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# TECHNICAL CHANGE, LEARNING, AND WAGES

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## ABSTRACT

This paper examines the relationship between technological change and wages using pooled cross-sectional industry-level data and several alternative indicators of the rate of introduction of new technology. Our main finding is that industries with a high rate of technical change pay higher wages to workers of given age and education, compared to less technologically advanced industries. This is consistent with the notion that the introduction of new technology creates a demand for learning, that learning is a function of employee ability and effort, and that increases in wages are required to elicit increases in ability and effort. A related finding is that the wages of highly educated workers (especially recent graduates) relative to those of less educated workers are highest in technologically advanced industries; this is consistent with the notion that educated workers are better learners.

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## I. Introduction

In a previous paper (Bartel and Lichtenberg (1987)) we investigated the effect of technological change on the education distribution of employment. We argued that the successful introduction of new technology requires significant learning on the part of employees, and hypothesized that highly educated employees enjoy a comparative advantage with respect to such on-the-job learning. This hypothesis implied that the "age" of a firm or industry's technology enters its cost-function non-neutrally, and that factor cost shares -- in particular, highly-educated labor's share in total cost -- should be functions of the age of technology. Our empirical results were consistent with this hypothesis. We found a significant inverse relationship at the industry level between the age of capital equipment -- a proxy for the age of technology -- and the share of highly educated workers in total employment or labor cost.

In this paper we examine the effect of technological change on the wage rate, holding constant employee education, age, and sex. We postulate that in order to satisfy the increased demand for learning by workers following the introduction of new technology, firms will find it expedient to pay higher wages to employees within given education and demographic groups. We test this hypothesis by estimating wage equations which include indicators of technical change on pooled, industry-level data.

In the next section we sketch a theory of technical change and learning that implies the existence of a link between wages and technical change. In Section III we briefly review previous theoretical and empirical research concerning the effect of technological change on wages. Section IV describes the econometric model and data used to test our hypothesis. Empirical results are presented and interpreted in Section V, and Section VI provides a summary and concluding remarks.

## II. Theoretical Framework

The replacement or modification of an existing technology by a new one represents a major "shock" to the production environment, and workers (and perhaps management as well) initially are very uncertain as to how they should modify their behavior. The transition from old to new technology results in job tasks and operating procedures which are not only different but, in the short run at least, less well-defined. Wells (1972, pp. 8-9) has argued, in the context of the "product life-cycle" model, that in its infancy "the manufacturing process is not broken down into simple tasks to the extent it will be later in the product's life." The introduction of new technology into a firm therefore creates a need or demand for learning on the part of the firm's employees.

We postulate that the rate at which an employee learns is a function of two variables: his or her ability and effort. Ability and effort are substitutes in the production of learning. As any teacher in a classroom setting knows, highly gifted (able) students may not perform any better than less gifted ones, if the latter work much harder.

The introduction of new technology, since it necessitates learning, results in an increase in demand for employee ability and effort. Both of these are scarce resources, which therefore have positive (shadow) prices attached to them.

As we have argued previously, a worker's ability to learn is an increasing function of his or her education, so that technical change will increase the relative demand for highly-educated workers. But even among workers with a given amount of education, there is likely to be considerable variance in ability. Due to their high demand for learning, firms undergoing technical change will want to employ the most talented people within education groups, as well as employing relatively highly educated workers.

Since learning is a function of effort as well as ability, employers introducing new technology will also seek to elicit high levels of effort from workers. We assume that workers prefer providing less effort to more effort, but that the firm can induce them to provide more effort by paying higher wages. There are two alternative possible justifications for this: compensating differentials, and efficiency wages. These differ according to whether or not the level of employee effort is costlessly observable to the firm. The compensating differentials argument implicitly assumes that the firm can monitor employee effort without cost, and that to induce workers to accept the greater disutility associated with higher effort, it needs to pay higher wages. The efficiency wage argument assumes that it is costly for the firm to monitor employee effort, and therefore that employees have the opportunity to shirk, but that their propensity to shirk is inversely related to the expected penalty of being detected a shirker. This expected penalty is the product of (a) the probability of being detected (a function of the firm's expenditures on monitoring employees), and (b) the penalty of being detected, assumed equal to the difference between the current wage and the opportunity wage. By paying a "wage premium" -- a wage in excess of the opportunity wage -- the firm can increase the expected penalty of being detected a shirker and hence reduce the extent of shirking. Whether or not effort is directly or costlessly observable to the firm, then, the firm can elicit greater effort by paying higher wages to workers of given ability.

