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TECHNOLOGICAL CHANGE AND WAGES: AN INTER-INDUSTRY ANALYSIS

Ann P. Bartel
Nachum Sicherman

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ABSTRACT

Previous research has found evidence that wages in industries characterized as "high tech," or subject to higher rates of technological change, are higher. In addition, there is evidence that skill-biased technological change is responsible for the dramatic increase in the earnings of more educated workers relative to less educated workers that took place during the 1980s. In this paper, we match a variety of industry level measures of technological change to a panel of young workers observed between 1979 and 1993 (NLSY) and examine the role played by unobserved heterogeneity in explaining the positive relationships between technological change and wages, and between technological change and the education premium. We find evidence that the wage premium associated with technological change is primarily due to the sorting of better workers into those industries. In addition, the education premium associated with technological change is found to be the result of an increase in demand for the innate ability or other observable characteristics of more educated workers.

Ann P. Bartel
Graduate School of Business
Columbia University
710 Uris Hall
New York, NY 10027
and NBER
ABARTEL@RESEARCH.GSB.COLUMBIA.EDU

Nachum Sicherman
Graduate School of Business
Columbia University
717 Uris Hall
New York, NY 10027
and NBER
nachum.sicherman@columbia.edu

I. Introduction

During the past decade there has been a considerable amount of research on the impact of technological change on the wage structure. One line of research is the set of studies that focussed on explaining interindustry wage differentials. These studies found a positive correlation between industry wages and technological change, using the capital/labor ratio or the R&D/sales ratio, as a proxy for technological change (Dickens and Katz, 1987; Haworth and Rasmussen, 1971; Hodson and England, 1986; Lawrence and Lawrence, 1985; and Loh, 1992). A second line of research attempted to explain the dramatic increase in the earnings of more educated workers relative to less educated workers that took place during the 1980s.[1] These studies, based largely on aggregate data, showed that skill-biased technological change was a major cause of the increase in the education premium (Allen, 1996; Bartel and Lichtenberg, 1987, 1991; Berman, Bound and Griliches, 1994; Berndt, Morrison, and Rosenblum, 1992; Bound and Johnson, 1992; Mincer, 1991; and Topel, 1994). A third line of research utilized individual or plant level data to study the wage impacts of technological change and found a positive relationship between a worker's wage and his use of various technologies (Krueger, 1993; Dunne and Schmitz, 1995; and Doms et.al., 1995).[2]

In this paper, we build on the first two lines of research. Utilizing data from the National Longitudinal Survey of Youth (NLSY), a sample of 12,686 individuals who were 14-21 years old in 1979 and interviewed annually through 1993, we study how technological change affected the

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[1]The college/noncollege relative wage has continued to rise during the early 1990s, but at a slower rate than in the 1980s. See Bound and Johnson (1995).

[2]The results from this line of research may reflect unobserved heterogeneity. Dunne and Schmitz (1995) were unable to control for worker quality. Doms et.al. (1995) showed that, although wages are higher in plants that use more technologies, these plants had higher wage workers even before the technologies were introduced. Dinardo and Pischke (1996) present evidence suggesting that Krueger's finding that workers who use computers on their jobs earn higher wages may be the result of unobserved heterogeneity.

1979-1993 interindustry wage structure.[3] Currently, data on the rate of technological change faced by the worker in his job is unavailable in any nationally representative micro dataset. We therefore utilize industry-level measures of technological change instead.[4] Since the measurement of technological change outside the manufacturing sector is very problematic (Griliches, 1994), our analysis is restricted to workers in manufacturing. Even within this sector, however, no single proxy is likely to be perfect. Unlike previous studies which have relied on one or two proxies for technological change, we link the NLSY with several alternative measures of technological change.[5] Specifically, our analysis uses the Jorgenson productivity growth series, the NBER productivity data, the Census of Manufactures series on investment in computers, the R&D/sales ratio in the industry, the industry's use of patents, and the share of scientists and engineers. This approach enables us to examine the robustness of alternative measures of technological change, thereby increasing our confidence in the results.

An alternative approach to studying the effects of technological change on wages is to conduct a time series analysis using changes over time in industry rates of technological change. Although the NLSY provides data for fifteen years, such an analysis is problematic for two reasons. First, individuals age over time. This makes it difficult to separate effects due to changes in the rate of technological change over time from the effect of the increased labor

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[3]Our results may not generalize to other time periods; as Goldin and Katz (1996) demonstrate, the relationship between technological change and the demand for skills changed during the twentieth century. The direction of the bias in skill-biased technological change appears to depend on the nature of the technological change.

[4]An alternative approach would be to collect data from a small sample of firms that are undergoing technological change and analyze the impact on their employees. The disadvantage of this approach is that the findings may not hold for individuals who work in other firms. See Siegel (1994) for a study restricted to high-tech firms on Long Island.

[5]Our approach of matching individual-level data with industry measures (previously used in Bartel and Sicherman (1995)) is similar to that of Allen (1996) and Mincer (1991) who both used CPS data to study time-series changes in the wage distribution.

market experience of the sample. As Blackburn and Neumark (1993) and Farber and Gibbons (1996) show, learning models suggest that, as workers accumulate experience, schooling may become less important and ability more important for wage determination. Second, a time-series approach would have to utilize changes in the measures of industries' rate of technological change. Year-to-year variation in these measures are likely to have significant measurement error and would not capture variations across industries in the true changes in rates of technological change (see Griliches and Hausman, 1986). Allen (1996) used this approach and concluded that some of his results were unreasonable; this is likely due to measurement error. The cross-sectional approach that we utilize has the important advantage of relying on inter-industry variations in technological change.

The industry-level indicators that we use were chosen to capture variations in the *rate* of technological *change* across industries. From one perspective, we can think of an industry that has a high rate of technological change as one in which workers are required to make frequent changes in job tasks and operating procedures (Jovanovic and Nyarko, 1995). Economists have suggested that in this environment, firms will increase their demand for workers who can more easily learn the new technology and adapt to change; these are more likely to be the more educated and more able individuals.[6] From another perspective, our proxies for the industry rate of technological change may capture variations in the *nature* of the industry's technology, i.e. some industries are "high-tech," while others are "low-tech." If physical and human capital are gross complements, then industries that use more sophisticated capital ("high tech") will also employ more skilled workers. In fact, the term "skill-biased technological change" refers to the shift from such "low tech" to "high tech" environments. The data that we use here, like that

[6]See, for example, Griliches (1969) and Nelson and Phelps (1966).

used by most researchers, does not allow us to differentiate between the two perspectives.[7] We therefore use the terms "high-tech" and "higher rates of technological change" interchangeably throughout the paper.

The second way in which we build on previous research is to exploit the panel nature of our data in order to study the role of unobserved heterogeneity in explaining both the interindustry wage differences and the variations in returns to schooling that are associated with technological change. We show that wages in industries with higher rates of technological change are higher even after controlling for a variety of individual characteristics including the AFQT score.[8] This result could reflect wage premia that are due to (1) industry effects such as compensating wage differentials or efficiency wages, or (2) labor mobility constraints that cause the effects of demand shocks to persist[9], or (3) continuous shocks in the industry. Alternatively, it could reflect the sorting of better workers into industries with higher rates of technological change.[10] We use a number of econometric procedures, based on fixed effects models, to conclude that sorting is the dominant explanation for higher wages in those industries. Although we find evidence of an industry wage premium after controlling for individual fixed effects, like Gibbons and Katz (1996), we show that this premium is not correlated with the industry rate of

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[7]In another study, Bartel and Sicherman (1995), we showed that a substantial part of the variation in the incidence of job training across industries is the result of differences in the *rates of change* in technologies in addition to the *nature* of the technology itself.

[8]AFQT is the Armed Forces Qualifications Test which 94% of the 1979 NLSY respondents completed. While some have used the AFQT scores as proxies for innate ability, others have argued that these scores also capture skills obtained at home and in school (Neal and Johnson, 1996). See Appendix A for more information on the AFQT.

[9]Neal (1995) has shown that there is substantial industry-specific human capital that is likely to lengthen the effect of differential demand shocks.

[10]Although research on the interindustry wage literature has concluded that unobserved individual components play a role, the magnitude of that role is subject to debate. For example, Murphy and Topel (1987) found that nearly two-thirds of the observed industry wage differences were caused by unobserved individual characteristics. Gibbons and Katz (1992) found that displaced workers maintain 45% of their pre-displacement industry wage premium when they are reemployed.

technological change. In our data, we also document the higher returns to education in high tech industries and show that this education premium is also due to the greater selectivity on individual unobserved characteristics. In other words, at higher rates of technological change, there is an increase in demand for the "ability" of the more educated workers.[11]

In the next section of the paper, we describe the data and the econometric framework for our analysis. Sections III and IV present our findings. Conclusions and policy implications are discussed in Section V.

II. Empirical Framework

A. Microdata

We use the main file and the work history file of the 1979-1993 National Longitudinal Surveys of Labor Market Experience of Youth aged 14-21 in 1979 (NLSY). The main file is the source of information on personal characteristics such as main activity during the survey week, education, ability scores, age, race, marital status, health status, etc. An individual enters our sample when he or she first reports that the main activity during the survey week was "in the labor force." The work history file contains employment related spell data, such as wages, tenure and separations. Our analysis is restricted to the job designated as the individual's "CPS job" which is the most recent/current job at the time of the interview. We exclude individuals who work outside of manufacturing because good measures of technological change are not available for the non-manufacturing sector. Details on the construction of variables and additional sample restrictions are discussed in Appendix A.

