TECHNOLOGY AND THE WAGE STRUCTURE

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June 1999
To appear in *Journal of Labor Economics*, April 2001

Dale Jorgenson and Barbara Fraumeni graciously provided their KLEM data set to use in this analysis. Larry Rosenblum of BLS guided me through the RENPR data. I have received helpful comments from participants at numerous seminars and conferences.

ABSTRACT

This paper reports direct evidence on how recent changes in technology are related to changes in wage gaps by schooling, experience, and gender. Wage gaps by schooling in the full-year 1979 and 1989 Current Population Surveys increased the most in industries with rising R&D intensity and accelerating growth in the capital-labor ratio. Estimates of the impact of high-tech capital are mixed, with wage gaps increasing the most in industries that were high-tech-capital intensive in 1979 and decreasing in the industries with the greatest increase in high-tech-capital intensity. Contrary to popular notions that technological change harms older workers, wage growth of experienced workers is much greater in R&D-intensive industries than in industries with little R&D activity. The gender gap narrowed more in industries that most intensively used high-tech capital in 1979, especially among younger women with a high school degree or some college.

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 now receiving considerable attention 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)). Berman, Bound, and Griliches (1994) find large within-industry increases in the share of nonproduction workers in U.S. manufacturing despite relative price shifts encouraging the opposite pattern. Their results also show that increases in the share of nonproduction workers are associated with R&D and computer investment. Berman, Bound, and Machin (1998) extend this work over a sample of OECD countries and find the largest increases in nonproduction shares tend to occur in the same industries. Autor, Katz, and Krueger (1998) find in the U.S. that the increased demand for skilled workers has been taking place over the last five decades and accelerated in the 1980s in manufacturing. They also find that the most skill upgrading took place in the industries that are most computer-intensive. These results support the hypothesis that skill-biased technological change (SBTC) has taken place, but do not deal directly with the question of whether SBTC is associated with changes in relative wages.

There is very little evidence relating technology indicators to changes in the wage structure. Bartel and Sicherman (1999) carefully examine the relationship between technology variables and wage levels using the 1979-93 National Longitudinal Surveys, but their work does not consider how such variables relate to changes in the wage structure over time. 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. Krueger (1993) found that workers using computers at the workplace earn 15 percent more than those who do not use computers. Because college graduates are more likely to use computers at work than workers with less schooling, Krueger contends that increased use of computers accounts for one-third to one-half of the observed increase in returns to schooling between 1984 and 1989.[1] This earnings premium also could reflect unobserved ability, if more able workers are assigned to jobs using computers (DiNardo and Pischke (1997)). Card, Kramarz, and Lemieux (1996) find wage growth in the 1980s was associated with computer use in 1989 for both men and women, using data aggregated by age and schooling. Studies using establishment data in manufacturing to examine the relationship between wage growth and the use of a wide range of advanced technologies at the end of the sample period (Chennells and Van Reenen (1997), Entorf and Kramarz (1997), and Doms, Dunne and Troske (1997)) have found no relationship. However, these studies lack controls for the use of advanced technology at the beginning of the sample period.

Despite traditional concerns that technological change can make the skills of older, experienced workers obsolete, the question of how technology has been affecting such workers has not received much attention. Wage differentials by experience have been widening, which could reflect greater training needed to cope with an increased pace of change. However, as noted by Bartel and Sicherman (1993), an unexpected change in the rate of technological change could lead to flatter pay profiles and earlier retirement.

The goal of this paper is to provide direct, broadly based evidence on how changes in technology are associated with changes in the wage structure in the 1980s. It focuses on wage changes between 1979, when wage gaps by schooling reached a trough and the business cycle was at a peak, and 1989, the next peak in the business cycle. The study will examine all industries, not just manufacturing. By including the early 1980s, this study can assess the role of computers when the use of PCs in the workplace was relatively limited. The data on high-tech capital (K_{HT}) also include scientific and engineering instruments and telecommunications equipment, the impact of which has not been assessed.

The main innovation of this study is to exploit variation across and within industries to determine how measures of technological change relate to changes in the wage structure, using the full-year Current Population Survey (CPS).[2] The use of industry data on technology variables is dictated by the lack of micro data linking workplace technology to wages that covers this time period (and covering industries outside of manufacturing). It is linked to cells broken down by schooling, experience, and gender categories in the CPS so that the analysis can be done in a fixed effects framework.

This study examines a wide range of indicators of technological change: research and development intensity, usage of various forms of K_{HT}, growth in the capital-labor ratio, growth in total factor productivity, and recentness of capital. Complementarity between capital and skilled labor is a well-established result in the literature on labor demand; this paper extends this concept by examining whether some types of capital are more complementary with skilled labor than others. To sum up, the features that distinguish this paper from others in the literature on wages and technology are its focus on wage growth (as opposed to skill upgrading and wage levels); the breakdowns of wage growth by schooling, experience, and gender within all industries (not just one dimension of wage change, not just manufacturing); the use of a wide range of technology indicators (not just computers); the measurement of technology indicators at the beginning and end of the sample period (not just one or the other); and the use of a fixed-effects framework to control for unobserved heterogeneity.

The paper is organized in the following way. Section 1 outlines a theoretical framework within which the approach used here has strong microfoundations and identifies critical underlying assumptions. Section 2 discusses the technology parameters used in the empirical analysis.

Any study examining changes in the interindustry wage structure would seem quixotic, because it is so stable over time.[3] 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 results of this paper, reported in Section 4, are that (1) increases in R&D and acceleration in the growth of the capital-labor ratio (K/L) coincide with increased wage gaps by schooling within industries and (2) increases in R&D are associated with wider wage gaps by experience. The results for K_{HT}-intensity are mixed; wage gaps increase with K_{HT}-intensity in 1979, but decrease with the log change in K_{HT}-intensity. Section 5 assesses how much of the observed change in the wage structure can be explained in terms of observable indicators of technological change.

I. THEORETICAL FRAMEWORK

The idea that human capital is complementary with physical capital, whereas both are substitutes for raw (unskilled) labor 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 link between human capital and technological change is based on the argument that educated individuals are better able to adjust to changing economic conditions (Nelson and Phelps (1966), Welch (1970), Schulz (1975), Bartel and Lichtenberg (1987)).

For technological change to result in changes in wage differentials that vary by sector, a necessary condition is that the labor market must consist of two or more sectors and the supply curve of skilled labor (S) in each sector must be upward sloping. If the supply of S (and U=unskilled labor) 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.

The magnitude of any change in wage differentials would depend on the magnitude of the S-biased technological shock, along with the absolute value of the elasticities of supply and demand in that 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 manufacturing). There would be greater excess demand for S in the sector where the new technology can be used most effectively.

Turning from these abstractions to the data, it is useful to consider three groups of workers: experienced workers, inexperienced workers with post-secondary education, and inexperienced workers with no more than a secondary education. Among experienced workers, consider a model where (1) S has a positive supply elasticity in each sector and (2) the supply of U is more elastic than the supply of S, conceivably even infinitely elastic. Here the change in w_s/w_u by sector increases with the technology-induced demand shock. This framework seems applicable for experienced workers for two reasons: industry-specific investments in training and greater payoffs to such training in sectors undergoing technological change. 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) have argued that 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, limiting the supply of trained workers. In business school parlance, it becomes cheaper to make than buy trained help.

The training of inexperienced workers with post-secondary education also frequently has an industry-specific component that makes such workers less than perfect substitutes. Some academic units focus on industries such as agriculture, education, journalism, law, medicine, and public administration, to name a few. Many degrees in engineering also have a large degree of industry-specificity.[4] The responsiveness of pay in the various markets for college graduates to supply and demand factors has been well-documented (Freeman (1986)), so as long as the impact of technological change varies across different industries, one should not be surprised to see a correlation between technological change and wage growth for this group that would persist for a decade or more if the pace of change is accelerating.

Johnson and Stafford (1996) have pointed out that the economy-wide consequences of S-biased technological change for unskilled workers depend on whether the change increases the ability of S to do tasks traditionally done by S (which they call skill-intensive technological change) or the ability of S to perform tasks traditionally done by U (skill-extensive technological change). In the former case, U benefits in absolute terms, but in the latter case U is worse off.

It is more difficult to argue that technological change should have an 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.

In summary, S-biased technology shocks lead to wider wage gaps by skill in a multi-sector model with industry-specific investments in human capital. This can be examined both by looking at wage differentials within each sector (which should widen with technology shocks) and by studying how inter-industry wage differentials change for each skill group (they should widen with technology for S, but not for U).

II. MEASURES OF TECHNOLOGICAL CHANGE

The theoretical literature provides relatively little guidance for empirical work. Taken literally, the term "technological change" can mean two very different things. The standard economic definition is 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 is 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 never can be completely resolved.

