical, numerical, verbal, interpersonal and supervisory skills. Since widely varying levels of different kinds of school-based training are necessary to adequately perform the tasks that define each occupation, a single years of schooling measure would almost certainly provide a poor index of the relative skills of, say, medical doctors, machinists, social workers and stockbrokers. Differences in the quality of schooling across schools and regions, and the use of this measure as a screening device for behavioral characteristics raise further questions about what schooling attainment really measures.

This paper attempts to account for skill composition and its change over time with direct measures of job skills and a more complete model of the demand for skills than appears in previous work. We have developed three alternative measures of direct job skill requirements from the Dictionary of Occupational Titles (U.S. Department of Labor, 1977): cognitive skills (CS), interactive (or "people") skills (IS), and motor skills (MS). Technical and organizational change is measured by TFP growth, capital vintage, computer-intensity, and the employment share of scientists and engineers. The effects of these variables are determined in tests that include measures of relative factor prices, capital intensity, establishment size, import shares, and union density.

In Section 1 we briefly review the recent literature of the demand for skills. Section 2 describes our three skill measures. In Section 3 we draw upon the case study literature to amend the basic factor substitution model and present our expectations of the effects of factor prices, technical change and various structural characteristics on industry skill levels (1985) and growth (1970-85). Section 4 provides an overview of the rankings of industries on each of the skill measures and reports the correlation of our job-based skill measures with educational attainment. Section 5 presents the results of regression analysis on the determinants of interindustry differences in the demand for skills. Concluding remarks are made in the last section.

1. Literature Review

Early econometric work on skill demand focused on the effects of factor prices on labor-labor and capital-labor substitution. Griliches

(1969) used production worker earnings and the gross rate of return on capital with industry and regional dummies to account for the ratio of "skilled" to "unskilled" workers (white collar/blue collar), years of schooling, and skills (education and earnings) per unit of capital, and concluded that the elasticity of substitution of 'raw' labor for capital was higher than that of skilled labor for capital. According to a comprehensive survey by Hammermesh, studies using this price-theoretic framework have consistently confirmed Griliches' finding of complementarity between physical capital and skilled labor. As Hammermesh (1986, p. 467) puts it, "at fixed output, employers will expand their use of skilled labor when the price of capital services declines".

But Denny and Fuss (1983) make the important point that these studies do not typically take into account the effects of technical change. With a direct measure of technical change, they attempted to explain changes in the occupational demand for labor in the Canadian telecommunications industry over the 1952-72 period. Their main finding was that capital-low skilled labor substitution was a technological effect, not a price effect (p. 163).

Several studies have investigated the effects of technology on the returns to schooling. As Mincer (1989, p. 34) has recently made clear, the two approaches are not inconsistent: "a popular economic hypothesis claims that education is complementary with physical capital and with technology." In this framework both capital accumulation and technological development lead to increased demands for "skill formation". Welch (1970) analyzed the returns to education in U.S. farming in 1959 and concluded that a portion of the returns to schooling results from the greater ability of more educated workers to adapt to new production technologies. Similar findings for the entire economy are reported by Mincer and Higuchi (1988), Mincer (1989) and Gill (1989), who use TFP growth to measure technical change.

But while productivity growth is likely to be the result of technical change in the long run, there is no obvious reason to expect a close fit between the two over shorter periods: changes in the scale of production, product mix, labor relations, inventory management and industry structure can all influence TFP growth. In this respect, Bartel and Lichtenberg's (1987) study is of particular interest since it addressed the same question by exploring the effects of newer vintages of capital on the share of labor costs accounted for by educated workers.[1] But none of this studies explored Mincer's "popular hypthesis" with a joint test of factor price, capital-intensity, and technical change variables in equations that control for such industry characteristics as plant size, unionization, and the degree of foreign competition.

But perhaps most significantly, recent econometric studies have relied on years of schooling or white collar/blue collar distinctions to measure skills. The consequence has been that much of the heterogeneity of the skills required in the workplace has gone unmeasured. As a composite of the grade level achieved in vocational, technical, scientific, liberal arts and professional programs, an industry's average schooling level is likely to have very little meaning as a measure of actual workplace skills. Since job skills are heterogenious, schooling attainment is more relevant for some types of skill than others. Indeed, for some occupations educational attainment may have little direct relationship to skills requirements per se, but is simply a credential used by employers as a low cost screen for applicants likely to be the best on-the-job learners (Thurow, 1975) and for desirable social and personal characteristics (Bowles and Gintis, 1976).

In contrast to the heavy reliance on educational attainment in the econometric literature, plant and industry case studies have focused on the changing demands for specific types of workplace skills. A number of studies have found that the skill content of many production and clerical jobs declines over time with the use of new production technologies as management attempts to lower wage costs and increase control over the work process (Zimbalist, 1979; Office of Technology Assessment, 1984, pp. 110-11). But there is also a growing consensus that computer-based technologies tend to require lower levels of traditional shopfloor skills and higher levels of abstract and synthetic reasoning abilities for production workers (Adler, 1986; Hirschhorn, 1986; Zuboff, 1988).

New information technologies may also be changing the job content and employment shares of middle and lower-level managers. For instance, Zuboff (1988, p. 358) found that in the plants she studied "the power of their information systems had undercut both (skilled and less skilled) dimensions of their job". According to Mathews (1989, pp. 112), new computer-based technologies are creating a workplace in which "the control and supervisory tasks of the managerial levels are drastically reduced" and the "growth in the number of levels between the apex and the shopfloor is halted, and to some extent even reversed."

Previous studies using DOT skills data have found that changes in the mix of jobs has led to a secular upgrading of cognitive skill requirements for the workforce as a whole (Rumberger, 1981; Spenner, 1983; Howell and Wolff, forthcoming).[2] This finding is not inconsistent with the deskilling hypothesis: as the motor skill requirements of low skill jobs decline it becomes possible to phase them out, leaving an occupational structure with a larger share of high cognitive skills (professional and technical workers) or interactive skills (managers, supervisors and administrators). That such a process has characterized recent employment trends in many sectors of U.S. industry is lent support by the industry case studies carried out recently by the Bureau of Labor Statistics (1985; 1986) in which the labor impacts of new technologies are almost invariably shown to reduce both the job content and the share of low skilled jobs while increasing the skill content and the share of the more highly skilled jobs. But there has been little empirical research with aggregate data that has attempted to determine the nature of the effects of factor prices, mechanization, and technical change on the demands for different kinds of workplace skills.