[11]We use the term "ability" to refer to unobserved characteristics. These characteristics could be innate or they could have been learned in school or in the family.

B. Measures of Technological Change

Since we do not have a direct measure of the rate of technological change faced by the individual in his or her place of work, we link the NLSY with several alternative proxies for the rate of technological change in the industry in which the individual works. As no single proxy is a perfect measure, it is important to use several alternative measures in the analysis; if similar results are obtained with different measures, we can have more confidence in the reliability of the findings.

The six measures of technological change that we use are (1) the ratio of investment in computers to total investments as reported in the 1987 Census of Manufacturers;[12] (2) the ratio of R&D funds to net sales reported by the National Science Foundation (1994); (3) total factor productivity growth calculated by Jorgenson et.al.(1987);[13] (4) the NBER total factor productivity growth series; (5) the number of patents used in the industry as calculated by Kortum and Lach (1995); and (6) the ratio of scientific and engineering employment to total employment calculated from the 1979 and 1989 CPS by Allen (1996). Appendix B contains the industry means for each of these measures and discusses the advantages and disadvantages of each proxy. The correlation matrix included there shows that no two measures are perfectly correlated, and, therefore, there is no redundancy in using all of them in our analysis. The correlations between the different measures range from .3 to .7, which is consistent with our view that each proxy is likely to capture a different aspect of technological change.

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[12]Berman, Bound and Griliches (1994) use this measure as a proxy for technological change in the industry.

[13]This series has been used extensively in previous research (Bartel and Sicherman, 1993, 1995; Lillard and Tan, 1986; Tan, 1989; Mincer and Higuchi, 1988; and Gill, 1990).

C. Matching the Microdata and Industry Measures

Our analysis relies on cross-section variations in technological change. All of the measures that we use have a common trait, i.e. they are proxies for the **industry** rate of technological change. We recognize that an industry measure of technological change may not have the same impact for all of the occupations in that industry. For example, an innovation in the industry's production processes may have little or no impact on clerical employees. By matching an industry measure of technological change to all of the individuals in that industry we are less likely to find a strong effect of technological change. Hence, our empirical results are likely to be **underestimates** of the true relationship.[14] We partially deal with this issue by conducting separate analyses for production and non-production workers.

In order to match the different measures of technological change to the industrial classification used in the NLSY (the Census of Population classification), we use industry employment levels as weights whenever aggregation is required. When we utilize the Jorgenson and NBER productivity growth measures, we characterize industry differences in the rate of technological change by using the mean rate of productivity growth over the ten-year time period from 1977 through 1987.[15] In the case of the share of investment in computers, we use the 1987 level. For the patent data, we calculate the number of patents used during the time period 1980-83 divided by the number used during the 1970s in order to control for systematic differences in the likelihood of patenting across industries.[16] In the case of the scientists and engineers

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[14]If the rate of technological change faced by workers in industry i and occupation j, T_{ij}, is given by $T_{ij} = T_i + V_{ij}$, where T_i is the industry rate of technological change, and V_{ij} is the difference between the industry and occupation means, then by regressing wages on T_i rather than the "true" measure, T_{ij}, the estimated effect of technological change on wages will be biased towards zero.

[15]Although the Jorgenson productivity series is now available through 1991, we have chosen to use the means over the 1977 to 1987 period because this time period captures a complete business cycle.

[16]The latest year for which the patent data are available is 1983. See Appendix B for details on the construction of the patent variable.

variable, we use the 1979 value for the 1979-1986 time period and the 1989 value for the 1987-1993 time period. We use the annual data on R&D/sales ratios for each industry to calculate a three-year moving average for the current year plus the preceding two years, e.g. averaging data for 1977-1979 for the 1979 NLSY, etc. Hence, with the exception of the R&D and scientists/engineers variables, we use a fixed time period measure of technological change which may act like a fixed effect for each industry, capturing other fixed attributes of the industry. We deal with this problem by including several industry characteristics in the regressions which may influence the relationship between wages and our measures of technological change. They are: the annual industry unemployment rate obtained from Employment and Earnings, annual measures of percent unionized in the industry compiled from the CPS by Hirsch and MacPherson (1993), and the annual rates of job creation and job destruction for both start-up and continuing establishments in the industry constructed by Davis and Haltiwanger (1992).

Another estimation issue is that the standard errors of our estimated coefficients may be biased downwards because industry-level shocks may be correlated across individuals within a given industry. We deal with this problem by estimating a random effects model which is described in the next section.

III. Why Are Wages Higher in Industries with Higher Rates of Technological Change?

Like previous researchers, we also find a positive correlation between technological change and wages. Figure 1 shows the gross relationships between wages and the various proxies for technological change where each unit of observation is either a two or three digit industry depending on the technological change proxy. The graphs show a positive relationship between wages and technological change. When we distinguished those measures of technological change that are input-based (investment in computers, use of patents, investment in

R&D, and scientists/engineers) from those that are output-based (Jorgenson TFP and NBER TFP), we found that the former had a stronger relationship with wages. Using input-based technological change measures, industries that are one standard deviation above the median have wages that are between 6 and 13 percent higher, while the comparable result for the output-based measures is 1.5 percent. Of course, these findings may in part be due to the fact that workers in industries with higher rates of technological change have more human capital, or that the industry rate of technological change is correlated with other industry characteristics that raise wages.

As Table 1 indicates, workers in industries with higher rates of technological change are more educated. In Table 1, we divided our NLSY sample into two groups based on whether an individual is employed in a low-tech industry or a high-tech industry, using the median as the cutoff point. Within each group of industries, we calculated the percentage of employees who are college graduates, for all workers, and for production and non-production workers separately. For all six measures of technological change, the percentage of college graduates is higher in the high-tech industries. Table 2 reports the AFQT scores for high school graduates and college graduates employed in low and high tech industries. For the high school graduates, we observe a dramatic gap in AFQT scores between high tech and low tech industries. This gap is not observed for college graduates. In other words, in high-tech industries there is strong selectivity on AFQT scores for high school graduates; workers with relatively low schooling are employed in these industries only if they have relatively high AFQT scores. The fact that we do not observe this type of selectivity for college graduates could be due to the nature of the test.[17] Elsewhere (Bartel and Sicherman, 1995) we have shown that the incidence of on-the-job training is higher in industries with higher rates of technological change. Hence these findings confirm

[17]It should be noted that the AFQT was normed for high school graduates, not college graduates, i.e. the test is, in effect, too easy for those with more education. As a result, AFQT scores do a better job of measuring ability differences for the former group.

that workers in industries with higher rates of technological change have more human capital, either by being more educated, more able, or by receiving more on-the-job training. The next step is to estimate the correlation between wages and the industry rate of technological change after controlling for a variety of individual and industry characteristics.

B. Controlling for Commonly Observed Characteristics

Consider the following linear model:

$$lnW_{ijt} = X_{it}\beta + Z_{jt}\gamma + \alpha TC_j + \epsilon_{ijt} \tag{1}$$

where

$$\epsilon_{ijt} = v_j + e_{ijt} \tag{2}$$

where lnW_{ijt} denotes the log of the hourly real wage of individual *i* who works in industry *j* at time period *t*, X_{it} denotes a vector of individual characteristics that may vary over time, Z_{jt} denotes a vector of industry characteristics that may also vary over time, and TC_j denotes the industry rate of technological change. We use several alternative measures of technological change, which are, with two exceptions (R&D/sales and scientists/engineers), fixed over time. The parameter ϵ_{ijt}, the random error associated with the observation lnW_{ijt}, is assumed to be the sum of the random effect associated with the *j* industry (v_j), and the *t* observation of individual *i* in industry *j* (e_{ijt}). Notice that we use this specification in order to obtain the correct standard errors for the estimated coefficient of the technological change variable. Later on we use a different specification (fixed effects) that better fits the data.

Table 3 reports the estimated coefficients of the random effects regressions, in which we control for a variety of individual and industry characteristics (listed in the footnote to the table).

The complete regression results, using one technological change measure, are shown in Appendix C. In order to make the coefficients comparable across the various technological change measures, all of the measures are expressed in standard deviation units. In most cases we find a positive and significant correlation between the rate of technological change and wages. In general, the results are stronger for the non-production workers; industries with a rate of technological change that is one standard deviation above the mean have non-production worker wages that are between 1.6 and 7.3 percent higher. For production workers, the effect is an increase that ranges from 1.5 to 4.5 percent. We compared these results to the coefficients from an OLS estimation (not shown here) and found that, when positive, the OLS coefficients had higher t-values, as expected.[18]

One possible explanation for the positive correlation between wages and the industry rate of technological change is that workers in industries with higher rates of technological change are more able. In other words, the observed premium reflects a selection process based on unobserved characteristics. The availability of "intelligence" test scores (AFQT) in the NLSY has been suggested by some researchers as a way to control for ability, an unobserved characteristic in most data sets[19]. Table 4 reports the estimation results of equation (1) including standardized AFQT scores in the regressions. Comparing Tables 3 and 4, we see that the coefficients that were significant in Table 3 remain significant in Table 4.

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[18]In the case of the two computer investment variables, however, the OLS coefficients were negative or zero.

[19]See, e.g., Blackburn and Neumark (1993), among others. Farber and Gibbons (1996) propose a procedure to separate the component of ability that is also unobserved by the employer initially, from that portion that is observed by the employer but not the econometrician.

