NBER WORKING PAPER SERIES

TECHNOLOGY AND THE WAGE STRUCTURE

Steven G. Allen

Working Paper 5534

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 1996

Dale Jorgenson and Barbara Fraumeni graciously provided their KLEM data set to use in this analysis. I have received helpful comments from seminar participants at North Carolina State, Maryland, NBER, Michigan State, Columbia, Princeton, the 1994 North American winter meeting of the Econometric Society, and El Centro de Estudios de la Realidad Economica y Social in Montevideo, Uruguay. This paper is part of NBER's research program in Labor Studies. Any opinions expressed are those of the author and not those of the National Bureau of Economic Research.

NBER Working Paper 5534
April 1996

TECHNOLOGY AND THE WAGE STRUCTURE

ABSTRACT

This paper reports direct evidence on how recent changes in technology are related to changes in wage differentials by schooling, experience, and gender. Wage differentials by industry in the full-year 1979 and 1989 Current Population Surveys are related to R&D intensity, usage of high-tech capital, recentness of technology, growth in total factor productivity, and growth of the capital-labor ratio. Returns to schooling are larger in industries that are intensive in R&D and high-tech capital. Technology variables account for 30 percent of the increase in the wage gap between college and high school graduates.

Steven G. Allen
College of Management
North Carolina State University
Box 7229
Raleigh, NC 27695
and NBER

The impact of technological change on the skill mix of the labor force is one of the oldest questions in the social sciences. It is receiving considerable attention now because wage differentials by skill have widened significantly since 1980 and because there is much indirect evidence indicating that technological change is responsible (Katz and Murphy (1992); Juhn, Murphy, and Pierce (1993), Bound and Johnson (1992)).

Direct evidence is harder to find. Mincer (1991) showed that relative earnings of college to high school graduates with 6-10 years of experience increased with R&D intensity in aggregate, annual data for 1963 to 1987. The most convincing work on the subject is Krueger (1993), who found that workers using computers at the workplace get paid 15 percent more than those who do not use computers and that increased use of computers in the workplace explains one-third to one-half of the observed increase in returns to schooling between 1984 and 1989. Yet many important questions remain. How important were computers in the first half of the 1980s, when the use of PCs in the workplace was relatively limited? What has been the impact of other technologies, especially instrumentation and telecommunications? Assuming the assignment of workers to jobs using advanced technology is nonrandom, how much of a role does unobserved ability play in any correlation between technology and wages?

The goal of this paper is to provide direct, broadly based evidence on how changes in technology affected the wage structure in the 1980s. The main innovation of this study is to exploit variation across industries to determine how measures of technological change relate to changes in the wage structure, using the full-year Current Population Survey.[1] This study will look at a wide set of indicators of technological change: research and

---

[1]Mishel and Bernstein (1994) use a similar approach, but focus primarily on overall wage inequality, as indicated by wage differentials for men between the 10th, 50th, and 90th percentiles. Within an industry, changes in these differentials reflect both changes in the wage structure and in observable labor quality. This study includes both men and women and focuses on changes in wages, controlling for labor quality as much as possible.

development intensity, usage of various forms of high-tech capital, growth in the capital-labor ratio, growth in total factor productivity, and recentness of capital. It will focus on wage changes between 1979, when the college/high-school wage gap reached a trough and the business cycle was at a peak, and 1989, the next peak in the business cycle.

The use of industry data is dictated by the lack of micro data linking workplace technology to wages that covers this time period (and covers industries outside of manufacturing). Some problems of interpretation arise, however, because the assignment of workers to industries is nonrandom. Section 1 outlines some theoretical frameworks within which the approach used here has strong microfoundations and some in which it does not. Section 2 describes the technology parameters used in the empirical analysis and assesses the strengths and limitations of these measures.

Any study using changes in the interindustry wage structure would seem quixotic, because it is so stable over time.[2] This is true in the sense that wage levels across industries are autocorrelated over very long time periods, but it also is misleading because, as shown in Section 3 below, there are sizable differences in important parameters -- the intercept, wage differentials by schooling and experience, and the gender gap -- over time within industries.

The main result of this paper, reported in Section 4, is that variations in innovative activity across industries and over time play an important role in explaining changes in the wage structure. This conclusion is based on two different approaches. In the simplest approach wage equations are estimated for each of 39 industries and the coefficients are then regressed on the technological change indicators. In the second approach wage

---

[2]The classic studies on this subject were done by Slichter (1950) and Cullen (1956). Modern extensions of this line of research include Dickens and Katz (1987), Krueger and Summers (1987), Helwege (1990), and Allen (1994).

regressions containing a set of industry dummies are estimated for each of 32 experience-schooling-gender groups. Predicted wages by industry are then regressed on the technological change variables. In both approaches the evidence shows that R&D and high-tech capital are associated with increased returns to schooling. There is also strong evidence that returns to schooling increased the most in industries with the largest increase in the capital-labor ratio. The final section summarizes the key findings and discusses their key implications.

I. THEORETICAL FRAMEWORK

For technological change to be driving recent changes in the wage structure, it must be biased in favor of skilled labor. In a one-sector model of the labor market with two types of labor (S = skilled, U = unskilled), such new technology has direct technical effects that increase (decrease) demand for S (U) holding output and factor prices constant and scale effects that lead to greater use of both (assuming no inferior input). Relative wages for S rise to clear the market, resulting in some substitution of U for S that offsets the initial technological shock. The absolute impact on wages and employment of each factor hinges on the magnitude of these effects, along with elasticities of labor supply -- w_s must rise as long as supply is not infinitely elastic; w_u need not.

In a model with two goods that vary in factor intensity, a technological shock biased toward S leads to expansion of the S-intensive sector and contraction of the U-intensive sector. (This adjustment in output mix will be even greater in an open economy.) The wage adjustment in this case helps equilibrate both the product and labor markets.

Wage differentials increase by the same amount in each sector.

If the change in wage differentials is to vary by sector, two assumptions are necessary. First, the impact of technological change on labor demand can be allowed to vary by sector. For instance, suppose that there are two sectors that are equally S-intensive, but one where new technology leads to a large shock in relative factor demand (e.g., continuous process industries) whereas the new technology has a negligible impact in the other sector (e.g., traditional manufactures). In this situation there would be greater excess demand for S in the sectors where the new technology can be used most effectively.

This will not translate into larger values of w_s/w_u in those sectors unless the supply of S to each industry is upward sloping. If the supply of S is infinitely elastic to all sectors at prices that produce equalizing differentials (i.e. cover the cost of training and education), then all technology-induced changes in the relative wage structure of a sector would be short-lived. There would not only be a return to uniform skill differentials by sector, but also a return to the value of w_s/w_u that prevailed before the technological change (absent a change in the cost of acquiring skills). In this view any observed variation in w_s/w_u across sectors would reflect inadequate controls for heterogeneity of workers or jobs. At the other extreme, S can be viewed as fixed in each sector and w_s/w_u would increase the most in the sectors subjected to the largest S-biased technological shocks.

The most plausible scenario for experienced workers is one where (1) S has a positive supply elasticity in both the short and long run in each sector and (2) the supply of U is more elastic than the supply of S. Because of industry-specific investments in training, experienced workers face significant wage losses if they change industries. A large share of on-the-job training is firm-specific and much general training is tied to a particular product market or technology. Empirical indications of the importance of industry-specific human capital are the low overall rate of inter-industry mobility among experienced workers (Murphy and Topel (1987)) and the wage losses faced by displaced workers who change industries (Neal (1995)).

Suppose further that the returns to training vary across industries, leading to variation in the wages of workers with the same levels of schooling and ability. Lillard and Tan (1986) show how the payoff to training is greater in sectors undergoing rapid technological change, mainly because very few firms will be at the cutting edge of a particular technology, which means the supply of trained workers is likely to be quite limited. In business school parlance, it becomes cheaper to make than buy trained help.

Assuming recent changes in technology have been biased toward skilled workers, firms that have been most affected would face multiple pressures to pay higher relative wages. The equilibrium wage would have to increase in order to retain experienced help and create incentives for workers to undergo additional training. Many firms also will want to avoid salary compression (or inversion) between experienced workers and inexperienced new hires. Otherwise teamwork and future training would be endangered.

The training of many inexperienced workers also has an industry-specific component, especially training obtained in technical colleges and universities. Some academic units focus on industries such as agriculture, forestry, mining, education, textiles, and journalism, to name a few. Many degrees in engineering, medicine, law, and public administration also have a large degree of industry-specificity.[3] This again means

---

[3]One indication that variation across types of schooling in industry-specific training influences wages is the persistent differences in starting salaries by college majors. Ehrenberg (1992) shows that in virtually every year between 1973 and 1988, salaries for engineering majors were highest,

that pay levels will vary across industries for workers with identical levels of education. The responsiveness of pay in the various markets for college graduates to supply and demand factors has been well-documented, so one would expect a strong correlation between indicators of technological change and wage growth across industries for this group.

Technological change should have little impact on interindustry wage differentials for inexperienced workers with relatively little schooling. Such workers have little to no industry specific human capital; their schooling also is unlikely to provide industry-specific skills.