2. The Measurement of Labor Skills

To generate direct industry-level measures of job skill requirements, we used the fourth (1977) edition of the Dictionary of Occupation Titles (DOT). For some 12,000 job titles, the DOT provides a variety of measures of job requirements. These data were collected between 1966 and 1974. A particularly valuable feature of the DOT measures is that they capture a variety of skill dimensions.[3]

The development of job-based skill measures at the industry level for different years required a consistent series of detailed occupation by industry employment matrices. For this, we use Census of Population employment data for 1960, 1970, 1980 and 1985.[4] Because Census occupation and industry classifications have changed substantially with each Census, the employment data for each year was transformed to match the 1970 classifications, and to achieve this consistency and at the same time maintain sufficient occupational detail, we aggregated the data to a 264 occupation and 64 industry level. Each industry skill score is a weighted average based on the occupational employment mix (staffing pattern) of the industry (see Howell and Wolff, forthcoming, for more details)

Our direct measures of job skill requirements capture three fundamental dimensions of skills - cognitive, interactive and motor. The cognitive skills (CS) measure is derived from a factor analytic test of a large number of DOT variables intended to measure various dimensions of cognitive skills (Miller et. al., 1980, Appendix F). This factor captured the largest share of the variation among the 46 variables in the test and was identified by the authors as "substantive complexity" since it was most highly 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 skills (ibid., p. 339).[5] At the top of the ranking (0-10) are lawyers (10), architects (9.5), mathematicians (9.5), social and natural science occupations (8.6-9.5), engineering occupations (7.4-9.0) and computer occupations (7.4-7.6). In the middle are teachers (5.0-7.2), electricians (6.0) and various managerial and administrative occupations (5.4-7.2), followed by foremen, machinists, mechanics and secretaries

(4.8-6.0) and other craft occupations (4.0-5.0). At the bottom are clerical occupations (3.0-4.0), operative and laborer jobs (1.0-3.0), and bootblacks (0).

Interactive skills (IS) are measured by the DOT "People" variable, which rates occupations on a scale of 0-8: mentoring (0), negotiating (1), instructing (2), supervising (3), diverting (4), persuading (5), speaking-signalling (6), serving (7), taking instructions (8). For example, scores of 0-1 are given to clergy, physicians, lawyers and judges. Slightly lower are social workers, teachers, school administrators and health administrators get scores of 1-3. Foremen and a variety of management and sales occupations range from 3-5. Scores of 5-6 are received by most clerical occupations, nurses and nurses aides, and engineering occupations. Most blue collar jobs had IS scores of 7-8.[6]

On a scale of 0-10, motor skills (MS) is a factor analytic measure that 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 (Miller et. al., 1980, p. 339). Some examples of occupation scores on MS are physicians (9.9), veterinarians (9.7), secretaries (8.3), machinists (8.0), civil engineers (7.5), electrical engineers (7.2), cashiers (7.3), sewers (7.2), registered nurses (6.6), truckdrivers (5.9). Occupations with the lowest MS scores include laborers (3.9), accountants (2.9) and university teachers (2.8).

It should be noted that since these job-requirements measures of skills are derived from the 4th edition of the DOT (1977), they reflect skill requirements for the period in which the data were collected, 1966-74. Consequently, changes in average industry skill scores between 1960 and 1985 reflect only changes in occupation mix.

3. Models of the Demand for Skills

We begin with the basic neoclassical factor substitution model applied to skill levels and its extention to changes over time:

(1a) $\quad Ln(SK) = \beta_0 + \beta_1 Ln(P_L) + \beta_2 Ln(P_K) + \ddot{e},$

(1b) $\quad \Delta(SK) = \beta_0 + \beta_1 \Delta(P_L) + \beta_2 \Delta(P_K) + \ddot{e},$

where the observations are industries and ln(SK) is the log of mean skill levels, Δ(SK) is the change in the mean skill levels, P_L is the price of raw (unskilled) labor services, P_K is the price of capital services, and ë is a stochastic error term. The model predicts that $\beta_1 > 0$ (labor-labor substitution) and $\beta_2 < 0$ (capital-skill complementarity).

As Griliches notes (1969, p. 465), a fundamental problem with the empirical implementation of this model is the absence of good measures of the price of "raw" labor (almost all workers have some skills) and the aggregate "price" of plant and equipment in an industry. But, whereas economists may not have access to reliable industry-level measures of P_L and P_K, these prices are presumably known to firms in a neoclassical world, and consequently the effects of relative factor prices should appear in the capital-intensity of production: K/L, the constant dollar value of net capital stock (K) used per full-time equivalent (FTE) employee. Higher prices of raw labor and lower prices for capital services would lead to a more intensive use of physical capital as substitution takes place away from unskilled workers toward skilled workers, each of whom works with more capital. As a result, alternative forms of Equation (1) are:

$$\text{(2a)} \qquad Ln(SK) = \beta_0 + \beta_1 Ln(P_L) + \beta_2 Ln(P_K) + \beta_3 Ln(K/L) + \ddot{e}$$

$$\text{(2b)} \qquad \Delta(SK) = \beta_0 + \beta_1 \Delta(P_L) + \beta_2 \Delta(P_K) + \beta_3 \Delta(K/GNP) + \ddot{e}$$

where it is predicted that $\beta_3 > 0$. In equation 2b, capital-intensity measured per dollar of industry value-added, $\Delta(K/GNP)$, replaces $\Delta(K/L)$ to avoid a possible spurious relationship between the change in L, which may reflect changes in occupation mix, and SK, which is a measure of occupation mix.[7] This model does not predict that the signs and significance of the coefficients should be sensitive to the type of skill (cognitive, interactive or motor) being explained; the results should be similar across skill dimensions.