Alternatively, technological change can mean a change in equipment and job requirements. The 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, K_{HT}-intensity, K/L growth, and the recentness of capital.[5]

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 constructed data (described in Jorgenson (1990)) for 35 industries using definitions that are 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 nature of R&D work varies in fundamental ways from other forms of work -- the tasks are nonroutine and undefined; the output is hard to measure; decisions have to be based on relatively little hard data and end up being based on intuition and politics (Pasmore (1997)). High wages are dictated by the need for continuous learning. In addition some reward for discoveries that can generate huge streams of future revenues is dictated by equity concerns. While these often take the form of bonuses and stock options, pay adjustments beyond a standard merit raise (of 1.5 percent on the margin) are made for key performers. In R&D shops, the dictate is "price the person, not the job (Gomez-Mejia, Balkin, and Milkovich (1990))."

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 full-year CPS.[6] 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. Because their employment share has risen, there can be little doubt that this occupational shift is driving the aggregate trends to some extent and that this is part of the explanation of changing wage structure that this paper seeks to develop. The danger is that the sampling frame of the CPS was not designed to measure the distribution of scientific personnel across one-and-two-digit industries. In industries where scientific personnel end up being over- or undersampled, average wages for college graduates will be over- or underestimated. As a result, a model linking contemporaneous values of wage differentials and a CPS-based proxy for R&D will overstate the wage impact of the technological changes resulting from increased innovative activity. To prevent this from happening, values of the R&D proxy from the 1980 and 1990 CPS are used in the regressions reported here. (The 1979 and 1989 values will be used when the discussion focuses on means by industry and aggregate trends.)

Most of the economic literature on the introduction of K_{HT}, including computers, into the workplace has found a positive correlation with wages and skill levels. In practice the impact of K_{HT} on skills and compensation depends not just on the knowledge and abilities needed to operate the new equipment, but also the change in work processes. Zuboff (1988) points out that information technology (IT) can be applied in two different ways. It always *automates* certain tasks, thereby making work more routine and lowering skill requirements. In many cases it also can *informate* (a term coined by Zuboff), which means that the technology generates more information about the underlying work processes. In the latter situation, work becomes more complex and analytical because of the lower costs associated with obtaining information and communicating with others about what it means.

Data on the stocks of various types of K_{HT} 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.[7] The allocations of capital expenditures by type of equipment within an industry are based largely on the occupational distribution. In other words, more computer capital gets allocated to industries with more programmers and systems analysts. At a minimum, this creates measurement error. Conceivably, it could create a built-in correlation between the capital measure and wage growth provided that those employed in computer-related occupations experience higher (or lower) wage growth relative to other occupations within a given educational group. BEA then used age-efficiency functions to aggregate the annual investment data into capital stocks. K_{HT} 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 or HTOK) and one based solely on assets 14 and 25 (called high-tech capital or HTK). 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; (3) communications capital accounts for more than half of HTOK; and (4) 83 percent of communications capital is used in a single industry.

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.

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. It is highly unlikely that technological change and any shocks to relative labor demand caused by such change are uniform.

Second, the technology indicator that seems to have undergone the largest change is the growth in K_{HT}, with a mean change (in logs) of 1.6 for both measures. The change in R&D intensity is a modest 0.5 percentage points in absolute terms, but a notable 18 percent in proportional terms.

Third, 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; a good property for a residual, but perhaps not-so-good a property for an empirical indicator of the use of advanced technologies or the pace of change.

Fourth, the technology variables show no consistent relationship between initial levels and 1979-1989 changes. The sectors with the largest increase in R&D intensity were those with the highest initial levels. However, and this will be important in interpreting the empirical results reported below, the growth in HTK/L was the greatest in those sectors which had the lowest initial levels.

Fifth, for the most part the indicators of technological change are largely independent. R&D intensity is highest in those industries with the greatest HTK-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 HTK-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 HTK/L 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, 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 CPS 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.[8] 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 39 industrial categories are listed in the first column of Table 2. They are highly similar to the categories used in the CPS "detailed industry" classification system.[9] 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 wage variable is the log of the ratio of usual weekly earnings to usual weekly hours for salaried workers and the log of the wage rate for hourly workers, schooling equals years of schooling completed, and experience is min(age-schooling-6, age-18). Estimates of the returns to schooling (from a Mincer model where schooling enters continuously), the wage gap (in logs) between workers with college and high school degrees (from a model where there are four schooling categories: less than 12 years, 12 years, 13 to 15 years, and 16 or more years) and the wage gap between workers with 0 and 30 years of experience for each industry (from the aforementioned Mincer model with experience as a quadratic) are reported in Table 2.

There is considerable dispersion across industries at any point in time in the wage equation parameters. Returns to schooling in 1979 averaged 5.7 percent, with a standard deviation of 1.4 percent and a range between 3.0 percent in eating and drinking places and 9.4 percent in business services. Returns to schooling in 1989 averaged 8.0 percent in 1989, with a standard deviation of 2.1 percent and a range 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. Industries with high returns to schooling also have greater returns to experience, with correlations of 0.342 in 1979 and 0.268 in 1989.

There also 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.

Does examining wage patterns by industry add any "new information" beyond what is already known from studies of changes in the skill mix? The three industries with the largest increases in the share of nonproduction workers are electrical machinery, nonelectrical equipment, and printing and publishing (Berman, Bound, and Machin). The former two have larger than average increases in wage differentials by schooling, whereas the latter has a smaller than average increase. Among the industries with larger than average increases in wage gaps by schooling, there are three (petroleum, rubber, miscellaneous manufacturing) with negligible changes in the share of nonproduction workers. The correlation between the change in returns to schooling and the change in the employment share of college graduates is 0.207, indicating that examining changes in the wage structure will produce more than a rehash of existing studies.

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.

Returns to schooling increased the most in industries that had the highest returns to schooling in 1979; the correlation coefficient is 0.414. Despite this overall pattern, some industries with low returns to schooling in 1979 (e.g., furniture, welfare and religious services) experienced larger than average increases in returns to schooling in the 1980s. Similarly, some industries with high returns to schooling in 1979 (e.g., business services, educational services) experienced below average increases in returns to schooling. The correlation between initial levels and changes in returns to schooling does not reflect an overall widening of the wage structure along all dimensions. The increase in the experience gap in the 1980s was inversely related to its level in 1979, with a correlation is -0.32.

The best way to get a sense of how much the effects of schooling, experience, and gender on wages vary by industry and year is to examine the partial sums of squares in the analysis of variance results in Table 3. The results are estimated from the pooled 1979 and 1989 Current Population Surveys. There are four categories for schooling (under 12, 12, 13 to 15, 16 and over) and experience (under 10, 10 to 19, 20 to 29, 30 and over). The results in column 1 are a standard accounting of the well-known changes in the wage structure by gender, schooling, and experience. Industry and industry-year interactions are added in columns 2 and 3; the total effect of each is quite sizable relative to the other variables in terms of both levels and year-interactions. Interactions with schooling, experience, and gender are respectively added to the year-industry effects in columns 4, 5, and 6; each adds a sizable amount of explanatory power. To reduce the computational burden of including all three sets of industry-year interactions at once, the set of industries is reduced to 16 major sectors in columns 7 and 8. These results show that the industry-year interactions with schooling, experience, and gender are independent of each other.

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, a shift-share analysis of the returns to schooling estimates in Table 2 is unable to account for 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 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 MODEL AND RESULTS

The empirical results reported below are based on a theoretical framework that treats industries as having separate labor markets, each with a different technological environment consisting of types of technology that are in place at a given point in time (K_{HT}, R&D) and the pace of change in the work environment (K recentness, average K/L growth, average TFP growth). The standard expression for wage behavior that has been used in the recent wage structure literature relates log wages to log or proportional variations in supply and demand. Supply shifts are presumed to be economy-wide with no inter-industry variation. Taking product demand, trade patterns, and labor institutions as beyond the scope of this study and assuming the overall degree of impact of technology can be approximated by a linear function of variables (in log or proportional form) produces the estimating equation

(1) $(w_s/w_u)_j = \beta_0 + \beta_1 RD_j + \beta_2 \ln(K_{HT}/L)_j + \beta_3 REC_j + \beta_4 DKL_j + \beta_5 TFP_j + \eta_j$,

whereas first differencing results in

(2) $d(w_s/w_u)_j = \delta_0 + \delta_1 d(RD_j) + \delta_2 d(\ln(K_{HT}/L)_j) + \delta_3 d(REC_j) + \delta_4 d(DKL_j)$
$+ \delta_5 d(TFP_j) + \varepsilon_j$.

There are a number of implied restrictions in (1) and (2) that turn out to be important empirically. The form of (2) implies that the lagged value of $(w_s/w_u)_j$ has a coefficient of minus one when the equation is rewritten so that the current value of $(w_s/w_u)_j$ is on the right hand side. It also implies that coefficients of current and lagged values of technology variables have equal and opposite signs. The sensitivity of the results to these restrictions will be indicated when the restrictions are rejected by the data and the results are sensitive in an economically meaningful way to the inclusion of the restrictions.