The empirical work reported below examines the relationship between indicators of technological change and changes in the wage structure within industries. Such work will yield important insights into the economy-wide linkage between technology and the wage structure provided that (1) the change in technology varies by sector; (2) the change in the wage structure varies across sectors; (3) there is a strong correlation between changes in technology and changes in wage differentials; and (4) the correlations cannot be attributed to other factors. The remainder of the paper lays out this case.

---

followed by chemistry, business, social sciences, humanities, and education. Even though such workers would be observationally identical in the CPS in that they all have 16 years of schooling, average starting salaries vary by as much as 40 to 50 percent. This is consistent with the market initially rewarding those who select majors that substitute specialized, job-oriented instruction in a narrow field such as accounting or civil engineering for courses in the liberal arts and sciences. Such a payoff would be necessary to offset the risk that the market for narrow skills could go sour. Differences in various dimensions of ability and working conditions also account for these persistent differences in starting salaries.

II. MEASURES OF TECHNOLOGICAL CHANGE

The human capital and factor demand literatures have pointed out a number of potential linkages between properties of the production function and returns to schooling or experience. One possibility is that human capital is complementary with physical capital, whereas both are substitutes for raw (unskilled) labor. This idea dates back at least to Griliches (1969) and appears to have widespread empirical support in the factor demand literature, as shown in Hamermesh (1993).

The mechanism that has received the most attention in the literature is the greater ability of educated individuals to adjust to changing economic conditions. Nelson and Phelps (1966) developed a model where education reduces the gap between the best available technology and the technology that is actually used. In their framework the marginal product of education is greatest when technology is changing most rapidly and when the gap between available and actual technology is greatest. Welch (1970) and Schultz (1975) emphasize the capacity of educated workers to make better allocative decisions about which products to make or combinations of inputs to hire. Highly educated workers also reduce uncertainty about the introduction of new technology, according to Bartel and Lichtenberg (1987).

The theoretical literature provides relatively little guidance for empirical work. Taken literally, the term "technological change" can mean two very different things. To most economists it boils down to the ability to produce more output with the same amount of inputs, usually the consequence of better knowledge or organization. The appropriate measure of this type of technological change would be total factor productivity (TFP) growth, the growth in output that cannot be explained in terms of changes in the quantity or quality of inputs. This measure is always problematic in empirical work because it is by definition a residual and questions about whether the data have been completely purged of all changes in input quantity and quality can never be completely resolved.

Alternatively, technological change can mean a change in equipment and job requirements. The widespread substitution of personal computers, software, and printers for typewriters would qualify as a change in technology under this definition, but not necessarily under the former. The distinction is important because recent changes in the wage structure may very well be attributable to the adoption of certain types of equipment that are highly complementary with skilled labor. To measure changes in equipment, this study examines R&D intensity, the growth in the capital-labor ratio, both in the aggregate and for particular types of capital, and the recentness of capital.

This study examines changes in wage equation parameters across 39 industries at the one or two-digit level of aggregation. Because only 19 industries are in manufacturing, a paramount consideration in the choice of right-hand side variables is the availability of data for nonmanufacturing industries. This is straightforward for TFP growth and the growth in K/L, because Jorgenson and Fraumeni have tabulated data for 35 industries using definitions that are reasonably close to the ones used for this study. The growth rates for 1970-79 are matched with the 1979 CPS, whereas the growth rates for 1980-85 are matched with the 1989 CPS.

R&D intensity is widely used (e.g., BLS, OECD) to indicate which industries qualify for "high tech" status. The R&D intensity measures published by the National Science Foundation are limited to manufacturing industries. A further limitation of these data is that they pertain to the industry where an innovation originates, not the industry where the innovation is actually used. An alternate measure was developed to incorporate the nonmanufacturing sector and possible spillovers of innovation across industry lines -- the percentage of employees who were scientists and engineers for each industry in the 1979 and 1989 CPS.[4] Unlike the corresponding measure published by NSF, this is not restricted to persons engaged in R&D activity, a potentially desirable property for industries that are heavy R&D consumers, but engage in very little R&D themselves.

The ratio of scientific and engineering employment to total employment is highly correlated with the measures published by NSF for manufacturing industries aggregated at the two digit level. The correlations for 1989 are:

CPS ratio and employment share of R&D scientists and engineers	0.960
CPS ratio and company's own R&D funds as a percent of sales	0.868

With such high correlations, the employment share of scientists and engineers should be a reasonably good indicator of innovative activity by industry.

Use of this measure in analyzing wage structure changes is problematic in one regard. Scientists and engineers are more highly paid than other college graduates, so that shifts in the composition of employment will automatically lead to greater wage growth for college graduates relative to other industries. The wage impact of the technological changes resulting from increased innovative activity will be overstated. Various tests to

[4]Scientists and engineers are defined according to the variable "detailed occupation" in the CPS. Because of changes in the occupational coding system between the 1979 and 1989 surveys, it is difficult to create a definition that is completely consistent for the two sample periods. In 1979 scientists and engineers consist of computer specialists (except computer programmers), engineers (except sales engineers), mathematical specialists, life and physical scientists, and operations and systems researchers and analysts. The corresponding occupational codes are 4 through 21, 23, and 34 through 55. In 1989 scientists and engineers are defined as engineers, mathematical and computer scientists, and natural scientists. The corresponding codes are 44 through 59 and 64 through 83. The first difference between the employment share of scientists and engineers in an industry is used as a right-hand variable below. The concordance between the two coding schemes indicates that 2 percent of 1979 scientists and engineers are likely to be classified as nonscientific personnel in the 1989 code and 1.2 percent of the 1989 scientists and engineers are likely to be misclassified in the 1979 code.

estimate the magnitude of this bias are reported below.

Data on the stocks of various types of high-tech capital for 1979 and 1989 were obtained from the Bureau of Economic Analysis' (BEA) RENPR files. Data on investment by industry were broken down by BEA into investment by industry and type of asset, based on historical patterns. BEA used the 1982 input/output table for 1989 and interpolated the values for 1979 from the 1977 and 1982 tables. BEA then used age-efficiency functions to aggregate the annual investment data into capital stocks. High-tech capital consists, as in Berndt, Morrison and Rosenblum (1992), of four asset codes in the BEA data set: office, computing, and accounting machinery (14), communications equipment (16), scientific and engineering instruments (25), and photocopy and related equipment (26). This study will focus primarily on two measures using these data: a capital-labor ratio based on all four types of capital (called high-tech and office capital in the tables below) and one based solely on assets 14 and 25 (called high-tech capital). The reasons for examining the latter measure are that (1) much communications and photocopy equipment is not very high-tech; (2) such equipment is related to white collar employment in a quasi-Leontief relationship; and (3) communications capital accounts for more than half of the high-tech capital in our data.

A limitation of this measure is the question of how applicable the 1982 capital flow patterns are to investment in the last half of the 1980s. The key factor differentiating the 1979 and 1989 values will be across-industry variation in the volume and timing of investment. Any inter-industry differences in the share of high-tech relative to total investment are unlikely to be picked up by this measure.

The ratio of net to gross capital stock in 1979 and 1989 from Fixed Reproducible Tangible Wealth in the United States was used to measure the recentness of the technology. This measure has two obvious limitations: it makes no distinction between plant and equipment, even though the latter is a much better indicator of recentness of technology than the former, and it pertains to private capital only, even though some of the industries include public sector workers.[5]

Some important characteristics of these technology measures stand out in Table 1. First and most importantly, the technology indicators vary widely across industries. In most cases the standard deviation is well above the mean. This means it is highly unlikely that technological change and any shocks to relative labor demand caused by such change are uniform.

Second, the technology indicators tend to be highly autocorrelated; the industries using the most advanced technologies in 1979 tend to be the ones using the most advanced technologies in 1989. The only measure that is not autocorrelated is the TFP measure. While this is a desirable feature for a residual, the TFP measure implies that there have been large shifts across sectors in the impact of technological change that are not apparent in the other measures.

Third, there is no consistent pattern across sectors between the use of advanced technologies in 1979 and the rate of increase in their use between 1979 and 1989. The sectors with the largest increase in R&D intensity were those with the highest initial levels. However, TFP growth and the growth in the high-tech K/L was the greatest in those sectors which were farther behind in 1979.

Fourth, for the most part the indicators of technological change are largely

---

[5]This study also looked at how bias in technical change affects wage function parameters, using the determinations of Jorgenson (1990). Capital-saving and labor-saving technical change had no explanatory power in their own right and had no influence on other parameters of interest, so they are excluded from the results reported below.

independent. R&D intensity is highest in those industries with the greatest high-tech capital intensity, suggesting some overlap between these two measures.