To summarize our argument, the introduction of new technology creates a demand for learning, and a combination of employee ability and effort is required for learning to occur. To some extent an increase in demand for ability can be satisfied by hiring more educated workers, but even within education groups workers are quite heterogeneous with respect to ability. Employers instituting technical change will tend to employ the most able individuals with given amounts of education, and will have to pay higher wages to do so. Paying higher wages will also elicit higher levels of employee effort, which will contribute further to the successful introduction of new technology.

The major implication of our argument is that workers in firms or industries experiencing rapid technical change will tend to receive higher wages than workers with similar education and demographic attributes in other firms or industries. These wage differences are due to differences in both unobserved ability and effort. In our empirical work we test whether technology-related wage differentials exist, but we cannot, and do not attempt to, allocate these differentials into ability- and effort-related components.

If this hypothesis is correct, then it, in conjunction with our earlier findings, suggests that "high-tech" industries (industries experiencing rapid technical change) are high wage industries for two distinct reasons, which we may refer to as between-group and within-group. Our earlier paper indicated that the introduction of new technology increases the relative quantity of highly educated workers, who of course tend to receive the highest wages. Technological change therefore increases the average wage rate by increasing the employment share of high-wage workers. But the hypothesis we have discussed implies that technological change also increases wages <u>within</u> education groups, thus further raising the average wage rate.

A further issue is whether technology-related differences in the demand for learning should result in differences in the relative wage structure, e.g. the relative wages of different skill or occupational groups. Most efficiency wage theories do not address this issue because they assume there to be only a single type of labor. But Dickens and Katz (1987) have shown empirically that industry wage premia tend to be strongly positively correlated across occupations: <u>all</u> workers in better-paid industries tend to receive high wage premia. Akerlof and Yellen (1988) have constructed a theoretical model based on sociological equity and social exchange theories which may account for this finding. They postulate <u>two</u> types of labor, and that work effort is inversely related to the (between-group) <u>variance</u> of the wage distribution, on the grounds that "firms with less variance in their compensation will have more harmonious labor relations and thus achieve higher output per worker." (p. 45). Their theory implies that differential demand for effort would have little or no effect on relative wages; equity considerations would force managers in industries requiring substantial learning and effort to raise all wages more or less proportionately.

In sharp contrast, the model developed by Lazear (1981) implies that in the presence of costly monitoring increased demand for effort results in a <u>steeper age-earnings profile</u> but not necessarily in a higher present discounted value of earnings over the life cycle. According to Lazear's model, to induce employees not to shirk, the employer need pay them wage premia only towards the end of their careers, not throughout their careers. Indeed, the optimal wage policy is one of deferred compensation: young workers tend to be paid less than the value of their marginal product, old workers more. If, as we have postulated, industries experiencing rapid technical change have higher demand for effort, then the Lazear model suggests that these industries would exhibit steeper age-earnings profiles than other industries. The high-tech wage premium would be higher for older workers than it would be for younger workers; indeed, the premium for younger workers might even be negative.