C. Controlling for Individual Fixed Effects

In order to test the hypothesis that the source of higher wages in industries with higher rates of technological change is worker skills not measured in equation (1), we consider the following fixed effect model:

$$lnW_{ijt} = X_{it}\beta + \alpha TC_{jt} + \mu_i + \epsilon_{ijt} \tag{3}$$

where μ_i is an individual fixed effect. By construction, this specification assumes that the premium to individual, unobserved skills, does not vary across industries nor over time.

Table 5 presents the results of estimating this equation. The positive correlation between technological change and wages that was observed in Table 3 is significantly weakened in Table 5. Any coefficients that remain significant in Table 5 are much smaller in magnitude compared to Table 3. Note that the reduction is much stronger for non-production workers since the AFQT score does not adequately control for "unobserved" heterogeneity among more educated workers. Based on the results in Table 5, we can conclude that unmeasured worker characteristics play an important role in accounting for the positive correlation between wages and technological change.

D. Individual and Industry Premia: Two-Stage Double Fixed Effects Model

In this section, we allow for the possibility that higher wages in high tech industries may reflect premia that result from the nature of the industry, holding all individual characteristics, either observed or unobserved, constant. Examples might be (1) compensating wage differentials, (2) efficiency wages, or (3) rapid growth of high tech industries resulting in disequilibria due to increased demand for workers in those industries[20]. The fixed effects estimates presented in Table 5 do not allow for the possibility that an individual's fixed effect may in part be an industry effect. Our objective in this section is to distinguish the wage differentials that are due to the sorting of better (more able) workers into industries with higher rates of technological change from the wage premia due to unobserved industry characteristics.

We estimate a "two-stage double fixed effects model". In the first stage, we estimate a standard fixed effects model (described below) that also includes industry dummies. This is done in order to obtain two estimated parameters: individual and industry "premia". The individual premium is the fixed component of the wage that is not explained by either observed characteristics or by any possible (fixed) premium due to industry affiliation.[21] These characteristics could include those that are observed by the employer but not by the econometrician, as well as characteristics that are unobserved, either by the employer or by the worker initially, but are learned or revealed over time. The industry premium is the component of the wage that is given to individuals while working in the industry, but is not due to any specific individual characteristics, either observed or unobserved. This premium captures all the reasons listed above (compensating wage differentials, efficiency wages, demand-induced disequilibria), excluding that which is due to the sorting of workers with higher unmeasured "ability" into industries with high rates of technological change. In the second stage, we obtain the correlations between the individual and industry premia and the industry rate of technological change.

[20]In order to test the hypothesis that industries with higher rates of technological change are paying higher wages due to employment growth, we estimated a variety of models attempting to control for the growth of employment in the industry. Our results were not affected by the inclusion of such variables and we found no correlation between the level of wages and the rate of growth of the industry. Topel (1986) finds that wages are higher in faster growing regions due to increased demand for workers.

[21]Since race and sex are fixed for individuals, it is impossible to identify their impacts using a fixed effects model. We deal with this problem in the second stage of the analysis, as described below.

Three data problems potentially hamper our analysis: (1) ambiguous industry reports resulting in erroneous industry changes,[22] (2) not enough "true" industry changes, and (3) non-random industry changes. We were able to deal fairly successfully with the first problem for workers who did not change employers. First, we corrected for some obvious errors in reported industry.[23] Then, for each worker, we assigned the modal industry for the period in which he or she worked with the same employer. We believe that the second problem listed above is not a significant one, as demonstrated by the data in Table 6 where we show the number of corrected industry changes for the individuals in our sample. Table 6 indicates that there is a reasonable amount of industrial mobility; for example, among the 193 individuals who were in the sample for seven years, 80% changed industry at least once. Finally, the third problem is that industry moves are endogenous. While some have tried to deal with this problem using data on displaced workers (e.g., Gibbons and Katz (1992)), most studies, including ours, do not attempt to deal with the problem. It is not clear, however, what the sign of the bias is in the NLSY.[24]

Stage I.

Consider the following fixed effect model:

$$\ln W_{it} = X_{it}\beta + \mu_i + \gamma' d_{it} + \epsilon_{it} \qquad \textbf{(4)}$$

[22]See Murphy and Topel (1987) for a treatment of this problem using a unique dataset.

[23]A detailed program of all industry corrections is available upon request.

[24]If, for example, workers in low tech industries are more likely to move to a low tech industry (and the same for workers in high tech industries), then our estimation procedure will result in an upward bias in the estimated individual premium and a downward bias in estimating the industry premium. An opposite pattern of mobility, however, will cause the opposite bias.

where lnW_{it} is the log of real wage of individual i at time period t. X_{it} is a vector of individual characteristics, and μ_i is the individual "fixed effect". d_{it} is a vector of dummy variables, indicating the industry in which the worker is employed in at time period t. γ' is a vector of industry effects. Both the individual and the industry effects are assumed to be constant over time. This specification assumes that all unobserved individual characteristics are valued the same in different industries.[25]

Assuming that ϵ_{it} can be characterized by an i.i.d. random variable with mean zero and variance σ_ϵ^2, we estimate equation (4) obtaining two parameters of interest: an estimated individual premium, ($\hat{\mu}_i$), and an estimated industry premium, ($\hat{\gamma}_j$). The fact that people change industries over the sample period enables us to differentiate the individual premium from the industry premium.[26]

Stage II

Two models are estimated in the second stage to obtain the correlations between the individual and industry premia and the industry rate of technological change.

Consider the following models:

$$\hat{\mu}_i = Z_i\gamma + \alpha(TC_i) + \varepsilon_i \qquad \textbf{(5)}$$

[25]Although industry technologies may be differentially sensitive to ability, ability will be equally rewarded in all industries in equilibrium.

[26]For details on the derivation of the estimated parameters and standard errors, see Appendix D.

where $\overline{TC_i}$ is the (weighted) mean of the rates of technological change in the industries in which the worker was employed during the sample period, and Z_i is a vector of race and gender dummies.[27]

$$\hat{\gamma}_j = \alpha_0 + \alpha_1(TC_j) + \varepsilon_j \tag{6}$$

where TC_j is the rate of technological change in industry j. Given that the dependent variables in equations (5) and (6) are estimated parameters, we estimate these equations using weighted least squares, where the weights are the inverses of the standard errors of the dependent variables.

The results of estimating the second stage equations are shown in Table 7. The main finding (column 1) is the existence of a significant correlation between the individual premia and all six indicators of technological change. When the sample is separated into the two occupational groups, the significant results hold for the non-production workers, but only the patents and scientists/engineers variables are significant for the production workers. We also find (not shown here) strong correlations between the race and sex dummies and the individual premia[28]. Industry premia, however, are not correlated with the industry rates of technological change with the exception of R&D and scientists and engineers, which are only significant for production workers. Hence, we conclude that the observed wage premium associated with technological change is primarily due to the sorting of more skilled workers (based on observed and unobserved characteristics) into those industries.

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[27]See footnote 21 for the reason for including these dummies.

[28]Both being female and non-white are negatively correlated with the individual premium. The correlation is substantially higher for sex. Since the inclusion of sex and race does not affect the partial correlation between the industry rate of technological change and the individual premium, we can conclude that the higher wages at higher rates of technological change are not affected by any sorting based on sex or race.

In order to consider whether the sorting of workers with higher premia to industries with higher rates of technological change occurs relatively early in the working life rather than over time, we conducted the following test. We compared the individual premia of workers in industries below the median rate of technological change to those who were above the median rate of technological change, first using the industry affiliation in the individual's first full time job, and second, using the last industry reported by the worker. Although the results supported our earlier finding, namely that the mean individual premium is higher in industries with higher rates of technological change, we found no evidence that the gap increased over time. We conclude, therefore, that the sorting of better workers into industries with higher rates of technological change is done relatively early.[29]

IV. Why Are Returns to Schooling Higher in Industries with Higher Rates of Technological Change?

As noted in the Introduction, many studies argue that one of the most important explanations for the increase in returns to schooling in the 1980s is skill-biased technological change. An important question is whether the increase in demand for educated workers reflects an increase in demand for schooling per se, or an increase in demand for other components of human capital such as ability, quality of schooling, or other factors typically not observed in the data. A number of papers provide evidence that it is the latter, not the former. Juhn, Murphy and Pierce (1993) show that the majority of the increase in wage inequality that occurred between 1963 and 1989 is due to an increase in the premium for unobserved dimensions of skill. Murnane, Willett and Levy (1995) show that between 1978 and 1986, the impact of basic

[29]This does not rule out the possibility that there are important individual characteristics that are revealed over time (see Farber and Gibbons (1996) for evidence of learning). These characteristics do not, however, seem to be important in explaining interindustry wage differences that are due to technological change.

cognitive skills on young workers' wages increased. Chay and Lee (1996) show, using CPS data, that the returns to unobserved skills rose anywhere from 12-15 percent to 20-35 percent during the 1980's, and as much as one-half of the within cohort rise in the college premium could be the result of increases in the skill premium.

In order to first verify that returns to schooling are higher in industries with higher rates of technological change, we estimate the following model:

$$lnW_{ijt} = X_{it}\beta + Z_{jt}\gamma + \delta(S_{it} \cdot TC_{jt}) + \epsilon_{ijt} \tag{7}$$

where,

$$\epsilon_{ijt} = v_j + e_{ijt} \tag{8}$$

This specification, assuming industry level random effects, is similar to that used in equation (1). The only modification is that here we interact "S", the individual's level of schooling, with the industry rate of technological change, thus allowing for the effect of schooling on wages to vary with the industry rate of technological change. Notice that vector X_{it} includes the level of schooling as an independent variable. It is important to remember that, unlike many of the studies cited above, our analysis is cross-sectional and therefore, the returns to schooling that we calculate will also reflect the influence of factors like the disequilibria discussed earlier.