Lastly, how do the highest ranking industries compare to the lowest ranking ones and is this consistent with the "popular wisdom" about the rate of change in the workplace? R&D intensity and high-tech capital intensity come out relatively well in this regard. Chemicals and petroleum refining have the largest R&D intensity in 1979; retail trade and personal services have the lowest values. Communications and utilities join chemicals and petroleum refining as the industries with the highest high-tech capital-labor ratios in both 1979 and 1989; agriculture, apparel, and retail trade trail. Some sectors with the highest levels of TFP growth (apparel in the 1970s, agriculture and lumber in the 1980s) do not seem to be leaders in technological change. Similar problems arise with K/L growth (high values for agriculture and leather, low values for financial services).

III. CHANGES IN THE INTERINDUSTRY WAGE STRUCTURE

The full-year Current Population Surveys for 1979 and 1989 are used to estimate changes in the wage structure across industries. The main advantage of these data sets is the very large sample size. The sample periods are selected to coincide with the upswing in returns to schooling in the 1980s. Fortuitously, the business cycle was nearing the end of a lengthy expansion in each of these years as well. The sample is restricted to persons between the age of 18 and 64 for whom the CPS reports average weekly earnings, usual weekly hours, race, sex, age, years of schooling, SMSA status and industry. In cases where usual weekly earnings was top coded at $999, a value of $1450 was assigned.[6] Observations with average hourly earnings above $125 were deleted from the sample; in most cases these persons were employed in occupations where such a high wage is implausible. No exclusions were made with respect to the minimum wage because it arbitrarily truncates the sample and the resulting bias could vary tremendously across industries.

Industries were defined with two criteria in mind: (1) adequate sample size in both periods and (2) consistency with industry definitions used for other variables in the analysis (e.g., TFP growth). The 44 industrial categories are listed in the first column of Table 2. They are mostly the same as the 51 categories used in the CPS "detailed industry" classification system. The sample size in many cases was substantial enough to permit a more disaggregated analysis, but there was rarely more detail available in the data sources on other industry characteristics.

The easiest way to illustrate the magnitude of interindustry differences in wage equation parameters is to estimate a conventional equation for each industry:

$$(1) \quad \ln(W_i) = a_0 + a_1{*}ED_i + a_2{*}EXPER_i + a_3{*}EXPER_i^2 + a_4{*}PARTTIME_i + a_5{*}NONWHITE_i + a_6{*}FEMALE_i + a_7{*}SMSA_i + u_i,$$

where W_i = usual weekly earnings divided by usual weekly hours for salaried workers and the wage rate for hourly workers, ED_i = years of schooling completed, $EXPER_i$ = min(age-ED_i-6, age-18), $PARTTIME_i$ = 1 if usual weekly hours is below 35 and 0 otherwise, $NONWHITE_i$ = 1 if race is black or other and 0 otherwise, $FEMALE_i$ = 1 if female and 0 otherwise, $SMSA_i$ = 1 for residents of SMSAs and 0 otherwise, and $u_i \sim N(0, s_u^2)$. In

[6]These assumptions are identical to those used in most studies, e.g. Bound and Johnson, Katz and Murphy.

another specification ED_i is replaced by three binary indicators of education level (11 years or less completed, 12 years, 16 or more) to obtain a direct estimate of wage gaps among workers with varying education levels. Estimates of the returns to schooling (a_1), the wage gap (in logs) between workers with college and high school degrees, and the wage gap between workers with 0 and 30 years of experience for each industry are reported in Table 2.

Four noteworthy results emerge from this analysis. First, there is considerable dispersion across industries at any point in time in the wage equation parameters. The rate of return to schooling in 1979 is 5.7 percent, with a standard deviation across industries of 1.4 percent. It ranges between 3.0 percent in eating and drinking places and 9.4 percent in business services. Average returns to schooling increased to 8.0 percent in 1989, ranging between 3.3 percent in eating and drinking places and 11.2 percent in medical services. The standard deviation increased to 2.1 percent.

Estimates of other wage function parameters are similarly dispersed. The mean log wage gap between college and high school graduates is 0.354 in 1979, but the standard deviation of the industry estimates is 0.10. Workers with 30 years of experience earn 50 percent more than workers with no experience in the average industry in 1979, but this experience differential is a mere 16 percent in welfare and religious services and a whopping 76 percent in construction.

Second, there is a tendency for industries with high returns to schooling to have greater returns to experience. The correlation between these variables is 0.342 in 1979 and 0.268 in 1989.

Third, there is considerable flexibility in the interindustry wage structure over time. In the average industry, the rate of return to schooling increased by 2.3 percent between

1979 and 1989. Yet returns to schooling barely changed or actually fell in three industries (lumber, restaurants, and entertainment) and rose by four percentage points or more in four others (nonelectrical machinery, miscellaneous manufacturing, petroleum, and welfare and religious). The standard deviation of the increase in returns to schooling across industries was 1.2 percent. The change in the log wage gap between high school and college graduates is also widely dispersed with a standard deviation of 0.082, relative to a mean of 0.127.

Fourth, the wage equation parameters are positively autocorrelated, as shown below:

Returns to schooling	0.856
Log wage gap between college and high school	0.735
Log wage gap between 0 and 30 years of experience	0.840

This makes it difficult to discount them as temporary disequilibria.

These findings seemingly run counter the conventional wisdom that the interindustry wage structure is highly stable. That wisdom is based on a different model than the one estimated here. It permits intercepts to vary by industry over time, but constrains all other wage equation parameters to be the same across industries. There are two issues here: (1) do wage equation parameters other than a_0 vary by industry in a cross section and (2) does the change in those parameters vary across industries?

Given the well-known explanatory power of binary indicators of industry in a cross section equation, the relevant comparison is between a model where a number of parameters vary across industry and one where only a_0 is allowed to vary by industry. The analysis in this paper will focus on the variation in returns to schooling and experience across industries and over time. The hypothesis that these industry interactions are zero is rejected with F(129, 160861) = 23.3 for 1979 and F(129, 167192) = 31.6 for 1989.[7]

The more crucial issue is whether the change in wage function parameters varies across industries. Consider now an unrestricted model where all parameters in (1) vary by year and a_0 through a_3 vary by industry <u>and</u> where the industry effects in 1979 are allowed to be different from the industry effects in 1989. The restriction that the industry-year interactions for a_1, a_2, and a_3 are zero is rejected with F(129, 327873) = 4.76. The restriction that the industry-year interactions for a_0 are zero is rejected with F(43, 327873) = 8.16. The restriction that all four sets of industry-year interactions are zero is rejected with F(172, 327873) = 8.60.

Because of the differences in parameters across industries, it is possible that shifts in employment shares could be partially responsible for rising returns to schooling and experience. However, one can account for no more than 4 percent of the aggregate increase in returns to schooling by shifts in employment. This evidence is consistent with the studies cited in the introduction which find that most skill upgrading has taken place almost entirely within industries.

To sum up, the analysis in this section shows that there is considerable variation in the wage structure across industries and over time within industries. Further, there is a correlation between returns to schooling and returns to experience across industries, in terms of both levels and changes. This is suggestive of the possibility that some common

---

[7]Much attention was given in the late 1980s to the importance of industry effects in explaining wage differences across individuals. In a simple cross section framework it appears that adding industry interactions with schooling and experience to (1) improves standard measures of goodness of fit about as much as adding a set of industry intercepts to (1). A model where a_1, a_2, and a_3 vary by industry has an MSE of 0.188 and an adjusted R^2 of 0.459 in 1989, whereas the model where a_0 varies by industry has an MSE of 0.190 and an adjusted R^2 of 0.452. For the purpose of contrast, note that in (1) the MSE is 0.214 with an adjusted R^2 of 0.384; in a model where intercepts and slopes vary by industry the MSE is 0.186 and the adjusted R^2 is 0.464.

factors on the demand side of the labor market are behind the economy-wide trend toward greater wage gaps by education and experience. The next empirical step is to examine various ways of estimating how changes in technology could be driving these trends.

IV. EMPIRICAL RESULTS

The first issue to be examined (in part A) is how returns to schooling and experience vary at a given point of time with technological change, followed by an analysis of changes in these parameters over time (part B). These initial results are obtained by regressing the wage equation estimates in Table 2 on the technological change variables. One limitation of this approach is that it ignores possible interactions between the coefficient estimates and other variables. For instance the relationship between wage differentials by schooling and R&D intensity may vary tremendously by gender or experience. The other limitation is that the focus on changes in wage differentials between groups does not identify how the groups are doing in absolute terms. R&D intensity can widen wage differentials either by lowering wages of workers with little schooling or by raising wages of highly educated workers.

To explore these issues, wage equations were estimated for 32 schooling-experience-gender groups, using categories identical to those in Bound and Johnson (1992). Each wage equation contained years of experience and binary indicators of schooling, race, part-time work, residence in an urban area, region (3), and industry (43). Predicted wages for a person with average characteristics were then calculated for each industry for each group.[8] The results of regressing the change in predicted wages on indicators of technological change are reported in part C.[9] Issues related to model specification and to the interpretation of the results are discussed in parts D and E.

A. Cross section analysis of returns to schooling and experience Table 3 reports regressions of returns to schooling on R&D intensity (based on employment of scientists and engineers), various indicators of high-tech capital intensity, capital recentness, growth in the capital-labor ratio, and total factor productivity growth. Separate regressions are reported for 1979 and 1989. The regressions are weighted by the inverse of the standard error of the dependent variable.

