Econ. Innov. New Techn., 1991, Vol. 1, pp. 215–231
Reprints available directly from the publisher
Photocopying permitted by licence only

THE AGE OF TECHNOLOGY AND ITS IMPACT ON EMPLOYEE WAGES

ANN P. BARTEL and FRANK R. LICHTENBERG*

Columbia University, Graduate School of Business, Uris Hall, New York, NY 10027 USA

(Received November 25, 1989; revised March 14, 1990)

This paper examines the relationship between wages and the "age" or "newness" of technology using pooled cross-sectional industry-level data and several alternative indicators of the age of technology. Our main finding is that industries with relatively young or immature technologies pay higher wages to workers of given age and education than industries with mature technologies. A one standard deviation decrease in the mean age of the industry's equipment leads to a three-percent increase in wages within demographic groups. This is consistent with the notion that the demand for employee learning is a decreasing function of the age of the technology, 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 industries using the newest technology; this is consistent with the notion that educated workers are better learners.

KEY WORDS: Wages, technology

I. INTRODUCTION

In a previous article (1987a) we investigated the effect of the "age" or "newness" of technology 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's 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 – are 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 article we examine the effect of the age of technology on the *wage rate*, holding constant employee education, age, and sex. We postulate that in order to satisfy firms' increased demand for learning by workers following the introduction of new technology, innovative firms will find it expedient to pay higher wages to employees within given education and demographic groups. Using pooled, industry-level data, we test this hypothesis by estimating wage equations which include indicators of the age of technology.

In the next section we sketch a theory of on-the-job learning that implies the

*Professor and Associate Professor, respectively, Columbia University Graduate School of Business. Both authors are Research Associates at the National Bureau of Economic Research. This research was supported by a grant from the National Institute of Education.

existence of a link between wages and the age of technology. In Section III we briefly review previous theoretical and empirical research concerning the effect of technological change (which influences the average age of technology) 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 of an existing technology by a new one represents a major "shock" to the production environment, and workers (and perhaps management as well) are initially 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." During the shakedown period, therefore, the firm's replacement of an old by a new technology increases its demand for learning on the part of its employees.

We postulate that the extent of learning by an employee is an increasing function of the employee's time devoted to learning and of other resources (such as the services of people providing training). The *quality*,as well as the *quantity*, of the employee's time determines the rate of learning. The quality of employee time is an increasing function of both employee *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. We assume that both ability and effort are "normal goods": ability and effort demanded by employers both increase when the rate of learning desired by employers increases. A reduction in the (average) age of technology, which results from the introduction of new technology, increases the demand for learning, and therefore the derived 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 a reduction in the age of technology 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 replacing old with new technologies 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 reducing the age of their technology will also seek to elicit higher 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. One important respect in which these justifications differ concerns 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

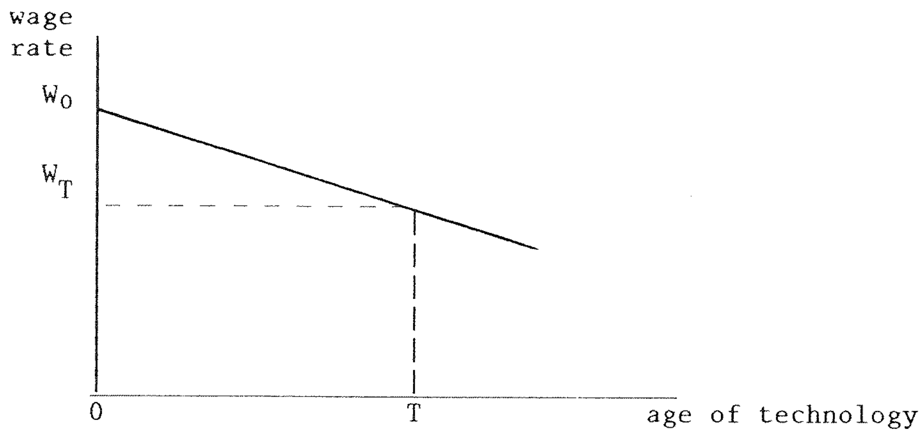

Figure 1

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.