The results of estimating equation (7) are shown in Table 8. We find a positive and significant correlation between technological change and the return to education for many of the indicators that we use. It is possible that this premium reflects returns to unobserved individual characteristics and/or unobserved industry characteristics. Indeed, when individual and industry fixed effects are added to the regressions, the coefficients on the technological change/education interaction term (shown in Table 9) become negative, and in two cases, are even significant.

To further test this hypothesis, we estimate the two-stage double fixed effects model described earlier, adding interaction terms between education and technological change to both stages. The results from the second stage are shown in Table 10 where we find a significant correlation, in column 1, between the individual premia and five out of six of the technological change measures, and insignificant correlations, in column 4, between the industry premia and all of the technological change measures.[30] The implication of these results is that the observed education premium in high-tech industries is due to the sorting of highly educated individuals on the basis of their unobserved characteristics (ability?) into the high-tech industries. At higher rates of technological change, schooling per se becomes less important than other characteristics (e.g. ability) that are correlated with schooling. The result reported in Table 2, that there is strong selectivity on AFQT scores for high school graduates in high-tech industries, supports this assessment.

V. Conclusions

Previous research has found evidence that wages in industries characterized as "high tech", or subject to higher rates of technological change, are higher. In addition, there is evidence that skill-biased technological change is responsible for the dramatic increase in the earnings of more educated workers relative to less educated workers that took place during the 1980s. In this paper, we matched a variety of industry level measures of technological change to a panel of young workers observed between 1979 and 1993 (the NLSY) and examined the role played by unobserved heterogeneity in explaining the positive relationships between technological change and wages, and technological change and the education premium.

We found that both the positive correlation between wages and technological change, and the positive correlation between the education premium and the rate of technological change are

[30]Some of the significant relationship between the individual premia and the technological change measures do not hold up when the sample is divided into the two occupation groups.

significantly weakened when we control for unobserved heterogeneity among individuals, using fixed effects estimation. Since the fixed effects estimates do not allow for the possibility that an individual's fixed effect may in part be an industry effect, we add industry dummies in order to obtain two estimated parameters, an individual premium and an industry premium. The individual premium is the component of the wage that is not explained by either observed characteristics or by any fixed premium due to industry affiliation. The industry premium is the component of the wage that is given to individuals while working in the industry, but is not due to any specific individual characteristics, either observed or unobserved. We found positive and significant correlations between the individual premia and technological change for both the wage level and the education premium. Although we did find evidence of the existence of an industry premium for both the wage level and the education premium, neither of these premia were correlated with the industry rate of technological change.

These findings imply that the observed effects of technological change on the wage structure are due to the sorting of individuals on the basis of their unobserved characteristics into industries with different rates of technological change. To the extent that these unobserved characteristics largely reflect an individual's innate ability, we can interpret these results as indicating that the more able individuals are sorted into the industries with higher rates of technological change, and that the education premium from technological change is due to an increase in demand for the innate ability of the highly educated workers that takes place at higher rates of technological change. If ability is truly innate and can not be learned in school, the wage differentials associated with technological change would not be expected to disappear over time. Alternatively, if our results are driven mainly by such unobservables as curriculum or the quality of schooling, our findings imply that, at higher rates of technological change, curriculum and/or school quality will become more critical to an individual's success in the labor market.

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Table 1

Percentage of College Graduates and the Rate of Technological Change Manufacturing Industries, 1979-93

Measure of Technological Change♠	Rate of TC	All Workers	Production Workers	Non-Production Workers
Investment in Computers (87)	Low	6.04	1.20	20.29
	High	14.30	2.41	29.02
Use of Patents	Low	6.46	1.11	20.96
	High	12.64	2.28	28.10
Investment in R&D	Low	7.12	1.32	22.09
	High	13.72	2.31	28.71
Percentage of Scientists & Engineers	Low	7.24	1.46	21.86
	High	11.85	1.82	27.71
Jorgenson TFP (77-87)	Low	8.28	1.52	23.96
	High	10.44	1.70	25.92
NBER TFP (77-87)	Low	8.97	1.58	24.68
	High	10.51	1.69	25.96

♠ Industries are considered low-tech if their rate of technological change is below the median. They are high-tech if their rate is above the median.

Table 2
AFQT Scores and the Industry Rate of Technological Change
High School ("HS") and College ("C") Graduates (standard dev. in parentheses)

Measure of Tech. Change	Rate of Tech. Change	All Workers		Production Workers		Non-Production workers	
		HS	C	HS	C	HS	C
Investment in Computers	Low	34.8	74.2	32.4	69.0	44.4	75.0
		(24)	(19)	(23)	(20)	(24)	(19)
	High	43.8	78.5	41.5	68.9	48.5	79.4
		(25)	(19)	(25)	(22)	(24)	(19)
Jorgenson TFP	Low	38.8	77.6	36.2	71.5	47.8	78.5
		(25)	(19)	(24)	(19)	(25)	(18)
	High	37.6	76.3	34.7	66.6	45.4	77.3
		(24)	(20)	(24)	(23)	(24)	(19)
Use of Patents	Low	35.7	75.8	33.3	70.1	45	76.6
		(24)	(19)	(23)	(20)	(25)	(18)
	High	41.3	77.4	38.5	68.2	48	78.5
		(25)	(20)	(25)	(22)	(24)	(19)
R&D / Sales Ratio	Low	36	76.5	33.6	71.3	44.6	77.2
		(24)	(18)	(24)	(17)	(25)	(18)
	High	42.8	77.2	39.9	66	49	78.4
		(25)	(21)	(25)	(25)	(24)	(20)
% Scientists & Engineers, 1979	Low	34.4	76.9	32.1	71.8	42.8	77.7
		(24)	(17)	(23)	(16)	(24)	(17)
	High	43.0	76.8	40.2	65.9	49.8	77.9
		(25)	(21)	(25)	(25)	(24)	(20)
% Scientists & Engineers, 1989	Low	35.3	76.5	43.9	77.2	33	71.4
		(24)	(18)	(25)	(18)	(23)	(17)
	High	43.0	77.2	49.4	78.3	40.1	66.0
		(25)	(21)	(24)	(20)	(25)	(25)
NBER TFP	Low	39.4	76.5	48.1	77.4	36.7	69.3
		(25)	(19)	(24)	(19)	(24)	(20)
	High	35.3	77.7	43.1	78.6	32.4	68
		(24)	(20)	(24)	(19)	(24)	(24)

Table 3
The Effect of the Rate of Technological Change on Wages
Workers in Manufacturing Industries, 1979-93
Industry Random Effects Regressions Results

Measure of Technological Change♠	All Workers	Production Workers	Non-Production Workers
Investment in Computers (87)	.026 (1.86)	.024 (1.25)	-.008 (.88)
Use of Patents	.023 (1.92)	.013 (1.43)	.027 (1.53)
Investment in R&D	.012 (1.31)	.015 (1.78)	.029 (4.48)
Percentage of Scientists & Engineers	.060 (4.19)	.045 (2.71)	.073 (4.22)
Jorgenson TFP (77-87)	.037 (3.11)	.021 (2.07)	.050 (4.05)
NBER TFP (77-87)	.012 (.68)	.012 (.64)	.007 (1.02)

♠ The other variables included in the regressions are marital status, race, sex, schooling dummies, if lives in an SMSA, labor market experience (and its square), tenure with employer (and its square), union membership, if works in durables, industry unemployment rate, industry means of job destruction and construction, and year dummies.

Absolute statistics are in parentheses.

Table 4
The Effect of the Rate of Technological Change on Wages
Workers in Manufacturing Industries, 1979-93
Industry Random Effects Regressions Results
Controlling for Standardized AFQT Scores

Measure of Technological Change♠	All Workers	Production Workers	Non-Production Workers
Investment in Computers (87)	.018 (1.29)	.014 (.75)	.003 (.23)
Use of Patents	.015 (1.37)	.010 (1.11)	.017 (1.04)
Investment in R&D	-.011 (1.04)	.011 (1.53)	.026 (3.69)
Percentage of Scientists & Engineers	.053 (3.72)	.041 (2.42)	.071 (4.35)
Jorgenson TFP (77-87)	.033 (2.70)	.020 (1.84)	.044 (4.27)
NBER TFP (77-87)	.011 (.60)	.010 (.52)	.009 (.67)

♠ See Table 3 for a list of other variables that are included in the regressions (in addition to the AFQT scores).

Absolute statistics are in parentheses.

Table 5
The Effect of the Rate of Technological Change on Wages
Workers in Manufacturing Industries, 1979-93
Individual Fixed Effects Regressions Results

Measure of Technological Change♠	All Workers	Production Workers	Non-Production Workers
Investment in Computers (87)	.006 (.96)	.011 (1.58)	-.019 (1.31)
Use of Patents	.003 (.38)	.001 (.14)	.002 (.18)
Investment in R&D	.003 (.44)	-.000 (.03)	-.000 (.05)
Percentage of Scientists & Engineers	.025 (4.68)	.017 (2.82)	.034 (2.80)
Jorgenson TFP (77-87)	.009 (1.43)	.017 (2.47)	-.014 (1.00)
NBER TFP (77-87)	-.005 (.91)	-.004 (.57)	-.018 (1.42)

♠ See Table 3 for a list of other variables that are included in the regressions.

Absolute statistics are in parentheses.