Returns to schooling are much higher in industries that are R&D intensive. Consider two industries, one with virtually no employment of scientists and engineers (e.g., apparel, retail trade) and another where 10 percent of the workers are scientists and engineers (e.g., chemicals, instruments, electrical equipment, nonelectrical machinery, transportation equipment). The wage gain associated with an additional year of schooling is two to three percentage points greater in the latter industry than the former.

Initially high-tech capital was defined as in Berndt, Morrison, and Rosenblum to

---

[8]Predicted wages were calculated for a white, full-time worker who lives in an urban area. His time is split between the Northeast (22.7 percent), Midwest, (25.8 percent), South (30 percent) and West (21.5 percent) in the same proportion as the pooled 1979 and 1989 samples. Years of experience were set to either 5, 15, 25, or 35 and years of schooling were set to either 9, 12, 14, or 16.

[9]Another approach that was examined involved estimating interaction terms between technological change over the CPS microdata. Although this method eliminates the need for two-step estimation and weighting, it creates two new problems: (1) the use of industry averages introduces measurement error into regressions over individuals (none of whom are employed in an average plant) and (2) wage equation coefficients can no longer vary by industry. Although these results turned out to be qualitatively consistent with those in Tables 3 through 6, they are not reported because they were highly sensitive to the specification at best and completely nonsensical at worst. For instance despite scores of studies indicating complementarity between capital and skilled labor, the coefficient of the interaction between growth in K/L and years of schooling was -0.101. Problems involved with this type of specification are discussed more formally in Moulton (1990).

include computers, telecommunications equipment, instruments, and photocopy and office equipment. In this case, reported in column 2, there is a weak positive relationship between the log of high-tech K/L and returns to schooling in 1979 and no relationship in 1989.

In this model, each type of capital is presumed to have the same impact on returns to schooling. This is equivalent to saying that the complementarity between skilled labor and capital is the same for computers as for photocopy machines, which is very much at odds with the conventional wisdom about the skills and training needed to successfully operate these types of equipment. To explore this issue further, the model was re-estimated with separate K/L measures for each type of capital. The results for both 1979 and 1989 show that industries that intensively utilize computers and instruments have higher returns to schooling, whereas those that intensively utilize telecommunications and photocopy/office capital have returns to schooling that are no higher than in other industries.

When high-tech capital is limited to computers and instruments in column 4, there is a very strong positive correlation with returns to schooling. Because of the correlation between R&D intensity and high-tech capital intensity, the coefficient of each is sensitive to the inclusion of the other, as can be seen by comparing columns 1, 4, and 5. The main conclusion to be drawn, however, is that returns to schooling are much higher in industries that are R&D and high-tech capital intensive.

There is little to be learned from the remaining technology indicators. TFP growth is unrelated to returns to schooling. Returns to schooling were lower in 1979 in industries with the most rapid growth in K/L and the most up-to-date capital stock, the opposite of what one would expect from the theory that capital and skilled labor are complements.

K/L growth and capital recentness are unrelated to returns to schooling in 1989.

Models identical to those reported in Table 3 were estimated for two other dependent variables: the log wage gap between high school and college graduates and the log wage gap between workers with 0 and 30 years of experience. The results for the former were very similar to those reported in Table 3, whereas there seems to be no relationship between these measures of technological change and returns to experience.

The employment share of scientists and engineers in the CPS is an indicator that the industry is either a producer or consumer of R&D activity. One check on the validity of the results for R&D and returns to schooling is to examine their sensitivity to different measures of R&D intensity. This was done for two measures published by NSF for manufacturing industries: the ratio of a company's own R&D to sales and the ratio of R&D employment to total employment. Because these measures are available only for manufacturing industries, the 1989 results in Table 3 are re-estimated for the smaller sample to facilitate comparisons. These results provide further evidence that R&D-intensive industries tend to have higher returns to schooling than other industries. The coefficient (S.E.) for the CPS measure is 0.305 (0.075) over manufacturing industries in 1989, with R^2 of 0.610 for a model identical to that in column 1 of Table 3. In the same type of model, the NSF employment share variable had a coefficient (S.E.) of 0.469 (0.108), with an R^2 of 0.638. Comparable results were obtained for the company's own R&D funds as a share of sales.

B. Changes in returns to schooling and experience across industries This is a stricter test of the relationship between R&D intensity and returns to human capital because increased measurement error on both sides of the equation reduces the odds of finding a sizable relationship. A regression of changes on changes also cancels any spurious correlation in the cross section results generated by unobservables that happen to be correlated with both returns to human capital and R&D intensity. Such a bias could be present in Table 3, although its direction cannot be predicted ex ante. Of course, changes in the employment share of scientists and engineers are not likely to be purely exogenous events. A larger share may reflect a response to an opportunity to innovate, but also it could be a consequence of reduced employment in other occupations or lower relative wages of scientific and engineering personnel in an industry.[10]

The functional form of the models of wage differentials in Table 3 will carry over to models of changes in wage differentials in Table 4 as long as the coefficients of the 1979 and 1989 values of the right-hand variables have the same absolute value and opposite signs. Column 1 of Table 4 has the same form as column 1 of Table 3, and the main result -- the impact of R&D intensity -- carries over from levels to changes. This was not the case for high-tech capital intensity, as can be seen by comparing column 2 of Table 4 to column 4 of Table 3. The implied restriction in column 2 is that the coefficients of high-tech capital intensity in 1979 and 1989 are equal and opposite in sign. This restriction is removed in column 3, where the results show that returns to schooling increased the most in industries with the greatest high-tech capital intensity in 1979 but were unrelated to the 1989 value. From a statistical standpoint, the restriction is rejected overwhelmingly with $F(1,33) = 11.17$.

The rate of return to schooling rose the most in the industries where R&D intensity grew most rapidly and that used high-tech capital most intensively. Consider two industries, each of which is a standard deviation away from the mean change in R&D

---

[10]Changes in wage gaps between workers with 0 and 30 years of experience were unrelated to any measure of technological change, and thus again are not reported.

intensity. R&D intensity fell by 0.8 percent in fabricated metals and rose by 1.7 percentage points in public utilities. Based on the estimates in Table 4, the rate of return to schooling would have increased by 0.5 to 0.6 percentage points more in the latter than in the former. To put this in perspective, the increase in returns to schooling in the average industry was 2.1 percent.

A similar comparison can be done for high-tech capital intensity, where banking and furniture rank at the 20th and 80th percentiles. The log difference in high-tech capital intensity between these industries is 3.2 (roughly the same as two times the standard deviation), which is associated with a 1.1 percentage point increase in returns to schooling. These calculations, along with the sizable R^2 of 0.401 in column 5, indicate that technological change has been a very important factor in determining how wage differentials have changed across industries.

The wage gap between high school and college graduates also grew more rapidly in industries that were high-tech capital intensive in 1979 and had growing R&D intensity. Repeating the comparison based on R&D intensity, the log wage gap would grow by .041 more in public utilities than in fabricated metals. In terms of high-tech capital intensity, the log wage gap would grow by .037 points more in banking than in furniture. The average growth of the log wage gap was 0.127, so once again the magnitudes of these effects are quite sizable.

<u>C. Changes in interindustry wage differentials by demographic group</u> Studying real wage growth between 1979 and 1989 by industry-demographic group allows for multiple observations for each wage differential for each industry, increasing the amount of data and permitting interactions in the model. It also enables changes in wage differentials to be interpreted more carefully. Do increases in R&D raise the wage gap between college

and high school graduates by raising the wages of college graduates, lowering the wages of high school graduates, or both?

Once again the analysis focuses on changes in interindustry wage differentials, this time for narrowly defined demographic groups. To test whether the measured changes in wages by industry for each group contain meaningful information, the hypothesis that there was no change in interindustry differentials was tested for each of the 32 groups.[11] It was rejected at the five percent level of confidence for all but seven groups: high school dropouts who are female and have less than 10 years of experience or are male with 20 to 29 or 30 plus years of experience; men with some college and 30 or more years of experience; male college graduates with 10 to 19 or 20 to 29 years of experience; and female college graduates with 30 or more years of experience.[12]

As a first step, the change in the log of predicted real wages for a sample consisting of all demographic groups was regressed on binary indicators of schooling, experience, and gender in Model 1 of Table 5; the technology variables are added linearly in Model 2. A complete set of interactions between the demographic and the technology variables is added in Model 3. The sample for each model contains 1223 observations.[13] Because the dependent variable is, in effect, a regression coefficient, each observation is weighted by the count of persons in the combined 1979 and 1989 CPS for a given demographic group who were employed in a given industry.

---

[11]This was done by estimating wage equations for each group with a single set of industry dummies and then adding a set of industry-year interactions. Controls for part-time status, race, region, experience, schooling, and residence in an SMSA and interactions between each of these and year also were included in the model.

[12]In two of these cases the null was rejected at the seven percent level of confidence.

[13]The sample shrank from a maximum possible sample of 1248 (=32 groups * 39 industries) because there were 25 cells where no one in a given CPS demographic sample was employed in a particular industry.