The major implication of our argument is that workers in industries utilizing technology of recent vintage 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 interindustry wage variation is "explained" by variation in the age of technology; however we cannot, and do not attempt to, allocate the explained variation into ability- and effort-related components.[1]

[1]If this hypothesis is correct, then it, in conjunction with our earlier findings, suggests that industries utilizing young technology are high-wage industries for two distinct reasons, which we may refer to as between-group and within-group. Our earlier paper indicated that a reduction in the age of technology increases the relative quantity of highly educated workers, who of course tend to receive the highest wages. Technological change, which lowers the age of technology, 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 *within* education groups, thus further raising the average wage rate.

between wages and R&D-intensity is *negative*. 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 (1987) 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 (TFP) growth constructed by Gollop and Jorgenson (1980). Numerous studies (see, e.g., Griliches and Lichtenberg (1984)) have shown that TFP growth is strongly positively related to R&D intensity; presumably therefore it is also inversely related to the age of technology. Tan's 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 (1988) 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 (1985). 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.

IV ECONOMETRIC SPECIFICATION

Our database consists of a sample of manufacturing industries observed in the three Census years 1960, 1970 and 1980.[4] From the Public Use tapes of 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.[5] We classify individuals on the basis of age, education and sex because these characteristics are good proxies for the individual's skill level and are therefore important determinants (or at least correlates) of wages.[6] Our unit of observation is one of these cells, resulting in

[4]A list of industries is provided in Appendix A.

[5]There were 7 age groups (14–17, 18–24, 25–34, 35–44, 45–54, 55–64, and over 64) and 5 education groups (completed years of schooling of less than 9, 9–11, 12, 13–15, and over 15). These are similar to the age and education groupings utilized by the Census Bureau in its published tabulations. See, for example, U.S. Bureau of the Census (1977, pp. 143–4).

[6]While we would prefer to have additional controls such as job tenure and/or the amount of specific training an individual possesses, the Census of Population does not contain this information.

approximately 2500 observations in each of the three years. The dependent variable is the logarithm of the mean wage rate of the individuals in the cell.[7]

For each of our 35 industries, we have obtained three indicators of the average age of technology used by the industry. The first is the age of the industry's equipment (AGEEQ) which is calculated from the Bureau of Industrial Economics' Capital Stocks Data Base. The reasons for a link between AGEEQ and the age of technology were discussed in our 1987 paper. If one accepts the notion of embodied technological change, then the age of the capital stock is a perfect (inverse) measure of the "newness" of the industry's technology. Even if technological change is not completely embodied, there is likely to be a strong relationship between the age of the capital stock and the age of the technology, since the introduction of new technology is often cost-reducing and therefore increases equilibrium industry output. This leads in turn to a higher rate of investment and a younger capital stock.

The second indicator of the average age of technology that we use is the ratio of the industry's purchases of electronic and computing equipment to its output (COMPUTERS) which was calculated from a series of Input-Output Tables. Since computer-aided-design and computer-aided-manufacturing are among the most modern techniques of production, a high value of this ratio is hypothesized to represent a low average age of technology.

The third indicator 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).[8] Lichtenberg and Griliches (1989) show that OWNRD is positively and significantly correlated with the fraction of an industry's products that are "new" products. This implies that OWNRD is inversely related to the mean age of an industry's products. Since the introduction of a new product often entails the adoption of a new process or technology to manufacture the product, the mean age of technology is likely to be lower in highly R&D-intensive industries. While information on AGEEQ and COMPUTERS is available for each of the three years in our analysis, OWNRD can only be measured in a single year, 1974. Although industries' relative R&D-intensities are known to be quite stable over time, the availability of only a single cross-section makes this variable a less reliable indicator.[9]