Table 6

Frequency of Industry changes

I. Using 83 industrial categories.

Years observed in the sample	No. of observations	Number of industry changes 0	1	2	3	4	5	6	7	8	9	10
1	1487	1										
2	694	.48	.52									
3	493	.34	.37	.28								
4	366	.33	.28	.28	.11							
5	273	.30	.22	.24	.17	.06						
6	234	.29	.2	.21	.15	.11	.05					
7	193	.20	.19	.20	.24	.13	.04	.01				
8	151	.22	.17	.19	.21	.10	.07	.05	.01			
9	93	.25	.11	.25	.10	.14	.10	.04	.02	-		
10	99	.24	.11	.20	.14	.14	.07	.06	.03	-	-	
11	101	.25	.11	.16	.12	.13	.16	.07	.01	-	-	-
12	66	.26	.12	.12	.08	.11	.12	.12	.04	-	.02	.02
13	46	.11	.17	.11	.15	.15	.13	.04	.09	.02	.02	-
14	35	.20	.17	.14	.09	.06	.11	.17	.03	-	-	-
15	12	.33	.08	-	.08	.08	.25	.17	-	-	-	-

II. Using 20 industrial categories.

Years observed in the sample	No. of observations	Number of industry changes 0	1	2	3	4	5	6	7	8	9	10
1	1487	1										
2	694	.55	.45									
3	493	.42	.36	.22								
4	366	.43	.27	.23	.07							
5	273	.39	.22	.23	.12	.04						
6	234	.37	.25	.20	.09	.06	.04					
7	193	.30	.21	.19	.17	.11	.03	.01				
8	151	.33	.19	.17	.15	.08	.05	.03	.01			
9	93	.37	.16	.18	.06	.12	.10	.01	-	-		
10	99	.35	.08	.20	.15	.11	.05	.04	.01	-	-	
11	101	.41	.13	.14	.15	.06	.09	.03	-	-	-	-
12	66	.36	.12	.09	.11	.15	.03	.09	.02	-	.03	-
13	46	.28	.15	.15	.04	.13	.11	.02	.11	-	-	-
14	35	.26	.20	.23	.06	.06	.11	.06	-	-	-	.03
15	12	.58	.17	-	.08	.08	-	.08	-	-	-	-

Table 7
Individual Premium or Industry Premium?
"Two Stages Double Fixed Effects Regressions"
Second Stage Estimation Results

Measure of Tech. Change♠	Individual Premium			Industry Premium		
	All Workers	Production Workers	Non-Prod. Workers	All Workers	Production Workers	Non-Prod. Workers
Investment in Computers (87)	.021	.007	.049	.020	.022	-.017
	(3.50)	(1.04)	(4.71)	(1.47)	(1.35)	(.78)
Use of Patents	.056	.040	.052	-.006	-.008	-.002
	(9.53)	(6.04)	(5.20)	(.34)	(.36)	(.15)
Investment in R&D	.033	.005	.045	.032	.034	.003
	(5.74)	(.77)	(6.78)	(8.22)	(7.08)	(.68)
% of Scientists & Engineers	.070	.044	.096	.025	.031	.008
	(11.1)	(6.31)	(9.73)	(3.94)	(3.46)	(.76)
Jorgenson TFP (77-87)	.021	.001	.066	-.007	-.006	-.001
	(3.43)	(.16)	(6.70)	(.34)	(.24)	(.10)
NBER TFP (77-87)	.010	.000	.023	-.002	-.005	-.010
	(1.65)	(.03)	(2.00)	(.15)	(.35)	(.34)

♠ The variables included in the first stage regression are listed in Table 3. In the second stage regressions we control for sex and race in the individual level regressions.

Reported are the coefficients of the partial correlation between the estimated individual/industry premium (after controlling for individual and industry fixed effects in the first stage regression) and the technological change variable. Absolute t statistics are in parentheses. See the text for more details.

Table 8
The Effect of the Rate of Technological Change on Wages
Interacted with Years of Schooling
Workers in Manufacturing Industries, 1979-93
Industry Random Effects Regressions Results

Measure of Technological Change♠	All Workers	Production Workers	Non-Production Workers
Investment in Computers (87)	.006	-.001	.004
	(3.49)	(.64)	(1.28)
Use of Patents	.010	.005	.007
	(6.52)	(2.50)	(2.43)
Investment in R&D	.006	.036	-.050
	(1.32)	(.53)	(.92)
Percentage of Scientists & Engineers	.012	.002	.013
	(7.33)	(.83)	(4.42)
Jorgenson TFP (77-87)	.001	-.009	.010
	(.68)	(2.03)	(2.52)
NBER TFP (77-87)	.004	.001	.003
	(2.82)	(.57)	(.87)

♠ See footnotes to Table 3.

Reported are the coefficients of the interaction between years of schooling and the industry rate of technological change. Absolute t statistics are in parentheses.

Table 9
The Effect of the Rate of Technological Change on Wages
Interacted with Years of Schooling
Workers in Manufacturing Industries, 1979-93
Individual & Industry Fixed Effects Regressions Results

Measure of Technological Change♠	All Workers	Production Workers	Non-Production Workers
Investment in Computers (87)	-.005 (1.03)	-.005 (.68)	-.001 (.11)
Use of Patents	-.004 (.90)	-.003 (.47)	-.003 (.32)
Investment in R&D	-.004 (1.37)	-.002 (.66)	-.000 (.03)
Percentage of Scientists & Engineers	-.011 (3.7)	-.012 (2.83)	-.008 (1.35)
Jorgenson TFP (77-87)	-.006 (1.43)	-.013 (2.06)	.005 (.58)
NBER TFP (77-87)	.003 (.75)	.002 (.27)	.006 (.73)

♠ See footnotes to Table 3.

Reported are the coefficients of the interaction between years of schooling and the industry rate of technological change. Absolute t statistics are in parentheses.

Table 10
Individual Premium or Industry Premium?
Interaction of Technological Change and Schooling
"Two Stages Double Fixed Effects Regressions"
Second Stage Estimation Results

Measure of Tech. Change♠	Individual Premium			Industry Premium		
	All Workers (1)	Production Workers (2)	Non-Prod. Workers (3)	All Workers (4)	Production Workers (5)	Non-Prod. Workers (6)
Investment in Computers (87)	.013 (4.71)	.013 (3.76)	.007 (1.48)	-.018 (.97)	-.042 (1.33)	-.012 (.40)
Use of Patents	.010 (3.96)	.006 (1.91)	.006 (1.41)	.000 (.01)	.038 (.05)	.015 (.57)
Investment in R&D	.010 (3.87)	-.002 (.60)	.009 (3.13)	.006 (1.41)	-.001 (.08)	.003 (.52)
% of Scientists & Engineers	.024 (8.74)	.011 (3.09)	.026 (6.20)	-.015 (1.41)	-.002 (.09)	-.015 (.78)
Jorgenson TFP (77-87)	.011 (4.02)	.010 (2.90)	.008 (1.75)	.022 (.54)	.080 (1.07)	-.010 (.33)
NBER TFP (77-87)	.001 (.31)	-.002 (.77)	.001 (.12)	.036 (1.34)	.027 (.53)	-.015 (.29)

♠ See footnotes to Table 3.

Reported are the coefficients of the partial correlation between the estimated premium of the individual/industry premium (after controlling for individual and industry fixed effects in the first stage regression) and the interaction between schooling and technological change. Absolute t statistics are in parentheses. See the text for more details.

Appendix A
Data

1. General

The data are from 1979-1993 National Longitudinal Surveys of Labor Market Experience of youth age 14-21 in 1979 (NLSY). Additional data are obtained from the NLSY work history file. The NLSY work history file contains primarily employment related spell data constructed from the main NLSY file. Both files are available in cd-rom format. Many questions are asked with regards to the time since the last survey. For the first survey (1979), the questions, in most cases, are with regards to the time period since January 1, 1978.

In addition to the NLSY, we use several other data sources that serve as alternative measures of industry rates of technological change. These data are described in Section II.

2. The Sample

The NLSY is based on a sample of 12,686 young people ages 14-22 who have been interviewed yearly since 1979. Not all individuals were interviewed each year. The first observation for an individual to be included in our sample is the first survey in which the main activity reported for the week prior to the survey (ACTIV) is working (1), with a job, but not working (2), or looking for a job (3). Following that, an individual is included in the sample as long as he is interviewed (even if leaving the labor market).

In all the regression analyses the following additional restrictions are imposed: The number of weeks worked since the last survey is at least 15, and the person has worked at least for half of the weeks that elapsed since the previous survey.[31]

The panel is unbalanced. The number of observations per individual varies.

3. Some details on specific variables

wages: We use the log of the hourly rate of pay on the current/most recent job. When individuals did not report their labor income in hourly rate, the reported income was divided by the time unit in which they were paid. The wage deflator used in the fixed-weighted price index for gross national product, 1987 weights, personal consumption expenditures (1979=.658, 1987=1, 1993=1.281).

Weeks between surveys: The number of weeks between surveys ranges between 26 and 552 weeks. The large numbers are the results of individuals not being surveyed for several years.
Industry Codes: We use the original reports of 3 digit industry codes, using the 1970 census classification. The different measure of technological change that we use are based on different industry classifications (e.g., SIC codes), and different levels of aggregation. We did the maximum matching between those measures and the reported industry in the NLSY. Details on the matching of each of the measures is available from the authors.

Schooling: Number of completed years of schooling, truncated at 18. If the variable is missing, we use the previous survey report.

[31]This last restriction is not imposed on observations from the 1979 survey.

Industry Unemployment Rate:
Annual male unemployment rate in the industry, 66-83 issues of employment and earnings. There are 31 categories.