In the model with no interactions, wage growth rises with schooling and experience and is greater for women than for men. The magnitude of these coefficients is very close to those reported in other studies using microdata. Model 2 shows that wage growth is greatest in industries with increasing R&D, decelerating TFP growth, and decelerating growth in K/L. As the results for Model 3 show, however, these patterns vary tremendously across different demographic groups.[14]

Rising R&D activity and intensive use of high-tech capital are associated with higher wages for college graduates, but are completely unrelated to wages of other educational groups. This implies that the correlations between these variables and returns to schooling (or college/high school wage gaps) in Table 4 reflect greater wage growth for college graduates in R&D-intensive industries, rather than a negative demand shock for high school graduates employed in those industries. The difference between the R&D (high-tech capital) coefficients for college and high school graduates in Table 5 is just about identical to the R&D (high-tech capital) coefficient in the Table 4 model of the change in the log wage gap between these two groups.

R&D-intensity also has differential effects on wage growth by experience. Rising R&D has no effect on workers with less than 20 years of experience, but is associated with much greater wage growth for workers with 20 or more years of experience. This is consistent with Lillard and Tan's (1986) findings.

One new and very important result in Table 5 is that wage growth for workers without college degrees is much lower in industries with accelerating growth in K/L. In contrast, wage growth for workers with college degrees is uncorrelated with the change in

[14]Interactions with capital recentness and TFP growth are included in Model 3, but not reported because they had no notable effect on any dimension of wage differentials.

K/L growth. Because K/L growth was greater in 1980-85 than in 1970-79, these results imply that acceleration in K/L growth contributed to the rising wage gap between college graduates and other workers.

The industries with the largest acceleration of K/L growth were mining, nonelectrical machinery, primary metals, fabricated metals, and leather. By no coincidence, employment fell by more than 15 percent in all of these industries and by more than 30 percent in three of them. Beyond the drop in employment, however, it is difficult to generalize about other conditions in these industries. Output fell considerably in leather and primary metals in the 1980s, reflecting increased competition from imports. In contrast, output almost doubled in nonelectrical machinery, reflecting vastly improved efficiency.

The results in Table 5 indicate that technology has affected the gender gap. Female wages grew more than male wages in industries that intensively use high-tech capital and industries where K/L growth accelerated in the 1980s.

How much has technological change contributed to changes in wage differentials? The increase in R^2 from 0.479 in Model 1 to 0.588 in Model 3 indicates these variables certainly matter. To see how much, let's repeat the exercise in section B using differences of two standard deviations for each variable. In this case, the wage differential between college and high school graduates would grow by 0.126 more in an industry one standard deviation above the mean for each of these technology variables than it would in an industry one standard deviation below the mean. This is actually slightly greater than the mean increase in the wage gap between college and high school graduates (0.119) across gender and experience categories in column 1. The reason is quite simple -- there is covariation between each of the technology indicators, making an industry that is one standard deviation above or below the mean in all three somewhat atypical. A more realistic comparison is between banking, which is at the 20th percentile of predicted growth in the wage gap (based on these three indicators), and entertainment services, which is at the 80th percentile. The estimates imply that the wage gap would grow by .057 more in banking than in entertainment, again a sizable difference relative to the mean growth in the wage gap of 0.119.

The next logical step is to extend the estimation framework to allow for a complete set of interactions by schooling, experience, and gender. To do this, separate log wage change regressions were run for each of the 32 demographic groups. These results are reported in Tables 6. Because 160 coefficients are hard to digest and the results are largely consistent with those in Table 5, the discussion focuses on new insights from the fully interactive approach.

R&D has the greatest impact on wage growth among college graduates, as can be seen by comparing the size of the R&D coefficients across the four panels in Table 6. The impact of R&D on wage growth is much greater for workers with 20 or more years of experience than for less experienced workers with one notable exception: among both men and women there is a very strong link between wage growth and R&D intensity for college graduates with less than 10 years of experience. This result is notable because this is precisely the group that has the greatest opportunity to arbitrage any interindustry difference in wage offers. R&D coefficients also are larger for women than men.

High-tech capital has a big impact on wage growth across all experience categories for women who are high school graduates and have some college. In contrast it has no impact on wage growth for male high school graduates and its impact on men with some college is, while generally positive, more modest than for women. The impact of high-tech capital is greatest for recent college graduates, echoing the results for R&D intensity.

The negative impact of growth in K/L on log wage change among workers who have not completed college is limited almost entirely to men. It is greatest (in absolute value) for men with the least experience. This is indicative of a mismatch between the skills of inexperienced men without college degrees and the requirements of modern technology.

D. Possible biases The main result of this study is that returns to schooling and the wage gap between high school and college graduates increased much more in industries with a rising employment share of scientists and engineers and industries that employ high-tech capital more intensively than in other industries. These results for R&D could reflect compositional factors if earnings in scientific jobs are higher than in other occupations and increase with years of schooling at the same or greater rate.

These assumptions can be tested over the CPS micro data by adding a binary indicator of scientific occupation and an interaction between this variable and years of schooling. The coefficient (S.E.) of the binary variable indicating employment as a scientist or engineer is 0.246 (0.007) in 1979 and 0.310 (0.006) in 1989. The interaction between years of schooling and this binary variable are both negative: -0.007 (0.003) in 1979 and -0.019 (0.003) in 1989. For college graduates, the occupational premium has actually shrunk from 0.134 to 0.006, indicating that occupational shifts are not driving the results.

Dropping scientists and engineers from the sample and constructing new dependent variables is an extreme, but instructive test. Part of the value of schooling at all levels is the option of becoming a scientist or engineer. Throwing an important occupation for college graduates out of the sample is not likely to give an unbiased estimate of returns to schooling. The results in Tables 4 through 6 reflect greater returns to schooling across all occupational groups, plus higher levels of earnings for scientists and engineers. Results obtained by dropping the latter group from the sample will indicate how technological change affects returns to schooling in nonscientific occupations. This answers a more narrow question -- how much complementarity is there between scientific personnel and highly educated and experienced workers in other occupations.

When this procedure is applied to the models in the fifth column of Table 4, the coefficient (S.E.) for R&D intensity fell by about one-third to 0.145 (0.102), whereas the coefficient for high-tech capital declined very modestly to 0.0032 (0.0008). Model 3 in Table 5 also was re-estimated after dropping all scientists and engineers from the samples of college graduates. The interaction coefficients between R&D intensity and wage growth of high school and college graduates were -0.055 (0.438) and 1.074 (0.586). This would mean that a one percentage point increase in R&D intensity would increase the log wage gap by 1.2, in contrast to 1.8 in Model 3 of Table 5. The interaction coefficients between high-tech capital intensity and wage growth of high school and college graduates were 0.0115 (0.0042) and 0.0002 (0.0035), values that are virtually identical to those in Table 5. These findings show that R&D activity and high-tech capital have an impact on relative earnings across a broad range of occupations, not just scientists and engineers. The results in earlier tables are not being driven by a simple association between R&D and high-tech capital, on the one hand, and above average earnings (relative to other college graduates) for scientific personnel.

Measurement error is another source of bias. Occupations are not always reported accurately and the sample size for some industries in the full-year CPS is too small to estimate the employment share of scientific personnel precisely. The NSF measure is conceptually different from the one developed here, but it is likely to have less measurement error for two reasons: (1) the data are firm-reported and (2) special efforts are made to include R&D-performing establishments in the sampling frame. To demonstrate the possible magnitude of bias caused by mismeasurement, the model in column 1 of Table 4 was estimated over 17 manufacturing industries for which NSF reports employment shares of R&D scientists and engineers. The coefficient (S.E.) of the NSF measure was 0.588 (0.213), whereas over the same sample, the coefficient for the CPS measure was 0.465 (0.258). The difference reflects measurement error, the possibility that R&D employment is more strongly related to earnings patterns than employment of all scientific personnel, or both.[15] In summary, these exercises indicate that sample composition is not driving the R&D results and that measurement error could be at least as serious a problem.

E. Could it really be unobserved worker quality? Chennells and Van Reenen (1995) and Entorf and Kramarz (1995) argue that because of the endogeneity of technical change, simple associations like those reported here and in Krueger (1993) cannot be interpreted as evidence that technology has caused recent changes in the wage structure. Instead, the associations may reflect two conditions that are present in the data but not observable to the data analyst: (1) high ability workers get matched with the more demanding high-tech jobs and (2) firms do not invest in new technology unless they have a capable work force. These two recent studies, along with Doms, Dunne and Troske (1995) all report evidence that shows that wage growth is no greater in plants investing in new technology than in

[15]A similar test was done for 1989 using NSF estimates of scientific and engineering employment in nonmanufacturing industries. The results were inconclusive; the coefficients and standard errors of the NSF measure were both 1.7 times larger than those of the CPS measure for this set of industries.

plants that do not.