We next modify the factor-price model by adding technological and organizational variables as suggested by the case study and econometric literature cited above. We use four variables as indicators of an industry's degree of technological progress and reorganization: (i) NEWK, the sum of constant dollar purchases of equipment over the previous ten years as a share of net capital stock; (ii) COMP/GNP, the sum of constant dollar purchases of office, computer and accounting machinery over the previous 7 years per constant dollar of industry GNP;[8] (iii) ENG/L and Δ(ENG/L), the number of computer specialists and engineers employed as a share of the total workforce and its change over time; and (iv) TFP, the annual rate of total factor productivity (TFP) growth.[9]

A number of structural and organizational dimensions of production may have independent effects on the demand for skills. These include:

(i) SIZE and Δ(SIZE), average number of full time equivalent employees per establishment and its change over time, or %LARGE and Δ(%LARGE), the share of employees working in establishments with 500 or more employees and the change in this share over time; (ii) UNION and Δ(UNION), share of employees covered by union contracts and the change in this share over time; (iii) Δ(EMPL), industry employment growth, measured by the change in the number of full-time equivalent employees; (iv) Δ(IMP/GNP), the change in the value of imports per dollar of industry value-added, which here serves as a rough proxy for international competitiveness, and (v) D-SERV, a dummy variable distinguishing goods from service industries.

A basic premise of this paper is that a reasonably adequate specification of a skills model requires that factor prices must be supplemented by some combination of these "structural" variables. The equations whose results are presented in Section 5 are:

(3a) $$\mathrm{Ln(SK)} = \alpha_0 + \alpha_1 \mathrm{Ln}(P_L) + \alpha_2 \mathrm{Ln}(P_K) + \alpha_3 \mathrm{Ln(K/L)} + \alpha_4 \mathrm{Ln(NEWK)} + \alpha_5 \mathrm{Ln(ENG/L)} + \alpha_6 \mathrm{Ln(COMP/L)} + \alpha_7 \mathrm{ln(UNION)} + \alpha_8 \mathrm{Ln(SIZE)} + \alpha_9 \mathrm{(D\text{-}SERV)} + \ddot{e}$$

(3b) $$\Delta\mathrm{(SK)} = \delta_0 + \delta_1 \Delta(P_L) + \delta_2 \Delta(P_K) + \delta_3 \Delta\mathrm{(K/GNP)} + \delta_4 \mathrm{Ln(NEWK)} + \delta_5 \mathrm{Ln(COMP/L)} + \delta_6 \Delta\mathrm{(ENG/L)} + \delta_7 \mathrm{(TFP)} + \delta_8 \mathrm{Ln(\%LARGE)} + \delta_9 \Delta\mathrm{(UNION)} + \delta_{10} \Delta\mathrm{(EMPL)} + \delta_{11} \Delta\mathrm{(IMP/GNP)} + \delta_{12} \mathrm{(D\text{-}SERV)} + \ddot{e}$$

Following Freeman and Soete (1987, p. 44), we expect that the effects of relative factor prices on the demand for skills is secondary to technological and organizational characteristics, and that only substantial and persistent movements in relative prices over the long-run will have noticable skill effects (α_1, α_2, δ_1, and δ_2 are not significant). These predictions reverse those of the factor price model.

After controlling for investments in new technologies, high capital intensity (K/L) may reflect the continued use of old technologies and methods of production that relied upon large scale operations and high shares of semi-skilled workers with specialized mechanical skills. These plants have also been characterized by a supervision-intensive approach to labor relations (Gordon, 1990) in which increasing capital-intensity was used to deskill the blue-collar workforce (Edwards, 1979; Shaiken, 1985). According to this view, high capital-intensity and its growth should be negatively associated with cognitive skills and motor skills, but positively linked to interactive skills (CS:α_3 and $\delta_4 < 0$; IS:α_3 and $\delta_4 > 0$; MS:α_3 and $\delta_4 < 0$). These predictions for CS and MS contrast directly with the capital-skill complementarity hypothesis.

To the extent that new technologies and organizational methods are embodied in new equipment, NEWK can be interpreted as a measure of industrial progressiveness. The variables COMP/L, ENG/L, and Δ(ENG/L) should capture in a more specific way the "high-tech" character of an industry's production technology. Finally, TFP may be interpreted as a measure of technical and organizational change not captured by the other measures. We expect that the effective implementation of new best-practice techniques raises the ratio of high to low CS jobs, leading to higher average cognitive skill levels. As a result, we expect that the intensity of use of new technologies will be positively associated with the level and growth of cognitive skills (CS: α_4, α_5, α_6 and δ_4, δ_5, δ_6, $\delta_7 > 0$). However, the case study literature suggests that information technologies may reduce the share and growth of workers who must have high interactive skills, such as middle-level managers and administrators. If this is the case, skill requirements as measured by IS may not be complementary with new technology (IS: α_4, α_5, α_6 and δ_4, δ_5, δ_6, $\delta_7 < 0$). This literature does not provide clear guidelines on the expected effects of technical change on MS. For example, although computer-based technologies appear to require more mechanics, fewer machinists and skilled operatives may be required (Turner and Gold, 1986). Consequently, our technology variables may have positive or negative MS effects (MS: α_4, α_5, α_6 and δ_4, δ_5, δ_6, $\delta_7 \gtrless 0$).

4. Descriptive Statistics on Industry Skill Levels and Skill Growth

Table 1 shows the ten industries with the highest and lowest absolute changes in average cognitive (CS), interactive (IS) and motor skill (MS) levels for 1970-85 (each industry score is based on occupation scores that range from 0-10). The 1985 average skill level for these industries is also presented; these levels range from 2.44 to 6.63 for CS, 0.86 to 4.83 for IS, and 4.14 to 6.27 for MS. The unweighted average skill level and average absolute change for the 43 industries is shown at the bottom of the table.

The rapidly growing CS industries are a mix of goods and service producers and tend to have higher than average CS levels 1985, with textiles as the one notable exception. The declining CS industries were mostly goods producers and tended to have below average CS levels, with the education sector as a significant exception. Turning to IS, the middle columns of Table 1 show that mining and service industries had the greatest increases, while both manufacturing and service sectors were represented among the industries with the greatest IS declines over the

1970-85 period. Similarly, goods and service industries appear among those with rapidly increasing and declining MS levels.