The Lazear model is not the only model that suggests that the slope of an industry's age-earnings profile might be related to its rate of technical change. Such a relationship may also be implied by the theory of on-the-job training (a branch of human capital theory). The theory of on-the-job training (OJT) was originally developed to explain why individuals' earnings tended to increase until late in their careers. This theory postulates that, early in a worker's career, his own time and other resources are invested to develop skills which will increase his future productivity. The upward slope of the age-earnings profile is interpreted to reflect the positive relationship between job tenure and productivity resulting from OJT investment. The greater the intensity of training, the steeper the profile. Several investigators have hypothesized that workers and firms in industries experiencing rapid technical change tend to invest relatively heavily in on-the-job training. Mincer and Higuchi (1988) postulated that "rapid technical change which induces greater and continuous training, is in part responsible for steeper profiles." Similarly, Tan suggested that "skill acquisition is greater in more technologically progressive firms." (p.3) In fact, he cites direct evidence that "higher rates of technical change are associated with increased reliance on in-house company training, and a lower probability of training from outside sources such as academic institutions, business and technical schools." (p.2). He therefore hypothesizes that "starting wages are lower, and subsequent rates of wage growth with tenure are higher, the more rapid the rate of growth in total factor productivity," (p. 12) a proxy for technological change.

Even if the intensity of investment in OJT is greater in industries experiencing rapid technical change, due to the possibility of skill obsolescence it is not clear that such industries should exhibit steeper age-earnings profiles. The introduction of new technology might be expected to reduce the current capital value of older workers' past training investments, hence their wage rate relative to that of younger workers.[1]

In addition to influencing the age-structure of earnings, an industry's rate of technical change could also affect the education-structure of earnings. Our previous paper indicated that the ratio of highly-educated to less educated <u>employment</u> tends to be highest in industries using relatively new capital equipment. If the supply of labor to particular industries were less than perfectly elastic, then one would expect the ratio of highly-educated to less educated <u>wage rates</u> to also be higher in these industries. The effect of technical change on this ratio, which might be interpreted as the "returns to education,"

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[1]Tan acknowledges that "no account is taken of the possible consequences of rapid technical change for the rate of skill depreciation" (p. 8) in his theoretical model.

could differ across age groups if education were subject to "vintage effects." If recently-acquired education confers a greater ability to adapt to changing technology than education acquired long ago, then one might expect technical change to increase the returns to education to young workers more than it would to older workers. We can investigate this possibility by estimating the effect of technology indicators on wage rates cross-classified by age and education.

This concludes our brief survey of theories and hypotheses suggesting the existence of a link between the level and/or structure of an industry's wages and its rate of introduction of new technology. In the next section we briefly summarize the limited previous empirical evidence concerning such a link.

## III. Literature Review

Dickens and Katz (1987) analyzed the relationship between wage rates and the industry's ratio of research and development (R&D) expenditure to sales -- controlling for a large number of other industry and worker characteristics -- using data from the 1983 Current Population Survey. Numerous studies (see, e.g. Griliches and Lichtenberg (1984)) have shown that R&D-intensity is a significant determinant of an industry's rate of total-factor-productivity (TFP) growth, a proxy for its rate of technical change. Dickens and Katz found that R&D-intensity was positively related to wages in the nonunion sector (the correlations were significant about half the time), but that this result was reversed in the union sector, where most specifications had a negative coefficient which was sometimes significant. Their evidence suggests that the union wage premium is lower -- perhaps even negative -- in R&D-intensive industries, but the effect of R&D-intensity on the overall (average) wage is unclear.

Tan also used Current Population Survey data (for both 1983 and 1984) to study the effect of technical change on wages, but his measures of technical change were industry-level estimates of total factor productivity growth constructed by Gollop and Jorgenson. His major findings were that starting wages (wages of young workers) were lower, and wage growth with job tenure higher, the higher the industry's rate of productivity growth during 1973-79. Thus, consistent with the Lazear and OJT models, the age-earnings profile is steeper in industries experiencing rapid technical change. Tan's estimates implied that at the sample mean value of job tenure, TFP growth has a positive net effect on wages; on average, then, wage levels are higher in high TFP-growth sectors. Tan also experimented with interactions between technical change and schooling but found these to be statistically insignificant.