The matching argument no doubt applies to some extent to cross sections of individual workers; the assignment of individual workers to jobs involving work with computers cannot be random. However, the evidence here is based on sizable aggregates of workers over a 10 year time period. First-differencing is eliminating time-invariant forms of heterogeneity in both workers and jobs. For this line of criticism to apply to the results reported in this study, one must truly believe that there has been a significant deterioration (improvement) in the quality of workers with relatively little (more) schooling in industries *that coincides with R&D intensity, high-tech K/L, or K/L acceleration.* For this to be true, one must either argue that (1) enough workers have changed sectors and changed labor force participation status to produce large changes in the micro and macro wage structure (despite the low volume of interindustry mobility and the persistent participation of most workers) or (2) there has been a very peculiar change-in-cohort-quality-by-industries process (one that bridges five 10-year cohorts).

But what about the evidence in the three recent studies? In every case, the authors regress changes in wages over a given time interval on the usage of high-tech capital at the end of that interval. This type of model will capture the impact of changes in technology on changes in wages only if the use of high-tech capital is uniform across all observations at the beginning of the sample period. This is highly unlikely, in light of the autocorrelation evidence for high-tech capital and R&D intensity in Table 1. Furthermore, when wage changes are regressed on 1989 levels of R&D intensity and high-tech capital intensity, there is still a strong association.

Evidence on employment provides a final indication that unobservables are not calling the tune. If the correlation across industries between the change in returns to schooling and the change in R&D intensity reflects a series of labor demand shifts, then one would expect to find increased employment of highly educated workers in such industries. To address this question, employment shares were calculated for the four schooling groups in each industry for 1979 and 1989. To prevent the estimates from reflecting simple arithmetic, workers in scientific and engineering occupations were excluded from these calculations. The change in employment shares was then regressed on the technology variables.

Employment of college graduates increased the most in industries with rising R&D and those that use high-tech capital intensively. This indicates a complementarity between innovative activity and highly educated labor that is consistent with the results for wage growth reported in Section IV, as well as with the Berman, Bound, and Griliches (1994) results for four-digit industries in manufacturing.

V. IMPLICATIONS FOR RECENT CHANGES IN THE WAGE STRUCTURE

This study has established a strong correlation between indicators of technological change and recent changes in the wage structure across a set of one and two digit industries. The results are particularly strong for R&D, high-tech capital, K/L acceleration and returns to schooling. If these variables are responsible for part of the increase in returns to schooling, two conditions must hold. First, the size of the coefficients must be sufficiently large. This has been established in section IV, where the results showed that (1) a two standard deviation change in these variables would produce large changes in relative wages and (2) for some demographic groups, one-third to one-half of the variance in wage growth across industries can be explained by technological variables.

Second, there should be some correspondence between the timing of swings in the technology variables and changes in returns to schooling. The number of R&D scientists and engineers per 1000 employees stayed constant at 2.7 throughout most of the 1970s. The R&D employment share started increasing in 1981 and rose steadily to 4.9 in 1989. R&D spending, as a percentage of net sales, fell throughout the 1970s and started to increase in 1980. Both of these trends track very closely with returns to schooling, as shown in Mincer's (1991) time series analysis.

There also was an acceleration in the use of computing equipment in the 1980s. Berman, Bound, and Griliches show that computing equipment accounted for no more than half of one percent of the capital stock in manufacturing before 1979; by the late 1980s, it accounted for over two percent. K/L growth accelerated in the 1980s as well (Table 1).

The results in Model 3 of Table 5 can be used to determine how much of the widening in the log wage gap between high school and college graduates can be explained by R&D, high-tech capital, and K/L acceleration. The increase in log of high-tech K/L is used to simulate the impact of rising high-tech capital, even though the model is specified in terms of the level of that variable. This is the most reasonable approach to use with that variable because (1) the coefficients obtained when using 1989 levels are very similar and (2) the hypothesis that the model should be specified in terms of changes instead of levels is strongly rejected by the data.

The employment share of scientists and engineers increased by an average of .6 percent in the 39 industries used in this study, which would lead to a 0.010 increase in the wage gap. K/L accelerated by .13 percent in the 1980s, leading to a 0.007 increase in the wage gap. High-tech K/L increased by 1.65, which increases the wage gap by .019.

All combined, then, these variables predict an increase in the wage gap of 0.036. In Model 1 of Table 5, the mean increase in the wage gap between college and high school graduates (across industries and eight experience-gender combinations) was 0.119. This means that observable indicators of technological change explain 30 percent of this dimension of the increase in wage inequality.

In addition to showing that direct measures of technological change have a large impact on wage differentials by skill, this paper also has shown that some measures are much better suited to the task than others. The purest measure conceptually is TFP growth, but it turns out to be completely unrelated to wage patterns empirically. Of the two measures with the greatest explanatory power, one focuses on specific types of equipment and the other focuses on a work environment (research) where high skills command a premium across all types of jobs, not just for scientific personnel. Furthermore, all forms of high-tech capital are not alike in terms of their impact on relative wages. Computers and instruments matter a lot, but not telecommunications and photocopy equipment.

It would be worthwhile to determine whether the approach used here would apply in other industrial settings. Wage differentials have widened in the United Kingdom while R&D activity has stayed flat; R&D has increased greatly in Japan, but not wage differentials. Another logical extension of this work would be to examine other potential shifters of labor demand, including international trade shocks. The methodology of this studu also can be used to examine how deunionization and concession bargaining have influenced the wage structure.

REFERENCES

Allen, Steven G., "Updated Notes on the Interindustry Wage Structure," Industrial and Labor Relations Review 48 (January 1995): 305-321.

Bartel, Ann P., and Frank R. Lichtenberg, "The Comparative Advantage of Educated Workers in Implementing New Technology," Review of Economics and Statistics 69 (February 1987): 1-11.

Berman, Eli, John Bound, and Zvi Griliches, "Changes in the Demand for Skilled Labor Within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures," Quarterly Journal of Economics 109 (May 1994): 367-398.

Berndt, Ernst R., Catherine J. Morrison, and Larry S. Rosenblum, "High-Tech Capital Formation and Labor Composition in U.S. Manufacturing Industries: An Exploratory Analysis," NBER Working Paper No. 4010, March 1992.

Bound, John and George Johnson, "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations," American Economic Review 82 (June 1992): 371-392.

Chennells, Lucy, and John van Reenen, "Wages and Technology in British Plants: Do Workers Get a Fair Share of the Plunder?" mimeo, Institute of Fiscal Studies, June 1995.

Cullen, Donald, "The Interindustry Wage Structure: 1899-1950," American Economic Review 46 (June 1956): 353-369.

Dickens, William T., and Lawrence F. Katz, "Inter-Industry Wage Differences and Industry Characteristics," in Kevin Lang and Jonathan Leonard (eds.), Unemployment and the Structure of Labor Markets (New York: Basil Blackwell, 1987).

Doms, Mark, Timothy Dunne, and Kenneth Troske, "Workers, Wages, and Technology," mimeo, Center for Economic Studies, U.S. Bureau of the Census, 1995.

Ehrenberg, Ronald G., "The Flow of New Doctorates," Journal of Economic Literature 30 (June 1992): 830-875.

Entorf, Horst, and Francis Kramarz, "Matching and New Technologies: Does Unmeasured Ability Explain Higher Wages of New-Technology Workers?" mimeo, University of Mannheim, June 1995.

Griliches, Zvi, "Capital-Skill Complementarity," Review of Economics and Statistics 51 (November 1969): 465-468.

Hamermesh, Daniel S., Labor Demand (Princeton: Princeton University Press, 1993).

Helwege, Jean, "Sectoral Shifts and Interindustry Wage Differentials," Journal of Labor Economics 10 (January 1992): 55-84.

Jorgenson, Dale W., "Productivity and Economic Growth," in Ernst R. Berndt and Jack E. Triplett (eds.), Fifty Years of Economic Measurement, NBER Studies in Income and Wealth, Volume 54 (Chicago: University of Chicago Press, 1990).

Juhn, Chinhui, Murphy, Kevin M., and Pierce, Brooks, "Wage Inequality and the Rise in Returns to Skill," Journal of Political Economy 101 (June 1993): 410-442.

Katz, Lawrence F., and Kevin M. Murphy, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," Quarterly Journal of Economics 107 (February 1992):35-78.

Krueger, Alan B., "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-89," Quarterly Journal of Economics 108 (February 1993): 33-60.

____, and Lawrence H. Summers, "Reflections on the Inter-Industry Wage Structure," in Kevin Lang and Jonathan Leonard (eds.), Unemployment and the Structure of Labor Markets (New York: Basil Blackwell, 1987).

Lillard, Lee A., and Hong W. Tan, Private Sector Training: Who Gets It and What Are Its Effects (Santa Monica: RAND Corporation Report R-3331-DOL/RC, 1986).

Mincer, Jacob, "Human Capital, Technology, and the Wage Structure: What Do Time Series Show?" NBER Working Paper No. 3581, January 1991.

Mishel, Lawrence, and Jared Bernstein, "Is the Technology Black Box Empty? An Empirical Examination of the Impact of Technology on Wage Inequality and the Employment Structure," mimeo, Economic Policy Institute, April 1994.