An issue that needs to be addressed is whether the industry age of technology is truly an exogenous variable. The frequency with which an industry replaces its technology, hence the mean age of its technology, may be viewed as depending on its location in the industry- (or product-) "life-cycle." The rate of technology replacement is likely to be highest in young, science-based industries, and lower in mature industries. We observe a distribution of industries at different points in their respective life-cycles: the biotechnology and semiconductor industries are in their infancy, whereas the tobacco and furniture industries are mature. Our model essentially

[7]The wage rate is calculated by dividing wage and salary income in the previous year by the product of weeks worked and hours usually worked per week in that year.

[8]Scherer also constructed an estimate of the amount of R&D "embodied" in materials and capital purchased from other industries. Previous studies (Griliches and Lichtenberg (1984), Bartel and Lichtenberg (1987a)) had failed to find a relationship between it and either TFP growth or educational attainment of the industry's employees, and we also found no relationship between it and wages.

[9]The simple correlations among our technology indicators in 1970 are as follows: (1) AGEEQ and OWNRD: -.586; (2) AGEEQ and COMPUTERS: -.464; (3) OWNRD and COMPUTERS: .431. The correlations in the other years are similar.

postulates that it is the rate and direction of scientific and technological progress that largely determines when – and indeed which – industries are born, and therefore that the distribution of industries by the ages of their technologies is exogenous, relative to their distribution by wage rates.

The following industrial characteristics are also included as controls in the wage equation: (1) UNION, the percentage of employees in the industry that are unionized, obtained from Kokkelenberg and Sockell (1985);[10] (2) AGEPL, the average age of plant in the industry, obtained from the Bureau of Industrial Economics' Capital Stocks Data Base;[11] (3) CAPLAB, the capital/labor ratio in the industry, (4) GROWTH, the growth rate of the industry's output over the last decade, (5) GROWTH1, GROWTH2, GROWTH3 and GROWTH4, the annual output growth rate in each of the last four years, and (6) PROFITS, defined as net income divided by the value of assets. The capital-labor ratio, output growth rates and profits 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:

$$\begin{aligned}\ln W_{ijt} \;=\; & \alpha_0 + \alpha_1\,\text{AGETECH} + \alpha_2\,\text{EDUC} + \alpha_3\,\text{SEX} + \alpha_4\,\text{AGE} + \alpha_5\,\text{YEAR} \\ & + \alpha_6\,\text{UNION} + \alpha_7\,\text{AGEPL} + \alpha_8\,\text{CAPLAB} + \alpha_9\,\text{GROWTH} + \alpha_{10}\,\text{GROWTH1} \\ & + \alpha_{11}\,\text{GROWTH2} + \alpha_{12}\,\text{GROWTH3} + \alpha_{13}\,\text{GROWTH4} + \alpha_{14}\,\text{PROFITS} + \varepsilon_{ijt}\end{aligned} \tag{1}$$

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

AGTECH = a vector including (some or all of) the technology-age indicators AGEEQ, COMPUTERS and OWNRD

AGE = a vector of dummy variables for the seven age categories

EDUC = a vector of dummy variables for the five education categories

SEX = a vector of dummy variables for the two sex categories

YEAR = a vector of dummy variables for the three years

We also estimate variants of eq. (1) including fixed (industry) effects γ_j, in which we include a separate intercept for each industry. Parameter estimates from an equation including fixed effects are based entirely on the *within-industry* moments (variances and covariances) of the variables, whereas estimates from an equation without fixed effects are based on the *total* (within- plus between-industry) moments of the variables. When fixed effects are included, the coefficients in eq. (1) measure the effects of deviations of the regressors *from their respective industry means* on the deviation of $\ln W_{ijt}$ from its respective industry mean. For example, the coefficient on AGEEQ

---

[10] Since the earliest data from this source are for 1974, we use 1974 unionization rates for 1960 and 1970, and the 1980 unionization for rates for 1980. UNION is an important control in our empirical model because one might hypothesize that a strong union presence will raise wages and therefore lead to the introduction of new labor-saving technology. This would induce a spurious negative correlation between wages and the age of technology in the absence of a control for unionization. However, Connolly et al. (1986) and Hirsch and Link (1987) found that unions tend to *retard* innovative activity.