The first issue to be examined (in part A) is how returns to schooling and experience vary at a given point of time with technology indicators, 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 technology variables. Limitations of this approach are that (1) it contains no controls for worker characteristics, (2) it does not permit interactions between the coefficient estimates and other variables and (3) the focus on changes in wage differentials between groups does not identify how the groups are doing in absolute terms (R&D can widen wage differentials by lowering wages of workers with little schooling or by raising wages of highly educated workers). The main reason for reporting these results is that they demonstrate in an easy-to-follow fashion some issues that arise in defining the relationship between wages and K_{HT}.

Wage equations were then estimated for 32 schooling-experience-gender groups, using categories identical to those in Bound and Johnson. Each wage equation contained years of experience and binary indicators of schooling, race, part-time work, residence in an urban area, region, and industry. Predicted wages for a person with average characteristics were then calculated for each industry for each group.[10] The results of regressing the change in predicted wages on indicators of technological change are reported in part C; some interpretation issues are discussed in part D. All models in Parts A and B are weighted by full-time equivalent (FTE) employment in each industry as reported in the National Income and Product Accounts (NIPA). In Parts C and D, the weights for each cell are estimated FTE employment, based on NIPA employment by industry and the distribution of workers by experience, education, and gender in each year of the CPS. Huber-White robust standard errors are used in all cases; in Parts C and D the models also allow for grouped errors by industry.

A. Cross section analysis of returns to schooling and experience Table 4 reports regressions of returns to schooling, the log wage gap between college and high-school graduates ($\ln(w_C/w_{HS})$) and the log wage gap between workers with 0 and 30 years of experience on R&D intensity (based on employment of scientists and engineers), various indicators of K_{HT}-intensity, capital recentness, growth in the capital-labor ratio, and total factor productivity growth. Separate regressions are reported for 1979 and 1989.

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 K_{HT} was defined as in Berndt, Morrison, and Rosenblum to include computers, telecommunications equipment, instruments, and photocopy and office equipment. In this case, reported in column 2, there is a positive relationship between the log of HTOK and returns to schooling in 1979 and no relationship in 1989.

This model presumes that each type of capital has 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 K_{HT} is limited to computers and instruments in columns 4 and 5, a much stronger correlation with returns to schooling emerges. Because of the correlation between R&D intensity and HTK/L, the coefficient of each is sensitive to the inclusion of the other, as can be seen by comparing columns 1, 4, and 5. The results in column 6 show that $\ln(w_C/w_{HS})$ rises with HTK-intensity in 1979 and with R&D in 1989.

CPS data from 1973-75 were used to determine whether the correlations between the technology variables and returns to schooling were present before the 1979-89 period. The following results replicate the models in columns 1, 4, and 5 of Table 4:

	(1)	(4)	(5)
R&D	0.279 (0.080)	0.174 (0.088)	
ln(HTK/L)		0.0039 (0.0016)	0.0055 (0.0014)

These results are extremely close to those for 1979 and 1989, suggesting a reasonably stable mapping between technology variables and wage coefficients across industries. Even with some variation in which industries are high-tech or average-tech across decades, the consequences for wages are similar.

There is much less to be learned from the remaining technology indicators. TFP growth and recentness are unrelated to returns to schooling. Returns to schooling were lower in 1979 in industries with the most rapid growth in K/L in the 1970s, the opposite of what one would expect if capital and skilled labor were complements. K/L growth is unrelated to returns to schooling in 1989.

Wage gaps by experience are largest in R&D-intensive industries. The log wage gap between workers with 0 and 30 years of experience is 0.07 to 0.09 higher in an industry where 10 percent of employees are scientists or engineers than in an industry where none are. The other indicators of technological change are uncorrelated with returns to experience.

B. Changes in returns to schooling across industries This is a stricter test because first differencing leads to increased measurement error, thereby reducing 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. Such a bias could be present in Table 4, although its direction cannot be predicted *ex ante*.

The functional form of the models of wage differentials in Table 4 will carry over to models of changes in wage differentials in Table 5 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 5 has the same form as column 4 of Table 4, and one main result -- the impact of R&D intensity -- carries over from levels to changes. However, the coefficient for log(HTK/L) changes signs, implying that wage gaps by education shrank in industries that had the largest increase in log(HTK/L).

A key restriction in column 1 is that the coefficients of log(HTK/L) in 1979 and 1989 are equal and opposite in sign. This restriction is removed in column 2, where the results show that returns to schooling increased the most in industries with the greatest HTK-intensity in 1979 but were unrelated to the 1989 value. From a statistical standpoint, the restriction is rejected with $F(1,32) = 10.70$. A model where the coefficient of 1989 log(HTK/L) is restricted to zero is reported in column 3. The results are quite close to those in column 2 and the null hypothesis for 1989 log(HTK/L) cannot be rejected.

With the relationship expressed in first differences, there is now a strong positive relationship between the increase in the returns to schooling and the acceleration of K/L growth. There is a 0.006 unit difference in the acceleration of K/L growth between the industries at the 20^{th} and 80^{th} percentiles (services and banking). This is correlated with an increase of 0.4 to 0.6 percentage points in returns to schooling.

The results for the change in $\ln(w_C/w_{HS})$ in column 4 also indicate that wage gaps shrank in industries with growing HTK/L and that wage gaps increased in industries with accelerating K/L growth. In this case the hypothesis that the 1979 and 1989 coefficients of log(HTK/L) sum to zero cannot be rejected ($F(1,32)=0.39$). There is no relationship between the change in returns to experience and any of the technology variables in column 5.

The rate of return to schooling rose the most in the industries where R&D intensity grew most rapidly. Consider two industries, each of which is a standard deviation away from the mean change in R&D 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 5, the rate of return to schooling would have increased by 0.9 to 1.2 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.

C. Changes in wage differentials by demographic group 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 allowing for interactions and controls for worker characteristics 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 wage differentials, this time for narrowly defined demographic groups. 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 6. 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. 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.[11] The sample for each model contains 1223 observations.[12]

Rising R&D activity is associated with more wage growth for college graduates, but is unrelated to wage changes for workers who have not attended college. This implies that the correlations between these variables and returns to schooling in Table 5 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. Returning to the comparison of public utilities and fabricated metals, the wage gap between college and high-school graduates would have increased by .036 in the former and decreased by .017 in the latter.

Technological change is commonly thought to be harmful to older workers. This conjecture is not supported by the results for Model 3. There is a strong, positive interaction between the R&D measure and the indicator of experience being 30 years and over. In contrast, R&D is unassociated with wage growth patterns across industries among workers with less than 30 years of experience. This is consistent with Lillard and Tan's theory and findings that R&D-intensive sectors invest heavily in training.

The impact of HTK-intensity on wage differentials is a function of the 1979 and 1989 values. For the log wage gap between college and high-school graduates the function is:

$$d\ln(w_{16}/w_{12}) \approx 0.0024*\ln(HTK/L)_{79} - 0.0176*d\ln(HTK/L)$$

Wage gaps by education grew the most in industries with high initial values of HTK/L and average to below average growth in HTK/L.[13]

To interpret these results, it is essential to keep in mind the initial distribution of ln(HTK/L) and the enormous changes that took place in the 1980s. The average industry saw its ln(HTK/L) increase by 1.6 from an initial value of -1.2, which implies a reduction of .031 in the log wage gap between college and high school graduates. The correlation between the change in HTK/L and the 1979 level was -0.5, which means that the biggest proportional increases in HTK/L occurred in industries that were least HTK-intensive in 1979. In these cases almost all of the increase in HTK consisted of computers. One plausible interpretation is that changes in work processes in these industries lagged behind the introduction of information technology, making skill-upgrading less intensive than in sectors that had been using mainframes and minicomputers at the beginning of the decade.

Casual inspection of the ln(HTK/L) coefficients in Model 3 suggests that the precision of the 1989 estimates leaves something to be desired. The hypothesis that all terms including $\ln(HTK/L)_{89}$ are zero is rejected at $F(8,38)=2.51$, but this joint test reflects the strength of a single coefficient – the interaction with 20 to 29 years of experience. The hypothesis that the coefficient of $\ln(HTK/L)_{89}$ and its interactions with all three education categories, female, and the other two experience categories are zero is not rejected ($F(7, 38)=1.18$, $p=0.337$).