Moulton, Brent R., "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units," Review of Economics and Statistics 72 (May 1990): 334-338.

Murphy, Kevin M., and Robert H. Topel, "The Evolution of Unemployment in the United States: 1968-1985," in Stanley Fischer (ed.), NBER Macroeconomics Annual 1987 (Cambridge: MIT Press, 1987).

Neal, Derek, "Industry-Specific Human Capital: Evidence from Displaced Workers," Journal of Labor Economics 13 (October 1995): 653-677.

Nelson, Richard R., and Edmund S. Phelps, "Investment in Humans, Technological Diffusion, and Economic Growth," American Economic Review 56 (May 1966): 69-75.

Schultz, Theodore W., "The Value of the Ability to Deal with Disequilibria," Journal of Economic Literature 13 (September 1975): 827-846.

Slichter, Sumner H., "Notes on the Structure of Wages," Review of Economics and Statistics 32 (February 1950): 80-91.

Welch, Finis, "Education in Production," Journal of Political Economy 78 (January/February 1970): 35-59.

Table 1. Summary statistics for measures of technological change

Means and Autocorrelations

R&D intensity	Hi-tech & off K/L	Hi-tech K/L	TFP growth	K/L growth	Recentness
Means (S.D.) of 1979 values					
0.029	-0.251	-1.181	0.003	0.000	0.581
(0.031)	(1.687)	(1.573)	(0.012)	(0.008)	(0.036)
Means (S.D.) of 1989 values					
0.034	1.320	0.467	0.002	0.001	0.540
(0.037)	(1.380)	(1.378)	(0.016)	(0.009)	(0.052)
Means (S.D.) of 1979-89 change					
0.005	1.571	1.648	-0.001	0.001	-0.041
(0.012)	(0.881)	(0.928)	(0.017)	(0.005)	(0.043)
Correlation between 1979 and 1989					
0.959	0.853	0.810	0.294	0.861	0.578
Correlation between 1979 and 1979-89 change					
0.433	-0.578	-0.492	-0.471	0.086	-0.131

Correlation matrix of 1979 levels

	R&D intensity	Hi-tech & off K/L	Hi-tech K/L	TFP growth	K/L growth
Hi-tech&off K/L	0.339				
Hi-tech K/L	0.394	0.653			
TFP growth	0.013	0.088	-0.210		
K/L growth	0.229	-0.035	-0.067	0.132	
K recentness	0.155	0.351	0.282	0.196	-0.161

Correlation matrix of 1989 levels

	R&D intensity	Hi-tech & off K/L	Hi-tech K/L	TFP growth	K/L growth
Hi-tech&off K/L	0.395				
Hi-tech K/L	0.436	0.814			
TFP growth	0.126	-0.124	-0.229		
K/L growth	0.158	0.069	-0.062	0.538	
K recentness	-0.045	0.262	0.259	-0.357	-0.560

Correlation matrix of 1979-89 change

	R&D intensity	Hi-tech & off K/L	Hi-tech K/L	TFP growth	K/L growth
Hi-tech&off K/L	0.041				
Hi-tech K/L	0.125	0.539			
TFP growth	-0.194	0.329	-0.065		
K/L growth	-0.032	0.294	0.206	0.241	
K recentness	0.099	-0.185	0.270	-0.484	-0.244

Table 2. *Returns to schooling and experience, 1979 and 1989 CPS, by industry*

Industry	Returns to schooling 1979	Returns to schooling 1989	Log wage gap for college, high school 1979	Log wage gap for college, high school 1989	Log wage gap for 0, 30 yrs. experience 1979	Log wage gap for 0, 30 yrs. experience 1989
Agriculture, resources	0.048	0.061	0.455	0.490	0.360	0.366
Mining	0.052	0.085	0.316	0.542	0.444	0.558
Construction	0.047	0.056	0.208	0.331	0.567	0.582
Lumber	0.055	0.060	0.274	0.400	0.450	0.507
Furniture	0.036	0.062	0.344	0.506	0.303	0.390
Stone, clay & glass	0.053	0.079	0.450	0.536	0.444	0.540
Primary metals	0.051	0.073	0.312	0.551	0.402	0.564
Fabr. metals, ordnance	0.058	0.077	0.386	0.464	0.474	0.555
Nonelectrical machinery	0.059	0.106	0.367	0.615	0.477	0.543
Electrical equipment	0.066	0.099	0.393	0.644	0.465	0.534
Transportation eqmt.	0.057	0.088	0.362	0.547	0.411	0.597
Instruments	0.067	0.092	0.373	0.521	0.372	0.462
Misc. manufacturing	0.057	0.111	0.368	0.597	0.426	0.492
Food and tobacco	0.047	0.064	0.322	0.493	0.384	0.501
Textiles	0.055	0.062	0.559	0.628	0.351	0.405
Apparel	0.035	0.053	0.385	0.707	0.222	0.276
Paper	0.060	0.086	0.393	0.528	0.369	0.576
Printing	0.058	0.070	0.291	0.345	0.561	0.582
Chemicals	0.073	0.104	0.395	0.567	0.423	0.510
Petroleum	0.067	0.106	0.365	0.578	0.432	0.477
Rubber	0.048	0.077	0.244	0.515	0.462	0.594
Leather	0.050	0.072	0.665	0.639	0.321	0.366
Transportation	0.052	0.068	0.272	0.389	0.459	0.564
Communications	0.047	0.068	0.231	0.316	0.522	0.669
Utilities	0.069	0.095	0.354	0.484	0.486	0.621
Wholesale trade	0.064	0.095	0.349	0.501	0.501	0.519
Eating & drinking places	0.030	0.033	0.172	0.281	0.213	0.270
Other retail trade	0.046	0.060	0.236	0.312	0.369	0.414
Banking & other finance	0.074	0.104	0.344	0.476	0.483	0.555
Insurance, real estate	0.065	0.095	0.287	0.450	0.375	0.432
Business services	0.094	0.109	0.460	0.629	0.423	0.477
Repair services	0.038	0.047	0.284	0.220	0.438	0.597
Personal services	0.038	0.046	0.180	0.322	0.270	0.315
Entertainment	0.057	0.063	0.323	0.366	0.507	0.489
Medical service	0.084	0.112	0.476	0.581	0.336	0.354
Hospitals	0.078	0.108	0.441	0.590	0.366	0.435
Welfare and religious	0.046	0.081	0.285	0.464	0.153	0.309
Educational	0.082	0.102	0.478	0.562	0.405	0.594
Other professional	0.077	0.094	0.390	0.456	0.480	0.495
Mean	0.057	0.080	0.354	0.491	0.408	0.489
Standard deviation	0.014	0.021	0.100	0.115	0.091	0.101
Standard errors:						
Mean	0.003	0.004	0.028	0.029	0.026	0.033
Standard deviation	0.001	0.002	0.015	0.017	0.011	0.018

Table 3. Cross section regressions of returns to schooling on technological change

1979 regressions					
R&D intensity	0.250	0.215	0.147	0.160	
	(0.075)	(0.077)	(0.083)	(0.071)	
Hi-tech&off K/L		0.0023			
		(0.0015)			
Hi-tech K/L				0.0044	0.0055
				(0.0013)	(0.0013)
Computer K/L			0.0029		
			(0.0022)		
Telecom K/L			0.0014		
			(0.0014)		
Instrument K/L			0.0021		
			(0.0010)		
Photocopy K/L			-0.0018		
			(0.0013)		
K recentness	-0.065	-0.098	-0.096	-0.108	-0.102
	(0.053)	(0.056)	(0.055)	(0.048)	(0.051)
TFP growth	0.001	-0.002	0.029	0.122	0.149
	(0.177)	(0.173)	(0.187)	(0.160)	(0.168)
K/L growth	-1.097	-1.067	-1.084	-0.978	-0.801
	(0.301)	(0.295)	(0.288)	(0.267)	(0.270)
Root MSE	0.013	0.012	0.012	0.011	0.012
R^2	0.369	0.414	0.494	0.528	0.456
1989 regressions					
R&D intensity	0.300	0.306	0.251	0.229	
	(0.085)	(0.093)	(0.100)	(0.096)	
Hi-tech&off K/L		-0.0004			
		(0.0030)			
Hi-tech K/L				0.0044	0.0078
				(0.0028)	(0.0027)
Computer K/L			0.0035		
			(0.0034)		
Telecom K/L			-0.0036		
			(0.0030)		
Instrument K/L			0.0024		
			(0.0013)		
Photocopy K/L			-0.0014		
			(0.0032)		
K recentness	0.028	0.034	0.078	-0.016	-0.049
	(0.070)	(0.079)	(0.085)	(0.074)	(0.078)
TFP growth	-0.350	-0.363	-0.282	-0.179	-0.042
	(0.271)	(0.288)	(0.296)	(0.288)	(0.301)
K/L growth	-0.414	-0.374	-0.095	-0.676	-0.728
	(0.496)	(0.568)	(0.584)	(0.515)	(0.550)
Root MSE	0.019	0.020	0.019	0.019	0.020
R^2	0.332	0.333	0.443	0.377	0.269

Each equation also contains an intercept; standard errors are reported in parentheses. Each equation is estimated over 39 industries and is weighted by the inverse of the standard error of the dependent variable. The mean (S.D.) of the dependent variable is 0.057 (0.015) in 1979 and 0.078 (0.023) in 1989.