Intelligence Measures:
During 1980, NLSY respondents were subjects in an effort of the U.S. Department of Defense and Military Services to update the norms of the *Armed Services Vocational Aptitude Test (ASVAB)*. A total of 11,914 civilian and military NLSY respondents (94% of the original 1979 sample) completed this test.
The ASVAB consists of a battery of ten tests that measure knowledge and skill in the following areas: (1) general science; (2) arithmetic reasoning; (3) word knowledge; (4) paragraph composition; (5) numerical operations; (6) coding speed; (7) auto and shop information; (8) mathematics knowledge; (9) mechanical comprehension; and (10) electronics information. The following information is available for each youth who participated in the Profiles testing: individual number correct or raw scores, scale scores, standard errors for each of the separate sections.
Two approximate and unofficial AFQT (Armed Forces Qualifying Test) test scores are computed from select sections of the ASVAB tests: AFQT81 and AFQT89. The AFQT is supposedly a general measure of trainability and a primary criteria of enlistment eligibility for the Armed Forces.

Appendix B
Indices for Industry Rates of Technological Change

We use six measures of technological change: (1) the total factor productivity growth series calculated by Jorgenson; (2) the NBER total factor productivity series; (3) the Census of Manufactures' data on investment in computers; (4) the R&D/sales ratio in the industry as reported by the NSF; (5) the number of patents used in the industry; and (6) the ratio of scientific and engineering employment to total employment calculated from the 1979 and 1989 CPS by Allen (1996).

The **Jorgenson total factor productivity series**, which is available through 1991, has been used extensively in previous research (e.g. Bartel and Sicherman, 1993, 1995; Lillard and Tan, 1986; Tan, 1989; Mincer and Higuchi, 1988; and Gill, 1990). In using the Jorgenson productivity growth series, technological change is measured as the rate of change in output which is not accounted for by the growth in the quantity and quality of physical and human capital. One problem with this approach is that technological change may not be the only cause of productivity growth. Other factors, such as fluctuations in capacity utilization and non-constant returns to scale, are also likely to affect productivity growth. In order to control for these effects, the empirical analysis includes controls for the industry unemployment rate and the rates of entry and exit of firms in the industry. The main advantage of the Jorgenson series is that changes in the quality of the labor input are carefully used to correctly measure net productivity growth. Also, the new Jorgenson series utilizes the BEA constant-quality price deflator; the earlier series underestimated productivity growth in high-tech industries (e.g. the computer industry) since quality improvements were not incorporated into the output price index. The major disadvantage of the Jorgenson series is that the data are reported for only 22 broad industry categories in the manufacturing sector, equivalent to two-digit SIC categories.

The **NBER productivity** database contains annual information on total factor productivity growth for 450 manufacturing industries for the time period 1958 through 1989.
The advantage of the NBER database over the Jorgenson database is its narrow industry categories yielding data on approximately 100 three-digit industries in manufacturing. The disadvantage is that the productivity growth measure was not adjusted for changes in labor quality.

The third measure of technological change that we use is **investment in computers**. During the 1980s, there was an enormous growth in the amount of computer resources used in the workplace. Indeed, it has been argued (see Bound and Johnson, 1992) that the most concrete example of technological change in the 1980s was the "computer revolution". Hence a more direct measure of technological change in the workplace may be the extent to which firms invest in information technology. Using data from the 1987 Census of Manufactures, we calculate the ratio of investment in computers to total investments. Berman, Bound and Griliches (1994) show this measure is a good proxy for technological change in an industry. The advantages of the computer investment measure are that (1) unlike data on R&D expenditures, it measures **use** (not production) of an innovation and (2) it is available for several hundred four-digit industries in the manufacturing sector, which reduces to approximately 100 three-digit industries for the NLSY sample.

The fourth proxy for technological change is the **ratio of company R&D funds to net sales** reported by the National Science Foundation (1993) for industries in the manufacturing sector. The advantage of this variable is that it is a direct measure of innovative activity in the industry, but as indicated above, the innovative activity refers only to the industry in which the innovation originates, not the industry where the innovation is actually used.

The fifth measure of technological change is the **number of patents used** in two-digit manufacturing industries. Patent data are generally collected by technology field and have not been available at the industry level. Using Canadian data, Kortum and Putnam (1995) presented a method for predicting patents by industry using the widely available information on the distribution of patents across technology fields. Kortum and Lach (1995) produced a similar series for the U.S. which we use here; their data are available for the time period 1957-1983. Since the likelihood of an innovation being patented has differed historically across technology fields, and, hence, across industries, we control for these systematic differences by constructing the following variable for each two-digit manufacturing industry: the number of patents used by the industry during the years 1980 through 1983 (which are closest to our starting year, 1987), divided by the number of patents used by the industry during the 1970s. The main advantage of proxying technological change by "use of patents" is that, like the computer investment variable discussed earlier, it measures the direct **use** of innovations. The disadvantage is that the data are only reported for twenty manufacturing industries. Lach (1995) shows that this measure is highly correlated with TFP growth.

The sixth measure of technological change is the **ratio of scientific and engineering employment to total employment** calculated from the 1979 and 1989 CPS by Allen (1996). Allen shows that this measure is highly correlated with the R&D to sales ratio in the industry. Like the computer investment and patent variables, it refers to the industry where the "innovation" is used, not produced. But, as Allen points out, since scientists and engineers are more highly paid than other college graduates, the wage impact of the technological change resulting from increased innovative activity may be overstated when this measure is used.

Indices for Industry Rates of Technological Change

I. Investment in computers as a share of total investment (1987)

CPS	Industry	Share of Investment	CPS	Industry	Share of Investment
189	Electronic computing equipment	.230	137	Pottery & related products	.051
207	Radio, T.V. & communication equipment	.189	378	Miscellaneous petroleum & coal products	.050
188	Office & accounting machines	.176	309	Floor coverings, except hard surface	.047
239	Scientific & controlling instruments	.175	159	Screw machine products	.046
397	Leather products, except footwear	.157	238	Cycles & misc. transportation equipment	.042
227	Aircraft & parts	.141	199	Household appliances	.041
338	Newspaper publishing & printing	.138	138	Misc. nonmetallic mineral & stone products	.038
258	Ordnance	.138	279	Grain-mill products	.038
198	Not specified machinery	.135	148	Primary aluminum industries	.038
229	Railroad locomotives	.132	169	Not specified metal industries	.038
209	Not specified electrical machinery, equipment, and supplies	.121	358	Soaps & cosmetics	.037
			178	Farm machinery & equipment	.037
339	Printing, publishing, & allied industries, except newspapers	.109	379	Rubber products	.037
			269	Dairy products	.037
257	Not specified professional equipment	.109	308	Dyeing & finishing textiles, except wool & knit goods	.036
197	Machinery, except electrical	.103			
398	Not specified manufacturing industries	.099	149	Other primary iron & steel Industries	.034
389	Footwear, except rubber	.097	278	Canning&preserving fruits/vegetables/sea foods	.033
259	Miscellaneous manufacturing industries	.092	128	Structural clay products	.031
187	Metalworking machinery	.090	337	Paperboard containers & boxes	.030
208	Electrical machinery, equipment & supplies	.089	387	Miscellaneous plastic products	.028
228	Ship & boat building & repairing	.087	369	Not specified chemicals & allied products	.027
119	Glass & glass products	.084	307	Knitting mills	.027
357	Drugs & medicines	.083	297	Misc. food preparation & kindred products	.026
248	Photographic equipment & supplies	.079	108	Sawmills, planing mills & mill work	.025
179	Construction & material handling machines	.077	368	Miscellaneous chemicals	.025
247	Optical & health services supplies	.076	329	Miscellaneous paper & pulp products	.024
299	Tobacco manufactures	.073	289	Beverage industries	.024
177	Engines & turbines	.072	367	Agricultural chemicals	.023
388	Tanned, curried, & finished leather	.072	347	Industrial chemicals	.023
158	Fabricated structural metal products	.067	298	Not specified food industries	.023
359	Paints, varnishes, & related products	.065	167	Metal stamping	.023
327	Miscellaneous fabricated textile products	.065	287	Bakery products	.020
319	Apparel & accessories	.065	219	Motor vehicles & motor vehicle	.020
237	Mobile dwellings & campers	.062	318	Miscellaneous textile mill products	.020
249	Watches, clocks, & clockwork-operated devices	.061	348	Plastics, synthetics & resins, except fibers	.018
168	Miscellaneous fabricated metal products	.059	139	Blast furnaces, steel works, rolling & finishing mills	.018
157	Cutlery, hand tools, & other hardware	.055			
118	Furniture & fixture	.053	377	Petroleum refining	.016
			328	Pulp, paper, & paperboard mills	.015
			147	Other primary iron & steel industries	.014
			288	Confectionery & related products	.014
			268	Meat products	.014
			127	Cement, concrete, gypsum & plaster products	.012
			317	Yarn, thread, & fabric mills	.012
			109	Miscellaneous wood products	.007
			349	Synthetic fibers	.002
			107	Logging	.000

II. Jorgenson's TFP

1	Non-electrical machinery	.025861	11	Instruments	.009004
2	Petroleum refining	.020192	12	Paper & allied products	.008890
3	Electrical machinery	.019077	13	Lumber & wood products	.008340
4	Apparel & other textile	.016959	14	Fabricated metal	.006900
5	Chemicals & allied	.016570	15	Leather	.006687
6	Textile mill products	.015416	16	Stone, clay & glass	.004865
7	Miscellaneous Manufacturing	.014244	17	Primary metals	.002812
8	Rubber & plastic	.012264	18	Food & kindred products	.002277
9	Other transportation equipment	.011727	19	Tobacco manufactures	-.001611
10	Furniture & fixtures	.010903	20	Motor vehicles	-.002123
			21	Printing & publishing	-.005576