Model 3 was re-estimated in two versions: one with all $\ln(HTK/L)_{89}$ terms restricted to zero (Model 3A) and one with all $\ln(HTK/L)_{79}$ terms restricted to zero (Model 3B). The results are as follows:

	Model 3A: $\ln(HTK/L)_{79}$ only	Model 3B: $\ln(HTK/L)_{89}$ only
Schooling below 12	-0.0070	-0.0086
	(0.0039)	(0.0061)
Schooling 13 to 15	0.0095	0.0096
	(0.0042)	(0.0052)
Schooling 16 & above	0.0091	0.0046
	(0.0038)	(0.0056)
Experience 10 to 19	-0.0038	-0.0020
	(0.0036)	(0.0053)
Experience 20 to 29	0.0032	0.0091
	(0.0047)	(0.0059)
Experience 30 & above	0.0018	0.0012
	(0.0030)	(0.0052)
Female	0.0169	0.0200
	(0.0033)	(0.0038)

In Model 3A, the coefficient of $\ln(HTK/L)_{79}$ increases with years of schooling and is estimated with a reasonable amount of precision (each of the three education interactions are significant at $p=0.10$ and two of the three are significant at $p=0.05$). In contrast, the coefficient of the $\ln(HTK/L)_{89}$ for college graduates is smaller than the coefficient for those with some college and is not estimated precisely. Even though Model 3 in Table 6 is defensible on standard econometric criteria, one might reasonably conclude that the noise-to-signal ratio of the measure of $\ln(HTK/L)$ for 1989 may be too high to draw reasonable inferences. Recall that the measure for 1989 is based on a 1982 input-output matrix allocating capital in each industry by type of asset, whereas the measure for 1979 is based on 1977 and 1982 data.

The results in Table 6 are robust across a variety of alternate specifications of Model 3. When the model is respecified so that w_{89} is the dependent variable, the expression for

$d\ln(w_{16}/w_{12})$ is essentially unchanged. The model also was estimated in a form with separate $\ln(K/L)$ terms for computing equipment and scientific and engineering instruments. The null hypothesis that a single set of coefficients is sufficient could not be rejected with $F(16, 1151) = 0.21$.

Another very important result in Table 6 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 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 at least 15 percent in 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 6 indicate that technology has affected the gender gap. Female wages grew more than male wages in industries that intensively used HTK in 1979 and in industries where K/L growth accelerated in the 1980s. Comparing two industries at the 20th and 80th percentiles of HTK-intensity in 1979, log wage growth for women (relative to men) was 0.050 larger in banking than in furniture. At the average value of K/L acceleration, log wage growth for women was 0.005 larger than for men.

To allow for a complete set of interactions by schooling, experience, and gender, separate log wage change regressions were run for each of the 32 demographic groups and are reported in Table 7. Because 192 coefficients are hard to digest and the results are largely consistent with those in Table 6, 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 7. Among men, R&D has the greatest impact on college graduates with 30 or more years of experience. This result is notable because this experience group has the lowest likelihood of moving across industries to arbitrage any difference in wage offers. In general, R&D coefficients increase with experience and are larger for women than men.

Wage growth for women with (1) less than 10 years of experience and who graduated from high school and (2) women with less than 20 years of experience and who attended college was much greater in industries with large initial values of HTK/L. The HTK/L results for men are difficult to categorize. In three out of four categories among college graduates, the coefficient of $\ln(HTK/L)_{79}$ is positive and roughly equal in absolute value and opposite in sign to the coefficient of $\ln(HTK/L)_{89}$, which implies wage growth falls with rising HTK-intensity. A completely opposite pattern prevails among men who are high school graduates and have 10 to 29 years of experience, with the coefficient of $\ln(HTK/L)_{89}$ now being positive and an implication of wage growth being greatest in the sectors where HTK-intensity increased the most. In 10 of the remaining 11 rows, there is no apparent relationship between HTK/L and wage growth. In some experience-education categories, e.g., high-school graduates and those with some college with less than 10 years of experience, rising HTK-intensity is associated with a reduced the gender gap in wages, possibly reflecting a higher rate of computer adoption in clerical and service than in production jobs.

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.

Overall the impact of technology variables is smallest for workers with the least experience and education, which is consistent with industry-specific human capital being a key mechanism through which technology affects wages. Acceleration in the capital-labor ratio is the only variable that is associated with earnings growth across industries for high school dropouts with less than ten years experience -- and this may reflect employment opportunities more than technology. This same pattern prevails among male high school graduates with less than 10 years of experience. In only low skill group, women with less than 10 years of experience who graduated from high school, is there a positive correlation between a high-tech indicator and wage growth.

D. Interpretation issues 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. There is also some indication that this wage gap widened the most in the industries that were most HTK-intensive in 1979. Part of the former result reflects higher salaries for scientific personnel relative to other college graduates. Although this is part of the aggregate puzzle that this paper seeks to explain, it would be useful to know how much of an impact the technology variables had outside of scientific occupations. To examine this issue, scientists and engineers were dropped from the sample and earnings differentials by industry and worker characteristics were re-estimated for 1979 and 1989. These results will answer a more narrow question -- how much complementarity is there between scientific personnel and highly educated and experienced workers in other occupations? The interaction coefficients (S.E.) for the equivalent of Model 3 in Table 6 are:

Schooling	R&D intensity	Ln(HTK/L) in 1979	Ln(HTK/L) in 1989
Below 12	-0.092 (0.342)	-0.0070 (0.0061)	-0.0002 (0.0093)
13 to 15	0.599 (0.348)	0.0161 (0.0073)	-0.0110 (0.0098)
16 and above	1.614 (0.704)	0.0201 (0.0089)	-0.0176 (0.0131)
Experience			
10 to 19	0.025 (0.357)	-0.0095 (0.0050)	0.0104 (0.0072)
20 to 29	0.792 (0.752)	-0.0088 (0.0081)	0.0206 (0.0103)
30 to 39	1.650 (0.628)	0.0026 (0.0072)	-0.0002 (0.0112)
Female	-0.032 (0.466)	0.0160 (0.0069)	0.0018 (0.0075)

Restricting the sample to nonscientific occupations has a moderate impact on the R&D coefficient. A one percentage point increase in R&D intensity would increase the log wage gap between college and high-school graduates in nonscientific occupations by 0.016, in contrast to 0.021 for all occupations. The coefficients of the HTK interactions are almost exactly the same as in Table 6. On balance, this evidence shows that R&D activity and HTK have an impact on relative earnings across a broad range of occupations, not just scientists and engineers.

As noted in Section 2, the measures of HTK partially reflect the distribution of computer-related personnel across industries, so one might argue that the results on high-tech capital also are nothing more than an indication of a wage premium for such workers. To test this conjecture, the percentage of workers in computer-related occupations was calculated for each industry in each year and this variable was added to Model 3 in Table 6, along with interactions with education, experience, and gender. If the results for HTK merely reflect occupational composition, then the HTK results should vanish once direct measures of computer occupations are added to the model. Instead the coefficients of the HTK interactions with schooling increased in absolute value and those that were statistically significant remained so. Further, the interactions between schooling categories and the computer occupation variable exhibited the same pattern as the HTK results: coefficients increasing in absolute value with schooling, positive coefficients in 1979 and negative coefficients in 1989.[14]

Another check on the robustness of the key findings is to use an alternative measure of R&D-intensity: the R&D to sales ratio as reported by the National Science Foundation. This measure is available for manufacturing industries only, but the key results for Model 3 in Table 6 continue to hold for the smaller sample. When R&D/Sales is used as the high-tech measure, there is still a strong, positive interaction with college education when either the level of R&D/Sales in 1979 or 1989 is used in the model. The coefficient of the interaction with R&D/Sales in 1979 is 0.022 (0.010) and in 1989 it is 0.015 (0.007). There is no relationship between the growth of R&D/Sales and wage growth.

The results in Tables 4 through 7 could 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. Chennells and Van Reenen (1997), Entorf and Kramarz (1997), and Doms, Dunne and Troske (1997) all report evidence that shows that wage growth is no greater in plants investing in new technology than in plants that do not.

Does this evidence imply that unobservable ability accounts for the R&D and HTK results? One of the main impacts of technology will be the entry of highly efficient new plants and the exit of obsolete plants, something that cannot be detected in a panel of plant data. But even if one ignores this issue, consider the model being estimated in these 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.[15] 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 K_{HT} and R&D intensity in Table 1. When this type of model is replicated by regressing wage changes in the 1980s on 1989 levels of R&D intensity and HTK/L, the interactions with schooling are as follows:

	1989 R&D intensity	1989 HTK-intensity
Schooling below 12	0.015 (0.107)	-0.0097 (0.0062)
Schooling 13 to 15	0.132 (0.144)	0.0101 (0.0053)
Schooling 16 & above	0.628 (0.115)	0.0074 (0.0048)

Overall, the results still show greater wage growth for college than high school graduates in sectors commonly defined as high-tech.

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 interindustry trends in R&D intensity, HTK/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 or (2) there has been a change in the relative quality of college and high-school graduates within narrowly defined categories.

A pure sorting interpretation of the results reported here would be that without mobility the wage structure would not have changed at all. Mobility is much greater for inexperienced workers, so one would then expect to see very strong results in Table 7 for inexperienced workers (and Bartel and Sicherman (1999) show in panel data that controlling for sorting by adding individual fixed effects has a large impact on estimates of interindustry wage patterns for young workers)[16] and much weaker results for experienced workers. In fact the impact of R&D and HTK on earnings growth is detectable across all experience levels. Further, the impact of mobility will be to make the observed change in wage differentials between 1979 and 1989 less than the full impact of a technology shock on labor demand, meaning once again that all of the results in Tables 6 and 7 *understate* the total impact of technology on wages.