These results underline the importance of distinguishing between types of workplace skills. As this table shows, the mining industries were among those with the greatest declines in CS and MS, but were also among the industries with the greatest growth in IS. Machinery, however, had very high CS growth but was near the bottom of the MS growth ranking. To take one final example, food processing shows very low or declining CS and IS growth, but rapidly increasing MS levels. Given these differences, it is unlikely that a single measure can adequately describe the skill mix of an industry, much less its change over time.

Previous studies have almost uniformly relied upon schooling attainment as a measure of workplace skills. Table 2 reports the correlation coefficients for our three measures of job-skill requirements and median years of schooling (ED). While CS and ED levels are closely correlated (.891) for 1985, the association between the 1970-85 change in these measures is much lower (.548). While IS is also fairly closely correlated to ED (.773) and CS (.728), the correlation between the change in IS and the change in ED is far lower (.432). Over this 15 year period IS and CS growth show almost no correlation (-.124).

It is perhaps not surprising that MS is negatively correlated to CS, ED and IS, but it of some interest that the coefficient is far larger between MS and IS (-.586) than MS and CS (-.158). The change in MS is even more negatively associated with IS change (-.777) but is positively correlated to CS change (.301). Industries with low IS and high MS growth include auto repair, food processing and radio/TV; those with low MS change and high IS growth include the four mining industries and construction.

The last column of panel B shows the coefficients for changes in the four measures of skills over the 1960-70 decade with the changes that took place in the 1970-85 period. The growth in pre-1970 and post-1970 CS and ED are very modestly associated (.26 and .266), but there is almost no correlation over these two periods for IS (.026) or MS (.054). This is consistent with the view that structural changes in the economy (energy prices, information and communications technology, and international competitiveness) have brought about fundamental changes in production, and consequently in skill composition, that distinguish the more recent period from the 1960's.

5. Regression Analysis

Skill Levels. For each of the three measures of job skills, Table 3 reports the results of the factor price model (equations 2a and 2b), the full model (equations 3a and 3b), and the full model for the goods industries (for definitions and sources see the Data Appendix). The factor price model fares poorly on all three skill dimensions. Neither the price of capital, the production worker wage, nor the capital/labor ratio is significant at the 10% level. In the more properly specified "full model" the wage has the correct sign and is highly significant in the CS and IS tests for all industries, but is not significant in the IS test for the goods industries and is insignificant with the wrong sign in both of the MS tests. Indeed, the positive and significant coefficients on the wage rate in the CS and IS tests can be explained not by substitution away from high-priced low skill labor, but by the standard expectation that labor market competition will lead to the payment of higher wages in industries with more highly skilled production workers.[10]

The capital-skill complementarity hypothesis fares poorly as well. Capital intensity (K/L) is <u>negatively</u> related to CS and MS levels in both tests of the Full Model and the coefficient is significant at the 5 percent level in all but the CS test for goods industries. In an identical test for median years of schooling (not shown), the results are similar; K/L has a negative sign, significant at the 10 percent level. The complementarity hypothesis is lent support only in the IS test for goods industries. On the other hand, these results are consistent with our reading of the case study literature: since the turn of the century, capital-intensity has historically been linked to confrontational labor relations in which craft workers were replaced by semi-skilled operatives and intensive supervision was required (Edwards, 1979, Chapter 7; Mathews, 1989, Chapter 7). The consequence in terms of our skill categories has been higher IS but lower CS and MS requirements.[11]

Following Griliches, we also tested the effects of factor prices on the use of skilled workers per unit of capital. Finding a significant negative sign on the wage variable, Griliches (1969, p. 466) concluded that this result "definitely implies a higher elasticity of substitution of "raw" labor for capital than for skilled labor." Although the signs in our equation for 1985 were the same as those found by Griliches using 1954 data, neither variable was significant and the equation as a whole performed poorly:

$$\mathrm{Ln(PT/K)} = \underset{(3.19)}{12.6} + \underset{(.29)}{.152}\ \mathrm{Ln(PRICE\ K)} - \underset{(1.22)}{.799}\ \mathrm{Ln(WAGE)} \qquad R^2 = .02$$

where PT/K is the number of professional and technical workers per dollar of net capital stock and the t-statistics are in parentheses. Our tests for 1970 and 1980 showed simlar results.

The technology variables (NEW K, COMP/GNP, and ENG/LABOR) that are significant at 10 percent carry a positive sign in each of the three skill equations. For SC and MS the ratio of computer specialists and engineers to total employment is a particularly significant determinant. This result for CS might be challenged as simply a statistical artifact of the fact that computer specialists and engineers have high cognitive skill levels, but the share of engineers and computer specialists in the full-time equivalent workforce ranged from just 0.04 to 15.0 percent in 1985, and only 8 of the industries had shares exceeding 6 percent. Computer intensity had significant positive effects on CS and MS in the goods industries. It's worth noting that computer intensity was also positive and significant for median years of schooling in an identical test.[12]

The results for remaining variables indicate that both CS and IS are higher in service industries and in those sectors with relatively small establishments and low levels of union coverage. This result is consistent with the view that unions have been most successful in the organization of large capital- and operative-intensive plants which tend to have low average CS and IS levels. This result may also be due to a retarding effect of unions on the substitution of higher skilled (management) workers for lower skilled (operative) workers. While union density is positively and significantly related to MS in 1985 for all industries, the coefficient becomes insignificant for goods industries alone.

Skill Change. We next consider the determinants of skill change over the 1970-85 period. Table 4 presents the results for equation 3b for CS, IS and MS. Again, the findings lend little support to the factor price model, which predicts that industries faced with relatively large increases in wage rates for low-skilled workers will show greater substitution toward higher skilled labor, all else equal. But in the goods industries, the nonsupervisory wage increases are negatively associated with CS growth, a finding that is significant at the 1 percent level. Similarly perverse, in the test for all industries the change in the price of capital is positively linked to CS change (significant at 10 percent). Whereas the factor price model predicts that high capital costs will act as a deterrent to the intensive use of physical capital, and consequently to the use of skilled labor (assumed to be complementarity), these results indicate just the reverse. As this table shows, the coefficients for the factor price variables in the IS and MS tests are insignificant.