III. TFP, NBER Dataset, Means over 1977-87

1	Electronic computing equipment	.17557
2	Not specified machinery	.04299
3	Synthetic fibers	.03719
4	Ordinance	.03564
5	Miscellaneous textile mill products	.03456
6	Grain-mill products	.02947
7	Radio, T.V., & communication equipment	.02815
8	Petroleum refining	.02704
9	Screw machine products	.02677
10	Not specified chemicals & allied products	.02449
11	Confectionery & related products	.02369
12	Miscellaneous plastic products	.02338
13	Knitting mills	.02100
14	Optical & health services supplies	.01840
15	Not specified electrical machinery, equipment, & supplies	.01782
16	Floor coverings, exc. hard surface	.01733
17	Agricultural chemicals	.01731
18	Rubber products	.01726
19	Miscellaneous fabricated textile products	.01714
20	Household appliances	.01540
21	Beverage industries	.01492
22	Industrial chemicals	.01460
23	Yarn, thread, & fabric mills	.01448
24	Sawmills, planing mills,a nd mill work	.01423
25	Paints, varnishes, & related products	.01346
26	Pulp, paper, & paperboard mills	.01342
27	Apparel & accessories	.01313
28	Plastics, synthetics & resins, exc. fibers	.01288
29	Structural clay products	.01273
30	Logging	.01255
31	Cement, concrete, gypsum, & plaster products	.01193
32	Electrical machine, equipment, & supplies, n.e.c.	.01168
33	Miscellaneous wood products	.01124
34	Miscellaneous chemicals	.01021
35	Dairy products	.01015
36	Bakery products	.00957
37	Other primary conferrous industries	.00953
38	Furniture & fixtures	.00882
39	Fabricated structural metal products	.00835
40	Dyeing & finishing textiles, exc. wool & knit goods	.00792
41	Printing, publishing, & allied industries, except newspapers	.00780
42	Blast furnaces, steel works, rolling & finishing mills	.00728
43	Not specified professional equipment	.00710
44	Office & accounting machines	.00655
45	Not specified metal industries	.00630
46	Photographic equipment & supplies	.00609
47	Miscellaneous paper & pulp products	.00516
48	Other primary iron & steel industries	.00489
49	Miscellaneous fabricated metal products	.00459
50	Canning & preserving fruits vegetables & sea fd	.00423
51	Footwear, except rubber	.00415
52	Miscellaneous petroleum & coal products	.003577
53	Mobile dwellings & campers	.003540
54	Meat products	.003251
55	Pottery & related products	.003249
56	Leather products, exc. footwear	.003090
57	Glass & glass products	.003054
58	Cutlery, hand tools, & other hardware	.001652
59	Paperboard containers & boxes	.001114
60	Not specified food industries	.001097
61	Not specified manufacturing industries	.000785
62	Miscellaneous manufacturing industries	.000784
63	Scientific & controlling instruments	.000705
64	Watches, clocks, & clock-work-operated devices	.000630
65	Miscellaneous food preparation & kindred	-.000138
66	Miscellaneous nonmetallic mineral & stone	-.000595
67	Drugs & medicines	-.000653
68	Motor vehicles & motor vehicle equipment	-.001119
69	Primary aluminum industries	-.001193
70	Cycles & miscellaneous transportation equipment	-.001255
71	Metal stamping	-.001359
72	Aircraft & parts	-.002037
73	Machinery, exc. electrical, n.e.c.	-.002936
74	Ship & boat building & repairing	-.003132
75	Soaps & cosmetics	-.003367
76	Newspaper publishing & printing	-.004294
77	Metalworking machinery	-.006743
78	Engines & turbines	-.009734
79	Farm machinery & equipment	-.017799
80	Railroad locomotives & equipment	-.020352
81	Construction & material handling machines	-.020607
82	Tanned, curried, & finished leather	-.029667
83	Tobacco manufactures	-.038326

IV. Company and other (except Federal) R&D funds as a percent of net sales in R&D-performing manufacturing companies, means over 1984-1990

Industry	Mean R&D
Office, computing, & accounting machines	12.5714
Drugs & medicines	8.7429
Scientific & mechanical measuring instruments	8.5000
Electronic components	8.2143
Instruments	7.3286
Communication equipment	5.2571
Industrial chemicals	4.2714
Motor vehicles & motor vehicles equipment	3.4143
Radio & TV receiving equipment	3.3857
Other chemicals	3.3429
Other machinery, except electrical	2.8714
Other transportation equipment	2.3143
Stone, clay, & glass products	2.2714
Other electrical equipment	2.2286
Rubber products	1.7286
Nonferrous metals & products	1.3143
Fabricated metal products	1.2000
Other Manufacturing Industries	1.0857
Stone, clay, & glass products	1.0857
Professional & scientific instruments	1.0857
Petroleum refining & extraction	0.9286
Paper & allied products	0.7286
Lumber, wood products, & furniture	0.6857
Ferrous metals & products	0.6000
Food, kindred, & tobacco products	0.5286
Textiles & apparel	0.4429

V. Patents Used by Industry (total of 1980-83 divided by 1970-79)

Office & computing machines	.4366
Communication & electronics	.4049
Petroleum refineries & extractions	.3962
Other electrical equipment	.3779
Prof. & scientific instruments	.3581
Other manufacturing	.3572
Drugs	.3528
Stone, clay & glass products	.3478
Transportation equipment	.3418
Industrial chemicals	.3418
Fabricated metals products	.3414
Other nonelectrical machinery	.3386
Primary metals products	.3301
Rubber & plastics products	.3299
Other chemicals	.3280
Paper products	.3275
Aircraft & missiles	.3199
Food & kindred products	.3176
Lumber & furniture	.3166
Textile & apparel	.2998

VI. Share of Scientists and Engineers in Different Industries

Industry	Share in 1989
Transportation Equipment	.116
Chemicals	.109
Electrical Equipment	.108
Federal Public Administration	.104
Non-electrical Machinery	.103
Other professional services	.091
Instruments	.085
Utilities	.074
Business services	.070
Mining	.068
Petroleum	.065
Communication	.061
State Public Administration	.044
Fabricated Metals	.039
Primary Metals	.033
Paper	.031
Stone, Clay	.028
Rubber	.027
Construction	.020
Agriculture	.017
Textile	.017
Insurance and Real Estate	.016
Food and Tobacco	.0157
Banking and Finance	.012
Wholesale	.012
Miscellaneous	.011
Leather	.011
Local Public Administration	.011
Education	.011
Transportation	.010
Lumber	.009
Hospitals	.008
Furniture	.008
Entertainment	.006
Printing	.006
Postal services	.005
Welfare and Religious	.004
Repair services	.004
Medical services	.004
Other retail trade	.0024
Personal services	.002
Apparel	.002
Eating and Drinking	.0004
Private Household workers	.0

VII. The Correlation Between the Different Measures of Technological Change

	Jorgenson TFP	NBER TFP	R&D to Sales	Patents
NBER TFP	.31			
R&D to Sales	.47	.65		
Use of Patents	.35	.65	.71	
Investment in Computers	.40	.52	.65	.65

Since each measure is based on a different industrial classification, we use the sample weights for the correlations.

Appendix C
Workers in Manufacturing Industries, 1979-93
Industry Random Effects Regressions Results
a Sample of all Coefficients Estimates
(Dependent variable: Log of Real Hourly Wage)

Independent Variables	All Workers	Production Workers	Non-Production Workers
Marital Status (married=1)	.0776	.0879	.0530
	(10.2)	(9.88)	(3.75)
Race (1=non-white)	-.068	-.0600	-.0624
	(8.74)	(6.71)	(4.21)
Sex (1=female)	-.1729	-.1924	-.1808
	(21.7)	(18.7)	(13.4)
Years of Schooling (excluded 12)			
1-8	-.2241	-.2114	-.2603
	(12.1)	(10.8)	(4.85)
9-11	-.1096	-.0913	-.1478
	(11.1)	(8.56)	(5.95)
13-15	.14316	.07979	.16894
	(12.7)	(5.43)	(9.16)
16	.44408	.24304	.43744
	(29.9)	(7.17)	(20.6)
17+	.62880	.31904	.62661
	(24.9)	(4.70)	(19.4)
Lives in an SMSA	.12004	.08846	.17904
	(14.2)	(9.32)	(10.3)
Market Experience	.03112	.01757	.05219
	(8.05)	(3.83)	(6.93)
Market Experience^2	-.0008	-.0001	-.0018
	(4.44)	(0.73)	(4.59)
Tenure	.05760	.06167	.04745
	(16.4)	(14.9)	(7.32)
Tenure^2	-.0028	-.0032	-.0020
	(9.51)	(9.27)	(3.73)
Union Membership	.11430	.14106	.06483
	(12.8)	(14.7)	(2.97)
Durables	.05038	.07907	.01995
	(2.77)	(3.56)	(1.04)
Industry unemployment	.00246	.00279	.00405
	(0.94)	(0.51)	(0.00)
Industry Job Creation (80-88)	-.0264	-.0232	-.0182
	(4.84)	(3.48)	(2.73)
Industry Job Destruction (80-88)	.00718	.00538	.0273
	(1.32)	(0.859)	(3.97)

(Appendix Table C - Cont.)