The second line of argument would require a process that bridges five 10-year cohorts. Deterioration of the quality of public schools might be a possible explanation for the patterns among inexperienced workers in Table 7, but this cannot apply to more experienced workers who completed their schooling at a time when all measures indicate school quality was rising.

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. This was done both with and without scientists and engineers to once again determine possible complementarity patterns with nonscientific personnel. The change in employment shares was then regressed on the technology variables and the results are reported in Table 8.

Employment of college graduates increased the most (and employment of high-school graduates increased the least) in industries with rising R&D. This indicates a complementarity between innovative activity and highly educated labor that is consistent with the results for wage growth reported here, as well as with the Berman, Bound, and Griliches (1994) and Berman, Bound, and Machin (1998) results for manufacturing. Although these arguments do not prove that unobservables had no role, they do force the argument on unobservables to be more encompassing -- it must explain how managers in high-tech industries were able to hire more college graduates and upgrade their quality with low odds of attracting experienced help from industries experiencing milder technology shocks.

V. IMPLICATIONS FOR RECENT CHANGES IN THE WAGE STRUCTURE

This study has examined a wide range of empirical indicators of technological conditions that might be thought to have an impact on labor market conditions. Although there are some new insights for wage gaps by experience and gender, the main results deal with returns to schooling. The results show a strong correlation between two technology indicators -- R&D and K/L acceleration -- and widening wage gaps by schooling. As for K_{HT}, there is a notable difference between the across industry results for HTK in Table 4 and the within-industry results elsewhere, a difference that future researchers should take to heart. The within-industry models show that the impact of HTK/L increases with its initial value but decreases with its rate of growth. These mixed results should not be all that surprising given the mixed-effects consensus in the sociological literature on the impact of technological change (Spenner (1988)). More careful examination of how the structure of organizations and work has changed with the introduction of information technology is needed to understand these patterns.

If technology variables are responsible for part of the increase in returns to schooling, two questions must be considered:

<u>A. Do the coefficients have sufficient explanatory power for 1979-1989?</u> This has been established in section IV, where the results showed that (1) a one standard deviation change in these variables would produce large changes in relative wages; (2) the addition of technology variables to the wage growth model in Table 6 increased R^2 from 0.466 to 0.582; and (3) for some demographic groups, one-third to one-half of the variance in wage growth across industries can be explained by technological variables.

The employment share of scientists and engineers increased by an average of 0.6

percent in the 39 industries used in this study, which would lead to a 0.013 increase in the log wage gap between college and high school graduates. K/L accelerated by .15 percent in the 1980s, leading to a 0.008 increase in the wage gap. In Model 1 of Table 6, the mean increase in the wage gap between college and high school graduates (across eight experience-gender categories in 39 industries) was 0.130, implying that observable indicators of technology can account for 16 percent of this dimension of the increase in wage inequality. Part of this effect represents the changing composition of employment among college graduates (more scientists and engineers), but much of it reflects higher earnings for all college graduates in R&D-intensive sectors. There also is evidence that the college-high school wage gap widened the most in industries that were most HTK-intensive in 1979, but it is difficult to quantify the contribution of this variable to the overall explanation of rising wage gaps by schooling because of the mixed results for HTK/L in 1989.

B. Is there a macroeconomic correspondence between the timing of swings in the technology variables and changes in returns to schooling? This study has emphasized the role of R&D and HTK in explaining the widening differential between college and high-school graduates in the 1980s. This evidence would be more credible if it could be placed in the context of a longer time period. There would be concern if one repeated this exercise for the 1970s and found that technology variables "predicted" an increase in wage differentials by education in an era when wage differentials were narrowing.

Evidence reported above for the early 1970s indicates larger returns to schooling in industries that are R&D and HTK-intensive. To explore this issue further, one must determine whether the decade-by-decade experience with R&D and HTK is consistent with the observed changes in wage differentials. Table 9 summarizes patterns since the 1950s. R&D spending, as a percentage of net sales, increased through the 1950s and 1960s, both periods when returns to schooling were rising. R&D fell throughout the 1970s, as returns to schooling fell, and started to increase in 1980. R&D levels in the 1980s came close to their peaks in the 1960s, with the increase in R&D activity coinciding with an increase in returns to schooling.

The number of R&D scientists and engineers per 1000 employees (as reported by National Science Foundation (1995)), follows an analogous pattern, falling from 6.4 in 1970 to 5.5 in 1976. It then increased from 5.8 in 1979 to 7.4 in 1989. Both of these trends track very closely with returns to schooling, as shown in Mincer's (1991) time series analysis.

The data for HTK/L indicate an acceleration of growth took place in the 1970s, followed by further acceleration in the 1980s. The capital-labor ratio for both computers and instruments increased at similar rates near 6 percent in the 1950s, but then both rates slowed considerably in the 1960s. In the 1970s, computer K/L grew at an annual average rate of 11.7 percent and this accelerated to 21.6 percent in the 1980s. Instrument K/L grew at an annual rate of 6.9 percent in the 1970s; this rate slowed to 4.5 percent in the 1980s. The combined growth of both types of HTK/L accelerated from 0.9 percent in the 1960s to 8.0 percent in the 1970s and 12.6 percent in the 1980s. The lack of any association between the trends in HTK/L and returns to schooling in the 1960s and 1970s, along with the mixed evidence reported here for the 1980s, is consistent with a mixed-effects conclusion on HTK and skill-upgrading.

In conclusion, in light of the results of this project, it is difficult to claim that there is no longer any direct economy-wide evidence that technology is not associated with the widening of wage gaps by schooling. The evidence is much stronger for R&D than it is for high-tech capital, including computers. There also is evidence that experienced workers in R&D-intensive sectors had greater wage growth than experienced workers in sectors with little R&D activity.

In addition to showing that direct measures of technological change are linked to changes in 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 measures used here that had some 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 capital are not alike in terms of their impact on relative wages. Computers and instruments matter a lot more than other types of capital.

Finally, this paper has shown that wage differentials by schooling and experience vary as much across industries as average wage levels. This paper has focused on technology variables, but there no doubt are other factors at work, such as collective bargaining and the organization of work across different occupations and skill levels, that need to be explored.

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Table 1. Summary statistics for measures of technological change

Means and Autocorrelations					
R&D intensity	**Log(HTOK/L)**	**Log(HTK/L)**	**TFP growth**	**K/L growth**	**K recentness**
Means (S.D.) of 1979 values					
0.028	-0.251	-1.181	0.003	-0.000	0.581
(0.030)	(1.687)	(1.573)	(0.012)	(0.008)	(0.036)
Means (S.D.) of 1989 values					
0.033	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					
0.954	0.853	0.810	0.294	0.861	0.579
Correlation between 1979 and 1979-89 change					
0.414	-0.578	-0.492	-0.471	0.086	-0.131

Correlation matrix of 1979 levels					
	R&D intensity	Log(HTOK/L)	Log(HTK/L)	TFP growth	K/L growth
Log(HTOK/L)	0.339				
Log(HTK/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	Log(HTOK/L)	Log(HTK/L)	TFP growth	K/L growth
Log(HTOK/L)	0.404				
Log(HTK/L)	0.448	0.814			
TFP growth	0.124	-0.124	-0.229		
K/L growth	0.172	0.069	-0.062	0.538	
K recentness	-0.044	0.262	0.259	-0.357	-0.560

Correlation matrix of 1979-89 change					
	R&D intensity	Log(HTOK/L)	Log(HTK/L)	TFP growth	K/L growth
Log(HTOK/L)	0.037				
Log(HTK/L)	0.136	0.538			
TFP growth	-0.196	0.328	-0.065		
K/L growth	0.007	0.294	0.206	0.241	
K recentness	0.146	-0.185	0.270	-0.484	-0.244

All means and correlations are unweighted.

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. Partial sums of squares from ANOVA models of ln(wage), pooled 1979 and 1989 full-year Current Population Surveys.

	df	1	2	3	4	5	6	df	7	8
Model SS		41105	50023	50225	51048	50670	50577		47909	49112
Model df		15	53	91	319	319	167		45	255
Year	1	9798	10373	5191	3389	4938	3958	1	6056	3290
Schooling	3	13761	10189	10102	3501	10014	9949	3	11338	4639
Experience	3	6225	4074	4039	3981	1614	4008	3	4243	2082
Gender	1	7130	3021	3010	2941	2950	1374	1	3730	1441
Year*gender	1	121	88	56	57	56	20	1	73	41
Year*schooling	3	323	206	102	39	102	100	3	148	72
Year*experience	3	75	44	27	28	15	29	3	29	22
Industry	38		8917	8716	6444	7830	6997	15	6611	3956
Year*industry	38			201	143	170	162	15	126	76
Year*industry *schooling	228				823			90		603
Year*industry *experience	228					445		90		310
Year*industry *gender	76						353	30		228
R^2		0.405	0.493	0.495	0.503	0.499	0.498		0.472	0.484
Root MSE		0.475	0.439	0.438	0.434	0.436	0.436		0.448	0.443

Each model is estimated over 267578 observations. F-statistics for each set of variables can be calculated by dividing the partial sum of squares by the degrees of freedom. All p-values are below 0.0001.