[11] Plant is defined as factory, office, and warehouse buildings as well as elevators, cranes, and heating and ventilating equipment that is essentially a part of the buildings. Other fixed structures such as blast furnaces, brick kilns, fractionating towers, shipways, and similar types of structures, and capitalized site improvements (but not land) such as roads, docks, tracks, parking lots, fences, and utilities are also included in plant.

Table 1. Dependent Variable: Ln (Average Wage in Age By Education By Sex Cell in an Industry) (t-statistics in parentheses)

	Without Fixed Effects				
	(1)	(2)	(3)	(4)	(5)
AGEEQ	−.051			−.022	−.026
	(−16.04)			(−5.28)	(−5.93)
OWNRD		.101		.075	.046
		(17.07)		(10.43)	(3.71)
COMPUTERS			3.19	1.93	2.09
			(13.55)	(7.47)	(7.30)
AGEPL				.004	.005
				(2.40)	(3.06)
UNION	.336	.386	.388	.399	.377
	(24.13)	(27.06)	(26.65)	(26.49)	(22.45)
CAPLAB					−.02
					(−.71)
GROWTH					.76
					(4.14)
GROWTH1					−.11
					(−2.69)
GROWTH2					.13
					(2.56)
GROWTH3					−.02
					(−.39)
GROWTH4					.18
					(3.05)
PROFITS					−.028
					(−5.30)
R^2	.986	.986	.986	.987	.987
N	7284	7106	7227	7106	7106

Note: All equations include AGE, EDUC, SEX, and YEAR vectors which are in all cases statistically significant.

indicates whether an industry that experienced an increase in this variable above the average increase experienced by all industries between, say, 1960 and 1970, had a significantly below-average increase in ln W_{ijt} during that period. We estimate versions of the model both including and excluding fixed effects because including them has both a potential advantage and a potential disadvantage. The advantage is that by including them we reduce the possibility of omitted-variables bias, since the fixed effects control for the influence of all unobserved determinants of industry wages that are constant (or slowly changing) over time. The disadvantage is that, as Griliches and Hausman (1986) have shown, including fixed effects tends to exacerbate the problem of errors-in-variables (measurement error), generally resulting in parameter estimates and t-statistics that are biased towards zero.

V. EMPIRICAL ANALYSIS

The results of estimating equation (1) by OLS 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 indicator of the age of technology is used separately and only the sex, age, education and union variables are

Table 2. Dependent Variable: Ln (Average Wage in Age by Education By Sex Cell in an Industry) (t-statistics in parentheses)

	With Fixed Effects		
	(1)	(2)	(3)
AGEEQ	−.017		−.024
	(−3.54)		(−4.75)
COMPUTERS		−1.68	−2.77
		(−1.04)	(−1.62)
AGEPL			.005
			(1.97)
UNION	.350	.360	.244
	(5.70)	(5.87)	(2.91)
CAPLAB			−.09
			(−.83)
GROWTH			−.13
			(.61)
GROWTH1			−.08
			(−1.59)
GROWTH2			.115
			(1.79)
GROWTH3			.06
			(1.33)
GROWTH4			−.125
			(−1.70)
PROFITS			−.133
			(−5.01)
R^2	.920	.920	.922
N	7284	7227	7106

Note: All equations include AGE, EDUC, SEX, YEAR and industry vectors that are in all cases statistically significant.

included.[12] All three technology measures have the hypothesized signs and are significant. Individuals in industries with new equipment, high R&D to sales ratios, or a large ratio of computer purchases 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.[13] These results are consistent with the demand for learning model discussed in Section II; workers in industries with young technologies receive higher wages than workers with similar education and demographic attributes in other industries because of differences in both unobserved ability and effort.