Mincer and Higuchi's study focused on differences between the U.S. and Japan with respect to earnings profiles and turnover rates. They used data from the 1979 Japanese Employment Structure Survey and from the U.S. Panel Study of Income Dynamics for the period 1976-81, in conjunction with TFP indices for (roughly 2-digit) U.S. and Japanese industries constructed by Conrad and Jorgenson. Their evidence confirms Tan's finding that high-TFP-growth industries exhibit steeper age-earnings profiles than low-TFP-growth industries. (The equations they estimated do not reveal the effect of TFP growth on starting wages or on the overall level of wages in the industry.) Age-earnings profiles in Japan tend to be much steeper than those in the U.S., and their estimates imply that as much as 80 percent of the difference in slopes may be accounted for by Japan's much higher recent rate of productivity growth.

In the next section we re-examine the relationship between technological change and wages, using a completely new data set which includes several alternative indicators of the rate of introduction of new technology.

## IV. Econometric Specification

We have described several hypotheses that predict a positive relationship between technological change and wages and, in some cases, a change in the slope of the age-earnings profile, and an increase in the returns to education. In this section of the paper, we describe the wage equation and data that will be used to test those hypotheses.

Our database consists of a sample of 35 manufacturing industries observed in the three Census years, 1960, 1970 and 1980. From the Censuses of Population, we selected individuals who were employed in each of these industries and created seventy age by education by sex cells for each industry. Our unit of observation is one of these cells, resulting in approximately 2400 observations in each of the three years. The dependent variable is the mean wage rate of the individuals in the cell. This specification assumes that age, education and sex are good proxies for the individual's stock of human capital.

For each of our 35 industries, we have obtained three indicators of technological change. The first is the age of the industry's equipment (AGEEQ) which is calculated from the Bureau of Industrial Economics' Capital Stocks Data Base. If one accepts the notion of embodied technological change, then the age of the capital stock is a perfect measure of the age of the industry's technology. Even if technological change is not completely embodied, there will be a strong relationship between the age of the capital stock and the age of the technology for two reasons. First, the introduction of new technology increases equilibrium industry output, leading to a higher rate of investment and a younger capital stock. Second, according to the product life cycle approach, once a stable production technique is established, intense capital investment occurs, thereby producing a correlation between age of the capital stock and age of the technology in a cross section of industries. The second technology variable that we use is the ratio of the industry's purchases of electronic and computing equipment divided by the industry's output (COMPUTERS). This measure is obtained from the Input-Output Tables. The third variable is the ratio of the industry's own R&D expenditures to its sales (OWNRD) which is obtained from the technology matrix constructed by Scherer (1984). While information on AGEEQ and COMPUTERS is available for each of the three time periods in our analysis, OWNRD can only be measured for one time period (1974), thus making this variable a less reliable indicator.

The following industrial characteristics are also included in the wage equation: (1) UNION, the percentage of employees in the industry that are unionized, obtained from Kokkelenberg and Sockell (1985); (2) AGEPL, the average age of plant in the industry, obtained from the Bureau of Industrial Economics' Capital Stocks Data Base; (3) CAPLAB, the capital/labor ratio in the industry, and (4) GROWTH, the growth rate in the industry's output over the last decade. The latter two variables are calculated from the Census/SRI/Penn Data Base which is derived primarily from the Annual Survey of Manufactures and the Census of Manufactures.

The equation that we estimate is:

$$\begin{aligned}\ln W_{ijt} = {} & \alpha_o + \alpha_1 \text{ AGE} + \alpha_2 \text{ EDUC} + \alpha_3 \text{ SEX} + \alpha_4 \text{ YEAR} + \alpha_5 \text{ TECH} \\ & + \alpha_6 \text{ UNION} + \alpha_7 \text{ AGEPL} + \alpha_8 \text{ CAPLAB} + \alpha_9 \text{ GROWTH} + \delta_t + \varepsilon_{ijt} \qquad (1)\end{aligned}$$

where $W_{ijt}$ = the average wage of individuals in the $i^{th}$ age by education by sex cell in the $j^{th}$ industry in year t

AGE = a vector describing the seven age categories

EDUC = a vector describing the five education categories

SEX = male or female

YEAR = 1960, 1970 or 1980

TECH = AGEEQ, COMPUTERS or OWNRD

$\delta_t$ = a set of time dummies used to control for the effects of changes over time in unmeasured determinants that are common to all industries.