Table 4. Cross section regressions of returns to schooling, wage gaps by schooling, and wage gaps by experience on technological change.

Dependent variable:	Returns to schooling	Returns to schooling	Returns to schooling	Returns to schooling	Returns to schooling	Ln(w_c/ w_{hs})	Returns to experience
1979 regressions							
R&D intensity	0.256	0.229	0.152	0.163		0.713	0.860
	(0.072)	(0.062)	(0.082)	(0.071)		(0.428)	(0.435)
Log(HTOK/L)		0.0032					
		(0.0012)					
Log(HTK/L)				0.0046	0.0057	0.022	0.009
				(0.0012)	(0.0010)	(0.009)	(0.010)
Log(Computer K/L)			0.0043				
			(0.0018)				
Log(Telecom K/L)			0.0014				
			(0.0009)				
Log(Instr K/L)			0.0016				
			(0.0010)				
Log(Photocopy K/L)			-0.0013				
			(0.0013)				
K recentness	-0.008	-0.045	-0.035	-0.043	-0.046	-0.646	-0.363
	(0.061)	(0.063)	(0.058)	(0.053)	(0.057)	(0.496)	(0.394)
TFP growth	0.071	-0.006	-0.008	0.130	0.169	1.398	-1.041
	(0.128)	(0.109)	(0.144)	(0.104)	(0.121)	(1.214)	(1.631)
K/L growth	-1.115	-1.085	-1.098	-0.947	-0.773	-0.640	0.636
	(0.410)	(0.421)	(0.452)	(0.421)	(0.418)	(3.036)	(1.936)
Root MSE	0.013	0.012	0.012	0.011	0.012	0.084	0.094
R^2	0.359	0.436	0.514	0.559	0.476	0.290	0.147
1989 regressions							
R&D intensity	0.333	0.313	0.244	0.220		1.465	0.737
	(0.080)	(0.080)	(0.093)	(0.075)		(0.545)	(0.316)
Log(HTOK/L)		0.0028					
		(0.0037)					
Log(HTK/L)				0.0090	0.0128	0.020	0.024
				(0.0038)	(0.0035)	(0.025)	(0.018)
Log(Computer K/L)			0.0058				
			(0.0040)				
Log(Telecom K/L)			-0.0034				
			(0.0025)				
Log(Instr K/L)			0.0031				
			(0.0014)				
Log(Photocopy K/L)			-0.0006				
			(0.0028)				
K recentness	0.078	0.051	0.106	0.003	-0.049	-0.402	-0.598
	(0.076)	(0.073)	(0.079)	(0.061)	(0.064)	(0.422)	(0.381)
TFP growth	-0.547	-0.423	-0.209	-0.033	0.175	0.686	-0.551
	(0.251)	(0.288)	(0.342)	(0.259)	(0.243)	(1.548)	(1.505)
K/L growth	-0.178	-0.461	-0.196	-0.816	-1.042	-3.522	1.893
	(0.494)	(0.603)	(0.596)	(0.511)	(0.533)	(3.468)	(2.886)
Root MSE	0.019	0.019	0.019	0.018	0.019	0.109	0.089
R^2	0.404	0.414	0.505	0.512	0.422	0.318	0.321

Each equation contains an intercept and is weighted by full-time equivalent employment; robust standard errors are reported in parentheses. The means and standard deviations of the dependent variables are reported in table 2.

Table 5. 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 $\ln(w_c/w_{hs})$	Change in returns to experience
Change in R&D intensity	0.475 (0.071)	0.361 (0.071)	0.347 (0.064)	3.020 (0.651)	0.853 (0.853)
Change in Log(HTK/L)	-0.0048 (0.0014)				
Log(HTK/L) in 1989		-0.0008 (0.0017)		-0.0395 (0.0185)	0.0022 (0.0182)
Log(HTK/L) in 1979		0.0041 (0.0013)	0.0036 (0.0008)	0.0335 (0.0113)	-0.0011 (0.0118)
Change in K recentness	-0.029 (0.047)	-0.028 (0.044)	-0.032 (0.043)	-0.029 (0.265)	-0.254 (0.343)
Change in TFP growth	-0.149 (0.111)	-0.055 (0.099)	-0.052 (0.098)	-0.348 (0.550)	-0.791 (0.662)
Change in K/L growth	0.934 (0.294)	0.707 (0.245)	0.652 (0.244)	6.102 (2.140)	-0.459 (2.182)
Root MSE	0.008	0.007	0.007	0.049	0.050
R2	0.523	0.622	0.619	0.502	0.129

Each equation also contains an intercept. Robust standard errors are reported in parentheses. Each equation is estimated over a sample of 39 industries and is weighted by the sum of full-time equivalent employment in 1979 and 1989. The mean (S.D.) of the dependent variable in columns 1 through 3 is 0.023 (0.011); in column 4, 0.137 (0.079); in column 5, 0.082 (0.055).

Table 6. Coefficients (standard errors) of wage growth regressions across schooling-experience-gender categories, 1979-89 CPS

	Model 1	Model 2	Model 3				
			Interactions with technology variables:				
	No tech Change Variables	No tech change interactions	Direct Effect	Change in R&D intensity	High-tech K/L in 1979	High-tech K/L in 1989	Change in K/L growth
Schooling below 12	-0.009 (0.006)	-0.003 (0.006)	-0.023 (0.014)	-0.098 (0.341)	-0.0070 (0.0061)	-0.0004 (0.0094)	0.395 (1.341)
Schooling 13 to 15	0.070 (0.007)	0.066 (0.007)	0.090 (0.018)	0.604 (0.348)	0.0161 (0.0073)	-0.0109 (0.0099)	1.038 (1.374)
Schooling 16 & above	0.130 (0.008)	0.118 (0.009)	0.132 (0.017)	2.132 (0.468)	0.0200 (0.0088)	-0.0176 (0.0127)	5.447 (1.904)
Experience 10 to 19	0.042 (0.008)	0.036 (0.006)	0.016 (0.016)	-0.081 (0.321)	-0.0090 (0.0051)	0.0087 (0.0072)	0.976 (1.231)
Experience 20 to 29	0.068 (0.007)	0.060 (0.007)	0.030 (0.020)	0.512 (0.740)	-0.0092 (0.0080)	0.0202 (0.0104)	1.592 (1.730)
Experience 30 & above	0.073 (0.007)	0.066 (0.007)	0.061 (0.017)	1.584 (0.623)	0.0024 (0.0070)	-0.0004 (0.0110)	1.543 (1.531)
Female	0.095 (0.011)	0.094 (0.009)	0.120 (0.016)	0.061 (0.478)	0.0154 (0.0069)	0.0024 (0.0076)	3.612 (1.569)
Change in R&D intensity		0.798 (0.296)	0.016 (0.538)				
High-tech K/L in 1979		0.0116 (0.0051)	0.0007 (0.0069)				
High-tech K/L in 1989		0.0015 (0.0063)	0.0003 (0.0088)				
Change in K recentness		0.015 (0.215)	-0.211 (0.250)				
Change in TFP growth		-0.032 (0.433)	-0.082 (0.789)				
Change in K/L growth		-2.218 (1.347)	-5.481 (1.757)				
Root MSE	0.077	0.072	0.070				
R^2	0.466	0.529	0.582				

Each equation is estimated over 1223 cells and is weighted by the sum of full-time equivalent employment in 1979 and 1989. Robust standard errors are reported in parentheses, with an adjustment for a common across-industry component. Model 3 includes interactions with capital recentness and TFP growth. The mean (S.D.) of the dependent variable is –0.054 (0.162).

Table 7. Coefficients (standard errors) of wage growth equations, by schooling, experience, and gender.