Changes in capital intensity, however, appear to have important effects for all three measures of skills, particularly in the goods industries. But the expectations of the factor price model are supported only for IS, a measure of the share of an industry's workers whose job involves instructing, supervising or persuading other workers or customers. In the CS and MS tests, growth in capital-intensity is negatively related to the upgrading of industry skill composition, a finding that again directly contradicts the capital-skill complementarity hypothesis but supports the results of the deskilling literature.

Our direct measures of technical change have their most significant effects on CS in the goods industries; growth in cognitive skills is strongly linked to high shares of new equipment in total capital stock (NEWK) and the growth of the share of high tech employees (ENG/LABOR). Computer intensity (COMP/GNP) has the expected positive effect on CS growth but is not quite significant at the 10% level. NEWK also had strong positive effects on IS growth, but computer-intensity is negatively related, a finding that is significant at 10 percent in the test for all industries.

Contrary to our expectations and the earlier literature, we find highly significant negative effects of TFP on CS and MS growth in the goods industries: productivity appears to be lagging in industries where rapid technical and organizational change is associated with rising cognitive and declining motor skill requirements. This result may be due to the more fully specified nature of our skills equations, and may be explained by the costly adjustments that can be expected to accompany fundamental structural changes in production, as suggested recently by David (1989) and Freeman (1989).

Finally, while the extent of the decline in union density among industries since 1970 appears to have had little effect on CS, IS or MS change, employment growth and changing import penetration had substantial impacts. CS and MS change is greatest in industries with the lowest increases in employment and import share, whereas IS levels grows fastest in industries with high employment and import share growth.

To briefly summarize the results reported in Table 4, the relative growth in cognitive skills across industries since 1970 is closely associated with technical and organizational change, production in large plants, and low or negative growth in capital-intensity, industry employment and import penetration. The growth in motor skills is also negatively related to increasing capital-intensity, employment and import shares. But the results for interactive skills are just the reverse: growing capital-intensity, employment and import shares are associated with increasing IS levels. Unlike the results for CS growth, direct measures of technical change have mixed effects on IS and MS growth.

Occupation Shares. Behind these changes in average industry skill levels are shifts in the underlying occupational employment distribution. Table 5 reports the results of attempts to account for changes in the share of the workforce employed in each of five large occupational groups since 1970. The results indicate that the share of professional and technical workers in industry employment grew fastest in industries with the most rapid technical change (NEWK, ENG/LABOR,) in large establishments (BIGEST). While this share is also positively associated (at the 5 percent level) with increasing capital-intensity, it is worth noting, particularly in light of the results for CS in Table 4, that this variable is negative and insignificant in tests limited to the goods industries (results not shown).

The results reported in column 2 are consistent with those reported in Table 4 for IS, lending support to our hypothesis that supervisory overhead is positively linked to capital-intensity [Δ(K/GNP)] and is negatively affected by the use of computer-based technologies [Ln(COMP/GNP)]. It is also of interest that the same is true for the growth in clerical and service worker shares. But while computer-intensity appears to decrease clerical and service employment shares, increasing shares of engineers has the opposite effect. These results underscore again that technical change, like worker skills, are multi-dimensional and attempts to adequately represent it may require several alternative measures.

The tests for craft workers and operatives/laborers were limited to the goods industries since almost all of these workers are employed there. The increase in the share of craft workers is associated with a young capital stock (NEW K) and increasing plant size but not with greater capital-intensity. The share of operatives and laborers declined most in the most technologically dynamic industries, as indicated by strength of the negative coefficient on young capital (NEWK) and productivity growth (TFP), and in industries with rapid increases in plant size and import penetration.

These occupation share results support our interpretations of the effects of technical change on the growth of average industry cognitive, interactive and motor skill levels that were reported in Table 4. The growth in average CS levels (Table 4) and the share of professional and technical labor (Table 5) are both strongly complementary with the increasing use of new technology. The effects of technical change on both average IS scores and the share of managers and administrators is mixed, with positive or negative impacts depending upon the measure of technical change and whether all industries or just the goods industries are examined. The statistical effects of our direct measures of technical change on motor skills in the goods industries are also mixed. At least in the case of capital vintage variable (NEWK), this is probably due to the offsetting effects on craft workers (positive) and operatives and laborers (negative).

6. Conclusion

Previous studies have attempted to explain the demand for skills within a factor substitution framework, focusing on the effects of relative factor prices and the complementarity between capital and skills. There has been a shift in emphasis in recent years towards econometric research that examines the link between technical change and skills. The aim of this paper was to extend this literature by exploring the effects of a variety of measures of technical and organizational change in a more fully specified model that replaces schooling attainment measures of skills with direct job-based measures.

We found that industry rankings on cognitive, interactive, and motor skills and their change over time are significantly different, suggesting the inadequacy of a single schooling attainment measure of worker skills. We also found that the growth in each of these skill measures does not appear to be continuous; there is little correlation between skill growth in the 1960's and skill growth since 1970, suggesting fundamental structural differences in production between the two periods that warrants further research.

Our tests of the determinants of skill levels in 1985 and skill change between 1970 and 1985 provided little support for either the standard factor substitution model or the widely accepted capital-skill complementarity hypothesis; our measures of factor prices and capital-intensity and their change over time were rarely significant with the correct sign, either for our three direct measures of skill requirements or for educational attainment. Growth in capital-intensity was found to be strongly associated with rising interactive skills and declining cognitive and motor skills. These findings are consistent with structural models of production, in which only persistent and substantial long-run trends in relative prices are expected to have an effect on the organization of production, and consequently on the skill composition of the workforce. They are also consistent with the results of many case studies, in which mechanization is found to be linked to the deskilling of production workers and to the increasing shares of managers and supervisors (interactive skills). With the transition to production methods based on information technologies, it is perhaps increasingly true that it is technical change, not mechanization per se that increases the demand for cognitive skills.