We also estimate a "fixed effects" variant of equation (1) where we add industry dummies $\gamma_k$ to control for the effects of any permanent differences across industries in unmeasured determinants of wages. Within this framework, the coefficients on the independent variables in equation (1) capture the partial relationships between deviations of these variables from their respective industry means and deviations of $\ell n\ W_{ijt}$ from its respective industry mean. A heuristic interpretation of this estimation procedure is that it reveals whether an industry that experienced an increase in AGEEQ above the average experienced by all industries between, say, 1960 and 1970, had a significantly below-average increase in $\ell n\ W_{ijt}$ during that period.

## V. Empirical Analysis

The results of estimating equation (1) without and with fixed effects are shown in Tables 1 and 2, respectively. Note that in Table 2, OWNRD has been excluded because we only have information on that variable for one time period. We begin with the results in Table 1 where in columns (1) through (3) each technology indicator is used

Table 1

Dependent Variable: Ln (Average Wage in Age By Education By Sex Cell in an Industry)

(t-statistics in parentheses)

Without Fixed Effects

| Independent Variable | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| AGEEQ | -.051<br>(-16.04) | | | -.022<br>(-5.28) | -.022<br>(-5.27) |
| OWNRD | | .101<br>(17.07) | | .075<br>(10.43) | .058<br>(4.94) |
| COMPUTERS | | | 3.19<br>(13.55) | 1.93<br>(7.47) | 2.24<br>(8.04) |
| AGEPL | | | | .004<br>(2.40) | .007<br>(4.16) |
| UNION | .336<br>(24.13) | .386<br>(27.06) | .388<br>(26.65) | .399<br>(26.49) | .412<br>(26.63) |
| CAPLAB | | | | | -.013<br>(-.38) |
| GROWTH | | | | | .971<br>(6.90) |
| $R^2$ | .986 | .986 | .986 | .987 | .987 |
| N | 7284 | 7106 | 7227 | 7106 | 7106 |

Note: All equations include age, education, sex and year vectors which are in all cases statistically significant.

Table 2

Dependent Variable: Ln (Average Wage in Age By Education By Sex Cell in an Industry)

(t-statistics in parentheses)

With Fixed Effects

| | | | |
|---|---|---|---|
| AGEEQ | -.017<br>(-3.54) | | -.018<br>(-3.67) |
| COMPUTERS | | -1.68<br>(-1.04) | -1.166<br>(-.71) |
| AGEPL | | | .004<br>(1.79) |
| UNION | .350<br>(5.70) | .360<br>(5.87) | .387<br>(5.23) |
| CAPLAB | | | .001<br>(1.14) |
| GROWTH | | | -.025<br>(-.15) |
| $R^2$ | .920 | .920 | .921 |
| N | 7284 | 7227 | 7227 |

Note: All equations include age, education, sex, year and industry vectors that are in all cases statistically significant.

separately and only the sex, age, education and union variables are included.[2] All three technology measures have the right signs and are significant. Individuals in industries with new equipment, high R&D to sales ratios, or a large share of computer purchases relative to the value of output, are paid higher wages than observationally equivalent individuals in other industries. In column (4) all three technology variables, as well as AGEPL, are used together and each is still significant. These results are consistent with the demand for learning model discussed in Section II; workers in industries experiencing rapid technical change receive higher wages than workers with similar education and demographic attributes in other industries because of differences in both unobserved ability and effort.

It is possible that our technology variables are highly correlated with the capital/labor ratio and the growth rate of output in the industry, two other possible determinants of wages. These two variables are added in column (5), and, remarkably, all three of our technology variables are still significant. CAPLAB has the wrong sign in column (5) but was positive and very significant when the technology variables were excluded. Previous studies that report a positive effect of CAPLAB on wages may therefore have obtained a spurious result that is due to the positive correlation between the capital/labor ratio and the rate of technological change in the industry. Our analysis implies that it is technological change, not the capital/labor ratio, that determines the wage premium.