Men	Mean (Std. dev.)	R&D intensity	Log(HTK/L) in 1979	Log(HTK/L) in 1989	Change in K/L growth	R^2
School<12						
Experience 0-9	-0.223	-0.537	-0.0078	0.0001	-4.546*	0.229
	(0.058)	(0.909)	(0.0108)	(0.0110)	(2.058)	
Experience 10-19	-0.094	-0.352	-0.0292*	0.0212	-8.122*	0.355
	(0.079)	(0.912)	(0.0113)	(0.0178)	(2.184)	
Experience 20-29	-0.125	1.079	-0.0040	0.0032	0.474	0.076
	(0.072)	(1.323)	(0.0154)	(0.0159)	(3.350)	
Experience 30+	-0.085	1.758*	0.0067	-0.0224	-3.210*	0.399
	(0.052)	(0.529)	(0.0092)	(0.0132)	(1.102)	
High school graduate						
Experience 0-9	-0.198	0.302	0.0053	-0.0112	-5.680*	0.232
	(0.056)	(0.882)	(0.0126)	(0.0159)	(2.580)	
Experience 10-19	-0.174	0.638	-0.0262*	0.0303*	-5.745*	0.365
	(0.046)	(0.447)	(0.0095)	(0.0127)	(1.419)	
Experience 20-29	-0.103	1.010	-0.0222	0.0371*	-5.580*	0.350
	(0.068)	(0.631)	(0.0126)	(0.0163)	(1.769)	
Experience 30+	-0.106	1.398	-0.0059	0.0161	-4.034*	0.318
	(0.063)	(0.708)	(0.0124)	(0.0146)	(1.961)	
Some college						
Experience 0-9	-0.127	0.716	0.0147	-0.0056	-5.384*	0.292
	(0.059)	(0.632)	(0.0135)	(0.0170)	(2.496)	
Experience 10-19	-0.110	0.540	-0.0109	0.0294	-0.709	0.267
	(0.055)	(0.450)	(0.0142)	(0.0162)	(2.069)	
Experience 20-29	-0.050	0.728	-0.0059	0.0263	-1.507	0.127
	(0.098)	(0.724)	(0.0284)	(0.0370)	(3.333)	
Experience 30+	-0.034	0.514	0.0101	0.0046	-2.933	0.147
	(0.101)	(1.441)	(0.0302)	(0.0357)	(2.719)	
College grad						
Experience 0-9	-0.032	2.559*	0.0318*	-0.0258	0.888	0.582
	(0.066)	(0.861)	(0.0140)	(0.0145)	(1.864)	
Experience 10-19	-0.039	1.649	0.0229	-0.0235	3.894	0.216
	(0.060)	(0.942)	(0.0128)	(0.0174)	(3.052)	
Experience 20-29	-0.039	0.247	0.0310	0.0007	-2.184	0.319
	(0.076)	(0.676)	(0.0232)	(0.0223)	(2.903)	
Experience 30+	-0.002	7.035*	0.0778*	-0.0936*	2.487	0.382
	(0.155)	(1.482)	(0.0316)	(0.0376)	(5.174)	

Each equation is estimated over as many as 39 industries and is weighted by the sum of full-time equivalent employment in 1979 and 1989. The change in TFP growth and capital recentness are included in each regression. Robust standard errors are reported in parentheses.

Table 7. Coefficients (standard errors) of wage growth equations, by schooling, experience, and gender.

Women	Mean (Std. dev.)	R&D intensity	Log(HTK/L) in 1979	Log(HTK/L) in 1989	Change in K/L growth	R^2
School<12						
Experience 0-9	-0.115	-0.429	0.0033	-0.0062	-0.252	0.138
	(0.068)	(0.969)	(0.0169)	(0.0193)	(3.777)	
Experience 10-19	-0.081	-3.059*	-0.0130	0.0120	-8.566*	0.358
	(0.082)	(1.192)	(0.0137)	(0.0175)	(3.606)	
Experience 20-29	-0.086	1.753*	-0.0077	0.0258	-0.860	0.314
	(0.090)	(0.690)	(0.0150)	(0.0212)	(3.271)	
Experience 30+	-0.073	1.326	0.0211	-0.0009	8.873*	0.411
	(0.082)	(0.694)	(0.0114)	(0.0136)	(3.888)	
High school graduate						
Experience 0-9	-0.101	-0.917	0.0224*	-0.0067	0.387	0.363
	(0.055)	(0.672)	(0.0092)	(0.0112)	(2.669)	
Experience 10-19	-0.026	0.394	0.0166	0.0069	0.819	0.358
	(0.064)	(0.898)	(0.0099)	(0.0136)	(2.808)	
Experience 20-29	-0.022	0.436	0.0145	0.0070	-0.368	0.382
	(0.065)	(0.603)	(0.0112)	(0.0150)	(2.367)	
Experience 30+	-0.022	0.647	0.0116	0.0074	0.101	0.347
	(0.057)	(0.685)	(0.0107)	(0.0171)	(2.193)	
Some college						
Experience 0-9	-0.039	0.511	0.0351*	-0.0091	-0.437	0.537
	(0.061)	(0.974)	(0.0089)	(0.0127)	(3.362)	
Experience 10-19	0.052	2.764	0.0395*	-0.0280	-0.986	0.330
	(0.090)	(1.465)	(0.0132)	(0.0182)	(3.939)	
Experience 20-29	0.089	2.666	0.0169	0.0039	-1.539	0.306
	(0.114)	(1.825)	(0.0209)	(0.0251)	(5.858)	
Experience 30+	0.057	2.230	0.0246	0.0135	-8.840	0.300
	(0.121)	(1.444)	(0.0268)	(0.0440)	(6.281)	
College grad						
Experience 0-9	0.048	3.772*	0.0191	0.0089	1.234	0.394
	(0.081)	(1.026)	(0.0148)	(0.0176)	(3.848)	
Experience 10-19	0.060	4.029	0.0262	-0.0138	8.352	0.357
	(0.094)	(3.703)	(0.0258)	(0.0390)	(9.001)	
Experience 20-29	0.055	6.796*	-0.0326	0.0628	2.168	0.467
	(0.119)	(2.798)	(0.0369)	(0.0544)	(11.314)	
Experience 30+	0.056	5.567	0.0398	-0.0366	-2.842	0.293
	(0.124)	(5.507)	(0.0529)	(0.0879)	(20.635)	

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. The change in TFP growth and capital recentness is included in each regression.

Table 8. Regressions of changes in employment shares by years of schooling, 1979 to 1989

Years of schooling:	Below 12	12	13 to 15	16 & above
Shares of all employees				
Mean (S.D.) of dependent variable	-0.076 (0.034)	0.007 (0.051)	0.025 (0.017)	0.044 (0.036)
Coefficients (S.E.):				
Change in R&D intensity	-0.670 (0.361)	-0.803 (0.356)	0.280 (0.139)	1.193 (0.307)
Log(HTK/L) in 1979	0.0005 (0.0057)	-0.0013 (0.0079)	-0.0041 (0.0026)	0.0049 (0.0058)
Log(HTK/L) in 1989	0.0044 (0.0071)	-0.0110 (0.0090)	0.0030 (0.0036)	0.0036 (0.0059)
Change in K recentness	0.030 (0.173)	-0.170 (0.174)	0.068 (0.079)	0.071 (0.216)
Change in TFP growth	-0.502 (0.480)	1.283 (0.454)	-0.062 (0.206)	-0.718 (0.376)
Change in K/L growth	-0.396 (1.154)	0.314 (1.346)	-0.901 (0.706)	0.982 (0.853)
R^2	0.192	0.579	0.277	0.564
Shares of nonscientific employees				
Mean (S.D.) of dependent variable	- 0.078 (0.034)	0.010 (0.050)	0.026 (0.018)	0.042 (0.034)
Coefficients (S.E.):				
Change in R&D intensity	-0.681 (0.367)	-0.426 (0.371)	0.350 (0.166)	0.756 (0.296)
Log(HTK/L) in 1979	0.0006 (0.0057)	- 0.0011 (0.0080)	- 0.0042 (0.0025)	0.0047 (0.0059)
Log(HTK/L) in 1989	0.0041 (0.0071)	-0.0117 (0.0092)	0.0032 (0.0037)	0.0044 (0.0059)
Change in K recentness	0.042 (0.175)	- 0.163 (0.183)	0.076 (0.084)	0.044 (0.230)
Change in TFP growth	- 0.516 (0.492)	1.312 (0.482)	- 0.030 (0.213)	- 0.766 (0.396)
Change in K/L growth	- 0.407 (1.184)	0.479 (1.373)	- 1.038 (0.722)	0.966 (0.859)
R^2	0.191	0.546	0.291	0.499

Note: Robust standard errors are reported in parentheses. Each equation is weighted by the sum of 1979 and 1989 full-time equivalent employment.

Table 9. Changes in high-tech K/L and research intensity, 1950-94

Average annual growth in K/L				Decadal mean	
Years	**Computers**	**Instruments**	**Combined**	**Years**	**R&D/GDP**
1950-59	0.060	0.063	0.062	1953-59	0.019
1960-69	-0.012	0.014	0.009	1960-69	0.028
1970-79	0.117	0.069	0.080	1970-79	0.023
1980-89	0.216	0.045	0.126	1980-89	0.026
1990-93	0.124	0.042	0.100	1990-94	0.027

Sources: RENPR files; NSF (1997)

DATA APPENDIX

The CPS Outgoing Rotation Group Annual files for 1979 and 1989 were used to construct the wage structure variables as well as the employment share of scientists and engineers, using methods described in the text. The versions used here come from the CD-ROM produced by Dan Feenberg at NBER for 1979-91. The files for May 1973-75 come from a 68 variable extract created for Professors Richard Freeman and James Medoff for their research on unions.