Our tests of CS change over the 1970-85 period support just this conclusion. Computer intensity, young capital stock, and high shares of engineers and computer specialists are all positively linked to CS growth, with very strong effects for the latter two variables. But TFP growth was strongly negatively associated with CS (and MS) growth, raising doubts about its adequacy as a measure of technical change, at least in the short run. We also found a strong positive relationship between plant size and its growth over time and increasing demands for cognitive skills and professional and technical workers, suggesting that large plants are at the vanguard of those technical changes that are complementary with high cognitive skills. On the other hand, union coverage is clearly associated with low average cognitive skills and appears to inhibit CS growth over time.

Demands for interactive and motor skills are less consistently related to technical change. Interactive skills appear to be in greater demand in industries that are investing heavily in new capital, although these effects are less strong in tests that include only the goods industries. However, computer-intensity has a strong negative effect on the share of managers and administrators, indicating that computer-based technologies may substitute for low/middle level managers and supervisors in many industries. While technical change is clearly associated with declining operative and labor shares of total employment, the effects on craft shares are mixed, which probably accounts for the weak effects of most of the technical change measures on motor skills.

These findings have the rather obvious, but important, implication that effective policy initiatives must be grounded in research that adequately captures the diversity of labor skills. This is underscored by recent debates on U.S. industrial competitiveness. Anecdotal evidence indicates that U.S. firms in the same product markets (automobile producers, for example) are far more manager- and clerical-intensive but much less engineer-intensive than Japanese firms, presumably giving the latter a decided advantage in labor costs and in the effective deployment of new computer-based technologies. In terms of our skill indices, this implies that the demand for skills in the U.S. is biased towards interactive (or supervisory) capacities and away from cognitive (or technical) skills, a distinction that may be of some importance for understanding differences in international competitiveness. But since both types of skill are associated with higher than average educational attainment, this distinction would almost certainly be lost by focusing on differences in schooling attainment. Taking a cue from the case study literature, there needs to be more econometric research that explicitly recognizes the diversity of skills required in the modern workplace.

Endnotes

1 However, Bartel and Lichtenberg's tests actually attempt to explain the educated labor share of labor costs, which is equivalent to the educated workers employment share only under their restrictive assumption that the ratio of less educated to highly educated wages is constant across industries. They offer no support for the reasonableness of this assumption.

2 Adler (1986, p.13) contends, for example, that "The more systematic surveys of automation's skill requirements... shows both a secular shift in the occupational structure, which has given more weight to the more-skilled occupations, and an increase in the skill requirements for most individual jobs.

3 See Miller et. al., (1980) for a detailed evaluation of the DOT indices.

4 Results for 1985 are based on 1980 occupation skill scores and a 1985 "synthetic" occupation by industry employment matrix. The latter was constructed using the so-called RAS (or biproportionality) method, based on the 1980 occupation by industry employment matrix and 1985 employment totals for the 267 occupations and the 64 industries, which were obtained from (U.S. Department of Labor, 1986).

5 A strong case for the use of factor-based scales is made by Miller et. al. (1980). They conducted a series of reliability tests and concluded that "the more reliable indicators of the features of occupations tapped by the worker traits and worker functions variables could be created by developing factor-based multiple-item scales to represent the various dimensions revealed by factor analysis. Such scales would have the advantage of greater internal reliability and consistency than single indicators..."(p. 188).

6 For comparablility with the other measures, we have rescaled this variable so that its values range from a low of 0 to a high of 10.

7 The correlation between $\Delta(K/L)$ and $\Delta(K/GNP)$, measured as absolute change, is .52, and the signs on $\Delta(K/L)$ in the tests otherwise identical to those in Table 4 are the same as those for $\Delta(K/GNP)$.

8 According to Gordon (1987, table 21), the current value weight for the share of computers in total OCA investment was 68 percent in 1979, rising to 75 percent in 1984. We chose to sum OCA investments over seven years on the grounds that it is a period long enough both to capture most of the computer stock in use and to avoid the undue influence of unusually large or small annual purchases of computers, and short enough to limit the mix of different generations of computers and to avoid the need for making assumptions about depreciation.

9 The effects of R&D spending were explored but are not presented for two reasons. First, it was not available at an industry level that was perfectly compatible with ours, leading to a loss of several industry observations. Second, R&D spending may have little to do with employment restructuring in the industry doing the spending, and recent attempts to distinguish own and other industry effects do not appear to be sufficiently reliable. See also endnote 12.

10 The wage variable is an average measure for all nonsupervisory workers. If nonsupervisory workers have relatively high skill levels in the high CS and IS industries they can be expected to be paid higher wages. This supposition was confirmed by a correlation coefficient of .781 between CS for all workers and CS for nonsupervisory workers. This coefficient is almost identical for IS (.783).

11 The results are similar for educational attainment. For example, the simple correlation between median years of schooling and net capital per

employee was just .02 for 1985 (43 industries). Our data also suggest that capital-skill complementarity has been weakening since 1970: the simple correlation between capital intensity and CS for the full set of 43 industries was .154 in 1970, .121 in 1980, and .096 in 1985.

12 In addition to these measures of technical change, TFP Growth and R&D spending as a share of industry GNP were included in other specifications. Neither was significant and their inclusion only lowered the adjusted R^2.

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Table 1
Skill Change: Highest and Lowest Ranking Industries, 1970-85