Table 4. Regressions of changes in returns to schooling on technological change

Dependent variable:	Change in returns to schooling	Change in returns to schooling	Change in returns to schooling	Change in returns to schooling	Change in returns to schooling	Change in coll/h.s. wage gap
Mean (S.D.) of dependent variable	0.021 (0.012)	0.021 (0.012)	0.021 (0.012)	0.021 (0.012)	0.021 (0.012)	0.127 (0.082)
Coefficient (S.E.):						
Change in R&D intensity	0.261 (0.137)				0.202 (0.120)	1.677 (0.794)
Change in high-tech K/L		-0.0023 (0.0020)				
High-tech K/L in 1989			0.0007 (0.0019)			
High-tech K/L in 1979			0.0032 (0.0017)	0.0036 (0.0010)	0.0034 (0.0010)	0.0116 (0.0067)
Change in K recentness	-0.070 (0.044)	-0.058 (0.046)	-0.036 (0.041)	-0.034 (0.040)	-0.034 (0.039)	-0.175 (0.266)
Change in TFP growth	-0.169 (0.127)	-0.167 (0.132)	-0.096 (0.118)	-0.094 (0.116)	-0.084 (0.113)	0.077 (0.743)
Change in K/L growth	0.328 (0.397)	0.476 (0.428)	0.472 (0.376)	0.507 (0.358)	0.496 (0.348)	3.807 (2.385)
Root MSE	0.010	0.011	0.010	0.009	0.009	0.062
R^2	0.185	0.133	0.352	0.350	0.401	0.274

Each equation also contains an intercept. Standard errors are reported in parentheses. Each equation is estimated over a sample of 39 industries and is weighted by the inverse of the standard error of the dependent variable.

Table 5. Coefficients (standard errors) of wage growth regressions across schooling-experience-gender categories, 1979-89 CPS

	Model 1	Model 2	Model 3			
	No tech change variables	No tech change interactions	Direct effect	Interactions: Change in R&D intensity	Interactions: High-tech K/L in 1979	Interactions: Change in K/L growth
Intercept	-0.190 (0.005)	-0.164 (0.006)	-0.179 (0.010)			
Schooling below 12	-0.009 (0.006)	-0.003 (0.006)	-0.019 (0.013)	-0.056 (0.577)	-0.0055 (0.0045)	-5.200 (1.570)
Schooling =12				0.044 (0.432)	0.0006 (0.0035)	-5.669 (1.235)
Schooling 13 to 15	0.070 (0.006)	0.065 (0.006)	0.077 (0.010)	0.162 (0.508)	0.0117 (0.0039)	-4.561 (1.468)
Schooling 16 & above	0.119 (0.006)	0.109 (0.006)	0.108 (0.011)	1.793 (0.513)	0.0120 (0.0040)	-0.496 (1.499)
Experience 10 to 19	0.044 (0.006)	0.039 (0.005)	0.038 (0.010)	-0.199 (0.480)	-0.0019 (0.0037)	1.250 (1.380)
Experience 20 to 29	0.067 (0.006)	0.061 (0.006)	0.052 (0.011)	1.326 (0.524)	0.0028 (0.0041)	2.749 (1.536)
Experience 30 & above	0.078 (0.006)	0.071 (0.006)	0.076 (0.012)	1.383 (0.529)	0.0021 (0.0041)	0.969 (1.548)
Female	0.095 (0.004)	0.092 (0.004)	0.114 (0.008)	0.129 (0.400)	0.0151 (0.0029)	3.581 (1.170)
Change in R&D intensity		0.748 (0.191)				
Change in high-tech K/L		0.0129 (0.0015)				
Change in K recentness		0.117 (0.055)				
Change in TFP growth		-0.104 (0.174)				
Change in K/L growth		-2.060 (0.553)				
Root MSE R^2	0.479	0.542	0.588			

Each equation is estimated over 1223 categories defined by industry (39), schooling (4), experience (4), and gender (2) and is weighted by the number of 1979 and 1989 CPS observations in each cell.

Table 6. Coefficients (standard errors) of wage growth equations, by schooling, experience, and gender

	Men				Women			
	R&D intensity	High-tech K/L	K/L growth	R^2	R&D intensity	High-tech K/L	K/L growth	R^2
School<12								
Experience	-0.708	-0.0056	-5.216	0.198	-1.154	0.0016	-0.406	0.166
0-9	(0.973)	(0.0075)	(2.289)		(1.191)	(0.0090)	(3.911)	
Experience	-0.320	-0.0127	-7.223	0.309	-2.957	-0.0044	-8.926	0.356
10-19	(0.984)	(0.0088)	(2.517)		(1.190)	(0.0087)	(4.171)	
Experience	1.063	0.0009	0.592	0.063	2.180	0.0025	-1.157	0.248
20-29	(1.011)	(0.0088)	(2.661)		(1.350)	(0.0103)	(4.926)	
Experience	1.554	-0.0070	-4.255	0.321	0.575	0.0180	7.572	0.397
30+	(0.604)	(0.0053)	(1.639)		(1.142)	(0.0083)	(4.349)	
School=12								
Experience	0.464	-0.0047	-6.209	0.238	-0.847	0.0161	-0.306	0.342
0-9	(0.758)	(0.0067)	(2.105)		(0.866)	(0.0057)	(2.476)	
Experience	1.066	-0.0033	-4.475	0.275	-0.497	0.0191	-0.619	0.329
10-19	(0.549)	(0.0051)	(1.572)		(0.928)	(0.0062)	(2.791)	
Experience	1.621	0.0030	-3.800	0.293	1.283	0.0148	-1.150	0.362
20-29	(0.775)	(0.0076)	(2.303)		(0.928)	(0.0062)	(2.780)	
Experience	1.498	0.0061	-3.239	0.272	0.441	0.0127	-1.818	0.250
30+	(0.706)	(0.0068)	(2.162)		(0.929)	(0.0060)	(2.745)	
13<School<15								
Experience	0.457	0.0116	-5.344	0.298	-0.350	0.0288	-0.787	0.538
0-9	(0.816)	(0.0065)	(2.281)		(0.902)	(0.0055)	(2.382)	
Experience	0.223	0.0128	0.808	0.168	1.433	0.0254	-2.860	0.287
10-19	(0.676)	(0.0063)	(2.031)		(1.467)	(0.0090)	(4.028)	
Experience	0.644	0.0142	0.655	0.096	4.279	0.0219	-1.457	0.360
20-29	(1.217)	(0.0116)	(3.756)		(1.727)	(0.0109)	(4.873)	
Experience	0.758	0.0130	-2.932	0.122	1.500	0.0337	-8.017	0.317
30+	(1.211)	(0.0113)	(3.872)		(2.127)	(0.0130)	(5.614)	
16≤School								
Experience	1.696	0.0156	-0.912	0.434	3.538	0.0317	5.311	0.477
0-9	(0.767)	(0.0063)	(2.250)		(1.309)	(0.0080)	(3.627)	
Experience	1.058	0.0090	1.638	0.140	3.030	0.0192	8.048	0.242
10-19	(0.841)	(0.0071)	(2.448)		(2.084)	(0.0122)	(5.797)	
Experience	0.618	0.0282	-2.448	0.313	10.140	0.0255	13.331	0.563
20-29	(0.914)	(0.0083)	(2.823)		(2.229)	(0.0129)	(6.467)	
Experience	3.420	0.0117	-4.100	0.117	4.470	0.0215	-7.240	0.311
30+	(2.043)	(0.0185)	(6.271)		(4.182)	(0.0193)	(10.320)	

Each equation is estimated over as many as 39 industries and is weighted by the number of 1979 and 1989 CPS observations in each cell.

Table 7. Regressions of changes in employment shares by years of schooling, 1979 to 1989

	Years of schooling			
	Below 12	12	13 to 15	16 & above
Mean (S.D.) of dependent variable	- 0.078	0.010	0.026	0.042
	(0.034)	(0.050)	(0.018)	(0.034)
Coefficients (S.E.):				
Change in R&D intensity	-0.515	-0.566	0.379	0.702
	(0.410)	(0.492)	(0.239)	(0.390)
Change in high-tech K/L	0.0063	- 0.0139	- 0.0020	0.0096
	(0.0032)	(0.0039)	(0.0019)	(0.0031)
Change in K recentness	0.037	- 0.170	0.046	0.088
	(0.135)	(0.163)	(0.079)	(0.129)
Change in TFP growth	- 0.854	1.325	0.004	- 0.476
	(0.342)	(0.411)	(0.200)	(0.326)
Change in K/L growth	- 0.453	0.246	- 0.847	1.054
	(1.106)	(1.329)	(0.646)	(1.053)
R^2	0.303	0.534	0.164	0.368

Nonscientific personnel are excluded from the calculation of employment shares.