Independent Variables	All Workers	Production Workers	Non-Production Workers
Year dummies (excluded 1979)			
1980	-.0639	-.0641	.01356
	(2.52)	(2.37)	(0.22)
1981	-.0891	-.0814	-.0174
	(3.58)	(3.03)	(0.30)
1982	-.0963	-.0863	.04926
	(3.36)	(2.71)	(0.80)
1983	-.1429	-.1285	-.0121
	(5.07)	(4.07)	(0.20)
1984	-.1879	-.1632	-.1428
	(7.82)	(6.10)	(2.58)
1985	-.1626	-.1498	-.0780
	(6.55)	(5.50)	(1.35)
1986	-.1761	-.1729	-.0718
	(6.96)	(6.22)	(1.22)
1987	-.1548	-.1671	-.0481
	(6.10)	(5.87)	(0.83)
1988	-.1370	-.1440	-.0526
	(5.22)	(4.88)	(0.89)
1989	-.1634	-.1868	-.0663
	(6.12)	(6.21)	(1.11)
1990	-.1983	-.2338	-.0625
	(7.21)	(7.55)	(1.02)
1991	-.1986	-.2171	-.0816
	(6.77)	(6.50)	(1.29)
1992	-.2196	-.2337	-.1026
	(7.23)	(6.76)	(1.58)
1993	-.2127	-.2354	-.0795
	(6.86)	(6.67)	(1.20)
Tech. Change	.02655	.02403	-.0078
	(1.86)	(1.25)	(0.88)
Constant	2.0265	2.0806	1.7748
	(29.6)	(25.1)	(19.6)
# of observations	13061	8704	4357

Appendix D

Industry Random Effects Estimation:

$$Y_{it} = X_{it}\beta + u_i + e_{it} \ , \quad i=1,\ldots,I \ ; \quad t=1,\ldots T \tag{9}$$

where we assume that:

$$X_{it} \perp u_i \ ,$$
$$X_{it} \perp \epsilon_i \ ,$$

and

$$u_{it} \perp \epsilon_i \ .$$

Then, the GLS estimation for β is:

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1}(X'\Omega^{-1}Y) = [(\Gamma'X)'(\Gamma'X)]^{-1}[(\Gamma'X)'(\Gamma'y)] \tag{10}$$

where:

$$\Gamma = \Omega^{-1/2}$$
$$\Gamma = I_? - \Theta I_I \otimes 1_{T\times T}$$

and

$$\Theta = \frac{\sigma_\epsilon}{\sqrt{T\sigma_u^2 + \sigma_\epsilon^2}} \ .$$

To calculate σ_ϵ^2, we run the fixed effects (FE) regression:

$$(y_{it} - \bar{y}_i) = (X_{it} - \bar{X}_i)\beta + (\epsilon_{it} - \bar{\epsilon}_i) \tag{11}$$

and calculate, from the residual e_{it}, $\hat{\sigma}_\epsilon^2 = \frac{1}{N(T-1)}\sum e_{it}^2$.

To calculate $\sqrt{T\sigma_u^2 + \sigma_\epsilon^2}$ we calculate the BE ("between") regression:

$$\bar{y}_i = \bar{X}_i\beta + v_i + \bar{\epsilon}_i \tag{12}$$

and calculate from the residual, e_i, $\widehat{\sqrt{T\sigma_u^2 + \sigma_\epsilon^2}} = T\sqrt{\frac{1}{N}\sum e_i^2}$.

This gives us $\hat{\theta}$, which we use to calculate $\Gamma' x$, which happens to be:

$$\Gamma' x = x_{it} - \theta\bar{x}_i \qquad \Gamma' y = y_{it} - \theta\bar{y}_i$$

and then run OLS on the transformed data.

Two Stage Fixed Effects:

$$y_{it} = X_{it}\beta + u_i + \epsilon_{it} \quad i=1,\ldots,I \ ; \ t=1,\ldots,T \quad , \tag{1}$$

where $X_{it} \perp \epsilon_i$, and

$$u_i = Z_i^{'}\delta + v_i \tag{2}$$

So, we use OLS for the first stage with industry dummies (this is the same as fixed effects) and set $\hat{u}_i$.
From (2), we can write:

$$\hat{u}_i = Z_i^{'}\delta + \omega_i \tag{3}$$

where $\omega_i = (\hat{u}_i - u_i) + v_i$, and $E(\omega_i \omega_i^{'}) = \Omega$.

Assuming that $\hat{u}_i$'s are independent, we can calculate the GLS estimator for δ:

$$\hat{\delta}_{GLS} = (Z'\Omega^{-1}Z)Z'\Omega^{-1}Z = [(\Gamma'Z)'(\Gamma'Z)]^{-1}[(\Gamma'Z)'(\Gamma'\hat{u})] \tag{4}$$

where $\Gamma = \Omega^{-1/2} = diag(E[\,|(u_i - \hat{U}_i)| + |v_i|\,])$.

We can run OLS on (3) and set, from the residual, $s_\omega^2 = \frac{1}{I}\sum e_i^2$.

We know that $\sigma_\omega^2 = \sigma_v^2 + \frac{1}{T}\sigma_u^2$. Since we can calculate s_u^2 directly, this gives us s_v^2. Thus, we can calculate:

$$\hat{\Gamma}'\hat{u} = \hat{u}\left(\frac{1}{\sqrt{\sigma_v^2 + \frac{1}{T}\sigma_u^2}}\right) \quad , \quad \hat{\Gamma}'Z = Z\left(\frac{1}{\sqrt{\sigma_v^2 + \frac{1}{T}\sigma_u^2}}\right) . \tag{5}$$

Figure 1: Average Industry Wages vs. Industry Rates of Technological Change

1970 two-digit industry reported

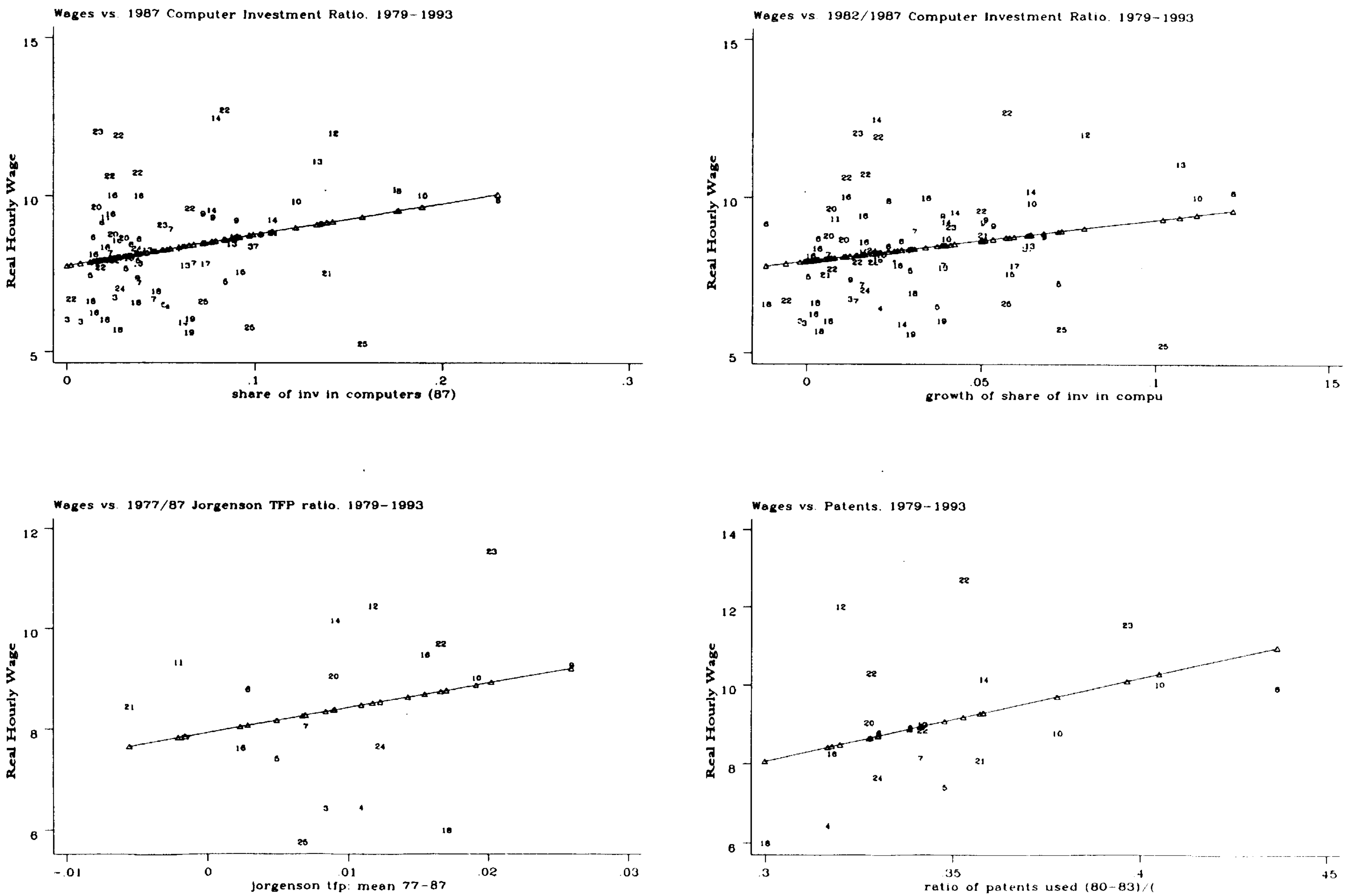

Figure 1 (ct'd): Average Industry Wages vs. Industry Rates of Technological Change

1970 two-digit industry reported