The NSF measures of R&D scientists and engineers per 1000 employees for 1979 and 1989 are reported in National Science Foundation, *Research and Development in Industry: 1989,* NSF 92-307, Tables B-20, B-21, and B-54.

High-tech capital is the net stock of each type of capital in 1987 dollars, as reported in the RENPR files maintained by the Bureau of Labor Statistics and provided to me by Larry Rosenblum in March 1995. Details about how these measures have been developed are reported in BLS Bulletin 2178, *Trends in Multifactor Productivity, 1948-83,* appendix C.

The capital stock variables used to construct the recentness measure are reported in the January 1986 (pp. 51-55) and September 1990 (pp. 99-100) issues of the *Survey of Current Business*.

The industry definitions for both high-tech capital and capital recentness are not always at the same level of aggregation as those used in this study. In particular, values for all retail trade were used for eating and drinking places and for other retail trade. Similarly aggregated data were used for (1) medical services and hospitals and (2) welfare and religious services and other professional services.

The KLEM85 data was sent to me in TSP load format by Barbara Fraumeni in August 1991. For 35 separate industries, the data bank contains price indices for output, capital, labor, energy, and materials (with 1982 as the base year), along with the value of capital, labor, energy, materials and transfers received. These series were then used to calculate real output, real inputs, and input shares (ignoring transfers and using for year t the average share in years t and t-1). TFP growth is the difference between the change in log output and the weighted sum of the change in log inputs; the growth in the capital-labor ratio is the difference between the log change in capital and the log change in labor. The values used for this study are averages calculated for 1970-79 and 1980-85. As a check on accuracy, values for 1947-85 also were calculated and compared to those reported in Jorgenson (1990, Table 3.2).

The following sets of KLEM industries were aggregated so that they could be matched with the industry definitions used in this study: metal mining, coal mining, crude petroleum and natural gas, and nonmetallic mineral mining; food and tobacco; motor vehicles and other transportation equipment; and electric and gas utilities. The KLEM data cannot be broken down very finely by industry in the service sector. It treats wholesale and retail trade as a single industry; “finance, insurance, and real estate” and “other services” receive the same treatment.

Appendix Table 1. Indicators of technological change.

	R&D Intensity		Log(HTK/L)		TFP growth		K recentness		K/L growth	
Industry	**1979**	**1989**	**1979**	**1989**	**1970s**	**1980s**	**1979**	**1989**	**1970s**	**1980s**
Agriculture	0.005	0.009	-3.981	-1.713	0.010	0.036	0.576	0.478	0.014	0.009
Mining	0.065	0.069	-1.407	1.552	-0.045	-0.029	0.544	0.443	0.003	0.018
Construction	0.015	0.015	-2.101	-0.844	-0.011	0.003	0.584	0.527	-0.006	-0.003
Lumber	0.008	0.008	-1.512	-1.524	0.000	0.020	0.570	0.491	0.005	0.005
Furniture	0.012	0.007	-2.460	-0.307	0.013	0.005	0.577	0.546	0.004	-0.002
Stone,clay,glass	0.026	0.027	-0.687	1.287	0.002	0.011	0.550	0.456	0.004	0.009
Primary metals	0.031	0.033	1.082	1.775	-0.006	0.020	0.559	0.455	0.004	0.013
Fabr. metals	0.047	0.038	-2.556	-0.187	-0.002	0.023	0.597	0.534	0.003	0.011
Nonelec. mach.	0.062	0.101	-0.369	1.593	0.024	0.028	0.613	0.555	0.001	0.010
Elec. eqmt.	0.085	0.107	-1.710	0.888	0.024	0.007	0.601	0.609	0.001	0.001
Transp. eqmt.	0.072	0.115	-0.782	0.744	0.002	-0.002	0.558	0.526	0.004	0.005
Instruments	0.085	0.108	-1.502	1.317	0.022	0.011	0.598	0.569	-0.001	-0.002
Misc. mfg.	0.018	0.010	-2.165	-0.412	0.001	0.005	0.580	0.488	0.002	0.004
Food, tobacco	0.013	0.015	-0.752	0.300	0.003	0.004	0.561	0.532	0.004	0.003
Textiles	0.012	0.017	-2.527	-1.116	0.013	0.009	0.525	0.473	0.005	0.008
Apparel	0.005	0.002	-2.901	-3.079	0.019	0.013	0.582	0.500	0.004	0.006
Paper	0.026	0.030	-1.605	0.589	0.004	0.005	0.574	0.552	0.005	0.004
Printing	0.008	0.006	-1.548	0.808	-0.009	-0.006	0.563	0.577	-0.008	-0.008
Chemicals	0.089	0.108	1.735	2.202	-0.001	0.004	0.582	0.505	0.005	0.002
Petroleum	0.087	0.064	1.908	2.854	-0.008	0.035	0.569	0.496	0.004	0.001
Rubber	0.026	0.027	-1.729	-0.274	0.010	0.014	0.573	0.512	-0.000	0.003
Leather	0.005	0.011	-2.364	-0.884	-0.005	0.017	0.542	0.457	0.016	0.024
Transportation	0.007	0.009	-2.202	0.083	0.016	-0.009	0.500	0.481	-0.000	0.003
Communication	0.056	0.061	-1.618	0.786	0.032	-0.001	0.621	0.566	0.013	0.012
Utilities	0.057	0.074	2.164	3.237	-0.011	-0.002	0.596	0.554	0.010	-0.001
Whol. trade	0.008	0.011	-0.875	1.186	0.002	0.008	0.612	0.618	-0.002	0.002
Restaurants	0.000	0.000	-3.569	-0.572	0.002	0.008	0.611	0.606	-0.002	0.002
Other retail	0.001	0.002	-3.569	-0.572	0.002	0.008	0.611	0.606	-0.002	0.002
Banking, finance	0.010	0.012	0.773	2.457	0.006	-0.019	0.637	0.618	-0.003	0.002
Insur, real est.	0.010	0.014	1.720	2.699	0.006	-0.019	0.621	0.602	-0.003	0.002
Business serv.	0.046	0.065	-1.308	0.554	0.001	-0.014	0.580	0.601	-0.011	-0.012
Repair serv.	0.003	0.003	-1.327	1.943	0.001	-0.014	0.584	0.590	-0.011	-0.012
Personal serv.	0.001	0.001	-2.758	-0.141	0.001	-0.014	0.572	0.587	-0.011	-0.012
Entertainment	0.002	0.005	-1.772	0.420	0.001	-0.014	0.551	0.547	-0.011	-0.012
Medical serv.	0.008	0.004	0.776	0.837	0.001	-0.014	0.612	0.602	-0.011	-0.012
Hospitals	0.007	0.008	0.776	0.837	0.001	-0.014	0.612	0.602	-0.011	-0.012
Welf., rel. serv.	0.002	0.003	-0.484	0.381	0.001	-0.014	0.643	0.530	-0.011	-0.012
Educ. serv.	0.009	0.011	-2.380	-1.869	0.001	-0.014	0.476	0.531	-0.011	-0.012
Other prof. serv.	0.086	0.080	-0.484	0.381	0.001	-0.014	0.643	0.530	-0.011	-0.012

[1]Autor, Katz, and Krueger (1997) have extended this work through 1993 with similar conclusions.

[2]Mishel and Bernstein (1996) 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.

[3]The classic studies on this subject were done by Slichter (1950) and Cullen (1956). Modern extensions of this line of research include Krueger and Summers (1987) and Allen (1995).

[4]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, 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.

[5]The data appendix reports the technology variables and provides further details on how they were calculated.

[6]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.

[7]There is a 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. Changes within industries in the share of high-tech relative to total investment will not be reflected in this measure.

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

[9]Five industries are lost (federal, state and local public administration, private household services, and postal) because there are no data for most of the technology variables. For the same reason, the following sets of CPS detailed industries were also combined: automobiles, aircraft, and other transportation equipment; agricultural production, agricultural services, forestry, and fisheries; railroads and other transportation; and fabricated metals and ordnance. Food and tobacco were combined because there were insufficient observations of workers in the tobacco industry in either CPS to estimate wage equation parameters with acceptable precision.

[10]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.

[11]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.

[12]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.

[13]The following restrictions on the model were all tested and rejected: (1) all ln(HTK/L) interactions equal zero; (2) ln(HTK/L) interactions for 1989 equal zero; and (3) ln(HTK/L) interactions for 1979 equal zero.

[14]Computer occupations include computer programmers, systems analysts, computer specialists not elsewhere classified, operations and systems researchers and analysts, computer operators, and key punch and peripheral operators. In the 1979 CPS the relevant occupational codes are 3-5, 55, 343, and 345; in the 1989 CPS they are 64, 65, 229, 304, 308, 309, and 385. Detailed results are available from the author upon request.

[15]Card, Kramarz, and Lemieux estimate the same type of model using data on individuals aggregated into age-education-gender cells.

[16]Their results are not directly comparable to those reported here because their model does not allow wage differentials to change over time.