	Cognitive Skills			Interactive Skills			Motor Skills	
	Change 1970-85	Level 1985		Change 1970-85	Level 1985		Change 1970-85	Level 1985
Highest:								
1. Radio/TV	.749	6.63	Coal Mg.	1.449	2.63	Auto Repair	.129	6.27
2. Bus/Pers	.623	4.01	Metal Mg.	.955	2.38	Amusements	.122	5.08
3. Telecomm	.493	4.62	Petrol Mg.	.735	2.61	Log/Wood	.094	5.14
4. Amusement	.464	4.71	NonMet.Mg.	.569	2.15	Tobacco	.071	5.22
5. Machinery	.358	4.40	Retail	.261	2.34	Food Proc.	.060	5.10
6. Utilities	.336	4.28	Bus/Pers.	.248	1.96	Education	.052	4.14
7. Tobacco	.280	3.34	Insurance	.215	3.23	Radio/TV	.050	5.63
8. Health	.276	4.67	Tobacco	.180	1.43	Wholesale	.015	4.54
9. Textile	.239	2.86	Construc.	.175	1.56	Textile	.007	4.54
10. Instruments	.201	4.31	Banking	.159	1.61	Retail	.000	4.62
Lowest:								
34. Fab.Metals	.028	3.86	Apparel	-.051	2.65	Apparel	-.162	4.42
35. Food Proc.	.017	3.09	Fab.Metals	-.060	1.37	Machinery	-.172	5.59
36. Metal Mg	-.001	3.75	Auto Repair	-.089	1.68	Petrol Rfg	-.175	5.30
37. Hotels	-.027	2.95	Agriculture	-.109	1.63	NonMet.Mg	-.186	4.98
38. Furniture	-.049	3.26	Hotels	-.134	1.86	Construc	-.232	5.94
39. Petrol Mg	-.131	4.41	Prof.Serv.	-.166	3.99	Telecomm	-.249	5.64
40. Coal Mg	-.148	3.12	Food Proc.	-.169	1.43	Banking	-.290	4.95
41. Petrol Rfg	-.163	4.42	Radio/TV	-.174	2.76	Petrol Mg.	-.474	4.96
42. Education	-.206	5.20	Education	-.361	4.83	Metal Mg.	-.523	5.10
43. Agric.	-.208	3.42	Chemicals	-.768	1.15	Coal Mg.	-.813	4.66
Industry Mean	.135	4.08		.109	1.99		-.101	5.24

Table 2
Correlation Coefficients: Industry Skill Measures
(43 industries)

A. 1985 Skill Levels:

	Cognitive Skills	Median Education	Interactive Skills
1. Cognitive Skills	---	.891	.728
2. Median Education	.891	---	.773
3. Interactive Skills	.728	.773	----
4. Motor Skills	-.158	-.270	-.586

B. Skill Change, 1960-85:

	$\Delta(CS^{7085})$	$\Delta(ED^{7085})$	$\Delta(IS^{7085})$	$\Delta(CS,ED,IS,MS)^{6070}$
1. $\Delta(CS^{70-85})$	----	.548	-.124	.260
2. $\Delta(ED^{7085})$	.548	----	.432	.266
3. $\Delta(IS^{7085})$	-.124	.432	----	.026
4. $\Delta(MS^{7085})$	.301	-.299	-.777	.054

Table 3
Regression Results for 1985 Skill Levels[a]
(t-statistics in parentheses)

	Cognitive Skills			Interactive Skills			Motor Skills		
	Factor Price Model	Full Model	Full Model: Goods	Factor Price Model	Full Model	Full Model: Goods	Factor Price Model	Full Model	Full Model: Goods
Constant	-.188 (.16)	-1.5^{**} (2.58)	-1.24 (1.55)	.309 (.16)	-3.32^{***} (3.03)	-3.89^{**} (2.28)	.908 (1.48)	1.31^{***} (2.74)	2.15^{***} (3.99)
K PRICE (1979)	.018 (.19)	.004 (.06)	-.014 (.51)	.055 (.47)	-.042 (.56)	-.101 (1.48)	-.033 (1.07)	-.029 (.97)	-.0008 (.18)
WAGE (1985)	.262 (1.47)	$.415^{***}$ (4.84)	$.318^{**}$ (2.41)	.9 (.3)	$.676^{***}$ (3.73)	.316 (1.24)	.104 (1.13)	-.089 (1.16)	-.06 (.75)
K/LABOR (1985)	-.009 (.22)	$-.033^{**}$ (2.06)	-.01 (.68)	.057 (.74)	.009 (.28)	$.092^{**}$ (2.40)	-.03 (1.43)	$-.036^{***}$ (3.09)	$-.029^{**}$ (2.08)
NEW K (1985)		.015 (.43)	.012 (.28)		-.025 (.32)	$.461^{***}$ (3.39)		$.013^{***}$ (3.44)	-.071 (1.66)
COMP/GNP (1985)		$.027^{*}$ (1.76)	$.053^{**}$ (2.5)		-.017 (.55)	.036 (.75)		-.005 (.37)	-.005 (.50)
ENG/LABOR (1985)		$.086^{***}$ (5.75)	$.108^{***}$ (4.16)		.042 (1.49)	-.003 (.07)		.017 (1.61)	$.037^{***}$ (3.23)
SIZE (1985)		$-.054^{***}$ (2.93)	$-.077^{***}$ (3.87)		$-.104^{**}$ (2.13)	$-.141^{***}$ (3.40)		.013 (.79)	.008 (.63)
UNION (1980)		$-.117^{***}$ (5.17)	$-.09^{**}$ (2.26)		$-.169^{***}$ (4.14)	.008 (.09)		$.052^{***}$ (3.0)	.009 (.41)
D-SERV		$.194^{***}$ (3.53)			$.339^{***}$ (3.65)			.017 (.54)	
Adjusted R^2	.016	.821	.873	-.02	.673	.698	.032	.477	.366
F-statistic	1.22	21.4	25.0	.74	10.2	9.1	1.43	3.14	3.02
N	41	41	29	41	41	29	41	41	29

* Significant at the 10% level; ** significant at the 5% level; ** significant at the 1% level in a two-tailed test.

Table 4
Regression Results for Skill Change, 1970-85[a]