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[2]For the sake of brevity, the coefficients on sex, age, education and year are not shown in the table. The standard findings were obtained

Table 2 reports the results of estimating equation (1) with fixed effects. Although the coefficient on AGEEQ declines about 2/3 in magnitude, it remains negative and significant, consistent with our hypothesis that the introduction of new technology increases the demand for learning. COMPUTERS, however, is no longer significant. Hence, AGEEQ appears to be the strongest indicator of technological change.

The analysis so far has assumed that the impact of technological change on wages is the same for all workers in the industry. We discussed in Section II how and why technological change might have different impacts on highly educated vs. less educated, and young vs. older workers. We now allow for unequal effects of technological change on different demographic groups by creating interaction variables between the technology measure and several age by education categories. The age categories are (1) ages 18-34 and (2) ages 35-64, and the education categories are (1) less than college graduate and (2) at least a college graduate. Tables 3 and 4 report these results from equations estimated without and with fixed effects, respectively. In these tables, we show the effects of technological change on the two age groups, the two education groups and the four age by education groups. The variables included in the equations are UNION, CAPLAB, GROWTH, AGE, SEX, EDUC, and YEAR. GROWTH is also interacted with age, education or both, depending on the interaction structure that is used for the technology variable. This means that if we do observe an impact of technological change on the

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in all of our equations. Men earn more than women and earnings rise with age and with education.

Table 3

Wage Effects By Age and Education,
from Equations without Fixed Effects

A. AGEEQ

| | Total | Educ ≦ 15 | Educ ≧ 16 |
|---|---|---|---|
| Total | -.041 (-12.19) | -.038 (-10.62) | -.056 (-6.67) |
| Ages 18-34 | -.032 (-6.19) | -.028 (-5.45) | -.066 (-7.02) |
| Ages 35-64 | -.046 (-11.10) | -.044 (-10.19) | -.053 (-6.05) |

B. COMPUTERS

| | Total | Educ ≦ 15 | Educ ≧ 16 |
|---|---|---|---|
| Total | 3.31 (14.25) | 3.20 (12.54) | 3.78 (7.25) |
| Ages 18-34 | 3.24 (9.35) | 3.17 (8.28) | 4.14 (5.51) |
| Ages 35-64 | 3.37 (11.15) | 3.23 (9.85) | 3.77 (5.35) |

C. OWNRD

| | Total | Educ ≦ 15 | Educ ≧ 16 |
|---|---|---|---|
| Total | .119 (12.28) | .119 (11.85) | .117 (6.17) |
| Ages 18-34 | .123 (9.83) | .123 (9.40) | .141 (5.05) |
| Ages 35-64 | .118 (10.67) | .118 (10.35) | .106 (4.50) |

Note: The age, education, sex and year vectors as well as UNION and CAPLAB are included in these equations. In addition, age-education interaction effects on GROWTH are used which correspond to the interaction effects on the technology variable.

Table 4

Wage Effects By Age and Education, from Equations with Fixed Effects

A. AGEEQ

| | Total | Educ $\leq$ 15 | Educ $\geq$ 16 |
|---|---|---|---|
| Total | -.016 | -.014 | -.029 |
| | (-3.38) | (-2.90) | (-3.33) |
| Ages 18-34 | -.005 | -.002 | -.037 |
| | (-.89) | (-.46) | (-3.93) |
| Ages 35-64 | -.023 | -.021 | -.026 |
| | (-4.30) | (-3.93) | (-2.94) |

B. COMPUTERS

| | Total | Educ $\leq$ 15 | Educ $\geq$ 16 |
|---|---|---|---|
| Total | -1.52 | -1.32 | -.61 |
| | (-.92) | (-.80) | (-.34) |
| Ages 18-34 | -1.64 | -1.41 | -.26 |
| | (-.98) | (-.85) | (-.15) |
| Ages 35-64 | -1.48 | -1.31 | -.66 |
| | (-.89) | (-.80) | (-.37) |

Note: The age, education, sex and year vectors as well as UNION and CAPLAB are included in these equations. In addition, age-education interaction effects on GROWTH are used which correspond to the interaction effects on the technology variable.

structure of wages in the industry, it cannot be attributed to a possible correlation between technological change and output growth.

In panel A of Table 3, the effect of technological change on relative wages is estimated with AGEEQ as the technology indicator. We see that <u>all</u> workers in industries with new technology have higher wages, ceteris paribus. Although all employed workers benefit from the introduction of new technology in their industries, we do see that some workers gain more than others. In particular, the wages of college graduates increase more than those of the less educated employees, but this difference is not significant when older workers are compared. The increase in the relative wage of college graduates, especially younger ones, is consistent with the comparative advantage theory proposed in our earlier paper. As new technology is introduced, there is an increase in the relative demand for highly educated individuals (especially those whose education is recently acquired). Wages rise if the supply of labor to particular industries is less than perfectly elastic.

Regarding the impact of technological change on the age earnings profile, the results in panel A are ambiguous. We find that the profile is steeper when we do not disaggregate by education, and, after disaggregating, only for the less-educated workers in the technologically advanced industries.[3] The fact that this does not hold for the college

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[3]It might be argued that the steeper age-earnings profiles in high-tec industries result from the negative correlation between innovation and percent unionized in the industry. Connolly et al. (1986) and Hirsch and Link (1987) have documented this negative relationship. We tested for this by adding an interaction term between UNION and AGE, and found that the AGEEQ-AGE interaction was unaffected; age-earnings profiles are steeper in industries introducing new technology.

graduates casts doubt on the validity of the specific-training hypothesis -- at least the one not allowing for skill obsolescence. If the introduction of new technology results in greater investments in the specific human capital of employees, we should have seen this effect most strongly for the highly-educated workers, given the positive correlation between education and training that has been observed in other studies. One possible explanation is that skill obsolescence is much stronger for the college graduates; thus, technological change reduces the wages of older college graduates relative to that of younger graduates. Finally, the results could be consistent with the Lazear model of deferred compensation if employers find it more difficult to monitor the shirking of less educated workers. We find this assumption rather implausible since the less educated workers are more likely to be performing repetitive tasks that are easily monitored.

In panel B, we use COMPUTERS as our technology indicator. The results here are basically consistent with those in panel A. All workers in industries with large computer purchases have higher wages and the relative wage of college graduates in both age groups rises. There is no support for the specific training hypothesis or the Lazear model since neither of the two age-earnings profiles becomes steeper. In panel C, the R&D variable is used to measure technological change. Again, all four groups have higher wages in industries with high R&D to sales ratios. The relative wage of college graduates in the young age group rises and there is no evidence that age-earnings profiles become steeper.

Finally, in Table 4, the relative wage results are presented from equations with fixed effects. The findings are virtually identical to those reported in Table 3. The introduction of new technology leads to an increase in the relative wage of college graduates, an increase in the relative wage of older workers when we do not disaggregate by education, and an increase in the slope of the age-earnings profile for the less-educated workers.

## VI. Conclusions

This paper examined the relationship between technological change and wages using pooled cross-sectional industry-level data and several alternative indicators of the rate of introduction of new technology. Our main finding is that industries with a high rate of technical change pay higher wages to workers of given age and education, compared to less technologically advanced industries. We have argued that this is consistent with the notion that the introduction of new technology creates a demand for learning, and a combination of employee ability and effort is required for learning to occur. A related finding is that the wages of highly educated workers (especially recent graduates) rise relative to those of less educated workers; this is consistent with the notion that educated workers are better learners.

The evidence presented in this paper is important for the following reasons. First, our results suggest that observed industry wage differentials can, indeed, be market-clearing. Industries that have a greater need for employees who are good learners will pay higher wages, in equilibrium, than industries less dependent on worker learning. Some researchers have argued that the existence of persistent industry wage differentials is proof of market failure. But the fact that these differentials are correlated with industry rates of technical change suggests that they are not a consequence of market imperfections, but instead reflect differential demand for ability and effort. A second implication of our results is that the continued growth of the high-technology sector in the United States will require a steady supply of workers who are good learners. This supply can be influenced by government education policies that will teach students to be better learners as well as by human resource management techniques that will elicit greater worker effort.

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