	Skill Change, 1970-85					
	Cognitive Skills		Interactive Skills		Motor Skills	
	Total	Goods	Total	Goods	Total	Goods
Constant	-.73* (1.9)	-1.05** (2.51)	-.34 (.79)	-2.28 (1.72)	-.206 (.77)	.39 (.85)
Δ(K PRICE) 1970-79	.717* (1.79)	.21 (1.28)	-.348 (.8)	-.999 (1.69)	.046 (.22)	-.014 (.05)
Δ(WAGE) 1970-85	-.0003 (.62)	-.0013*** (5.68)	.00004 (.00)	.0005 (.33)	-.0002 (.67)	-.001* (1.75)
Δ(K/GNP) 1970-85	-.048 (.99)	-.114*** (6.87)	.204*** (4.09)	.166** (2.66)	-.146*** (3.13)	-.186*** (6.32)
Log(NEW K) 1985	.156** (2.08)	.29*** (3.97)	.16** (2.31)	.534** (2.21)	.027 (.05)	-.031 (.29)
Ln(COMP/GNP) 1979-85	.014 (.58)	.026* (1.93)	-.102* (1.83)	-.058 (.8)	.047 (1.47)	.042* (1.78)
Δ(ENG/LABOR) 1970-85	.0002 (.11)	.006*** (9.46)	.004 (1.39)	.007 (1.28)	-.004*** (3.37)	-.0003 (.22)
TFP 1970-85	.02 (.77)	-.032*** (4.97)	-.029 (1.48)	-.068 (1.32)	.003 (.11)	-.031** (2.34)
Ln(BIGEST) (1970)	.081** (2.31)	.082*** (3.82)	-.0005 (.01)	-.07 (.62)	-.006 (.16)	.029 (.6)
Δ(UNION) 1970-80	-.006* (1.93)	-.0012 (.56)	-.00001 (.00)	.0129 (.99)	.00001 (.0)	.006 (1.33)
Δ(EMPL) 1970-85	-.0001 (.08)	-.002*** (3.24)	.0014** (2.27)	-.0017 (.7)	-.0015*** (2.98)	-.0029** (2.57)
Δ(IMP/GNP) 1970-85		-.047*** (3.71)		.168** (2.2)		-.09*** (3.82)
D-SERV	.312*** (3.2)		-.07 (.98)		.099** (2.39)	
Adjusted R^2	.408	.872	.397	.51	.471	.803
F-statistic	3.51	18.4	3.39	3.65	4.24	11.35
N	41	29	41	29	41	29

a. All change variables are absolute differences, except TFP Growth. See Data Appendix for definitions and sources.
* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level in two-tailed test.

Table 5
Regression Results for Changes in Occupational Shares, 1970-85[a]
(t-statistics in parentheses)

	All Industries			Goods Industries	
	Professional & Technical	Mgrs & Admin[b]	Clerical/ Service[b]	Craft Workers	Operatives & Laborers
Constant	-.074**	36.9	-6.75	-.249**	.404***
	(2.61)	(.83)	(.38)	(2.15)	(4.21)
Δ(K/GNP) 1970-85	.011**	.264	.202**	-.006	-.008*
	(2.14)	(1.47)	(2.24)	(1.08)	(1.85)
Ln(NEW K) 1985	.019***	6.84	2.46	.05**	-.084***
	(3.25)	(.79)	(.72)	(2.33)	(4.69)
Ln(COMP/GNP) 1985	-.003	-10.64***	-4.35***	.001	-.003
	(.78)	(4.08)	(2.96)	(.22)	(.71)
Δ(ENG/LABOR) 1970-85	.0005***	.043	.114***	-.0005*	-.0002
	(3.62)	(.68)	(2.94)	(1.89)	(.93)
TFP 1970-85	.003	1.99	2.53*	.0049*	-.005**
	(1.34)	(.74)	(1.71)	(1.81)	(2.69)
Ln(BIGEST) 1970	.011***	12.2***	-1.25	.01	-.012*
	(4.31)	(5.59)	(.64)	(1.42)	(1.92)
Δ(Size) 1970-85	.195*	-.228***	.101**	.322***	-.503***
	(1.81)	(3.19)	(2.37)	(2.92)	(7.24)
Δ(UNION) 1970-80	-.0005*	-.036	.04	.0012	-.0006
	(1.89)	(.43)	(.79)	(1.59)	(.78)
Δ(EMPL) 1970-85	.0001	.111	-.048	-.0004	.0002
	(1.36)	(1.22)	(.97)	(1.67)	(.90)
Δ(IMP/GNP) 1970-85				.006	-.0107***
				(1.26)	(3.57)
D-SERV	.033**	4.68	-3.30		
	(2.37)	(1.22)	(.61)		
Adjusted R^2	.294	.614	.374	.365	.55
F-statistic	2.66	7.35	3.39	2.61	4.42
N	41	41	41	29	29

a. See Table 4 and the Data Appendix for definitions and sources.
b. The dependent and change (Δ) variables in columns 2 and 3 are measured as percentage changes beccause this form produced far better results for these two occupation groups. The signs of the variables where t > 1 are identical to those in tests with absolute change measures.
* Significant at the 10% level; ** significant at the 5% level; ** significant at the 1% level in a two-tailed test.

Appendix

Data Sources and Methods

K Price: 3 year average of the price of capital input (Jorgenson, Gollop and Fraumeni, 1987, Appendix C, pp. 432-77).

WAGE: average hourly earnings of production workers (mining, construction and Manufacturing) and nonsupervisory workers (all other industries) (U.S. Department of Labor, 1985 and 1988).

K/LABOR: constant dollar net capital stock (Musgrave, 1986) per full time equivalent employee (National Income and Product Accounts [NIPA] on diskette).

K/GNP: constant dollar net capital stock per constant dollar GNP (NIPA on diskette).

NEW K: sum of constant dollar purchases of equipment over previous 10 years (Bureau of Industrial Economics [BIE] computer tape) per constant dollar net capital stock (NIPA on diskette).

COMP/GNP: sum of constant dollar purchases of office, computer and accounting machinery over previous 7 years (BIE computer tape) per constant dollar of industry GNP.

ENG/LABOR: computer programmers, computer systems analysts, computer specialists, n.e.c., and engineers (derived from decennial Census data) as a share of full-time equivalent employees (NIPA on diskette).

TFP: average annual rate of total factor productivity growth (computed from NIPA on diskette).

SIZE: full time equivalent employees (NIPA) per establishment (U.S. Department of Commerce, County Business Patterns).

BIGEST: share of employees in establishments with 500 or more employees (U.S. Department of Commerce, County Business Patterns).

UNION: share of employees covered by union contracts (1970: Freeman and Medoff, 1979; 1980: Kokkelenberg and Sokell, 1985).

IMP/GNP: Imports for consumption (1970: U.S. Department of Commerce, 1974, Table 3b; 1985: U.S. Department of Commerce, 1988, Table No. 1352) per current dollar GNP (NIPA).

EMPL: full time equivalent employees (NIPA)