Equipment includes all production machinery, transportation equipment (automobiles, trucks, etc.) and office equipment; including motors, lathes, punch presses, and similar machinery and equipment for use in production, as well as office equipment and machines, computers, furniture and fixtures for offices, cafeterias, dressing rooms, and warehouse equipment such as lifts.

[12]The coefficients and t-values on SEX, AGE, EDUC and YEAR are as follows: MALE, .40(61.9), AGE1, −.59(−33.6), AGE2, −.46(−43.1), AGE3, −.20(−20.0), AGE4, −.06(−5.6), AGE5, .01(.56), AGE6, .03(3.21), EDU1, −.63(−83.4), EDU2, −.51(−69.0), EDU3, −.40(−56.4), EDU4, −.27(−35.5), YEAR60−, −1.03(−105.3) and YEAR70, −.66(−80.2). (The seven age and five education categories are defined in footnote 5.) Hence we observe wages rising with age and education and wages rising secularly over the period 1960-1980.

[13]Because technology is embodied in equipment more than it is in plant, AGEEQ is a stronger indicator of technology age than AGEPL. These two variables are strongly positively correlated (r = .5), so when both are included, AGEPL'S coefficient is "perverse". Excluding AGEEQ makes the AGEPL coefficient negative and significant.

The quantitative significance of this finding can be measured in several ways. First, the results in columns (1)–(3) imply that a one-standard-deviation change in any of the three technology indicators would lead to an approximately three-percent change in wages. Another approach is to calculate the partial R^2 for each of the technology variables. The results are: .04 for AGEEQ, .04 for OWNRD, and .03 for COMPUTERS.[14] In their analysis of interindustry wage differentials, Dickens and Katz (1987) found that, controlling for personal characteristics such as age, education, sex, marital status, unionization and occupation, industry dummy variables explained an additional 7–10 percent of the wage variation in the 1983 Current Population Survey. Hence, our findings on the explanatory power of the technology variables are reasonable in light of previous research findings. Indeed, one interpretation of our results is that close to 50 percent of the explanatory power of industry dummy variables is due to the interindustry variation in the age of technology.[15]

While our finding of a significant inverse relationship between wages and the age of technology is consistent with our hypothesis concerning the demand for effort and ability, we should consider whether it is also consistent with other interpretations. One might conjecture that new technology tends to be labor-replacing, and therefore that its introduction results in a reduction in the overall workforce. This could induce a "spurious" negative correlation between wage and age for two reasons. First, the workforce reduction might be focused on unskilled, untrained workers, and the data at the level of aggregation used by us might show higher average wage rates due to firing policy. Second, the workforce reduction would result in an increase in the capital-labor ratio, which would tend to increase wages.

Although in principle such factors might be operating, in a previous paper (1987b) we presented evidence that was markedly inconsistent with these scenarios. First, industries with young technologies experience much *higher* employment growth than those using old technologies. Between 1960 and 1980, total employment in highly R&D-intensive industries increased 89%, while that of other manufacturing industries increased only 15%. Highly R&D-intensive industries experience much higher labor productivity growth, hence much lower growth in unit labor requirements (labor per unit of output). But the effect on labor demand of higher labor productivity growth is more than offset by higher output growth. (Real output growth in the "R&D-intensive" and "other" sectors was 358% and 84%, respectively.) The more rapid productivity growth in R&D-intensive industries results in greater cost (and price) reductions, and thus in a more rapid descent along the product-demand curve. The data therefore do not support the view that the replacement of old technologies precipitates workforce reductions.

Neither do they suggest that industries introducing new technologies tend to have high capital-labor ratios. On the contrary: we found that the capital-intensity of highly R&D-intensive (low capital-age) industries was 31–50% lower than that of other industries. This is consistent with product life-cycle theory, which postulates that capital-intensity is an increasing function of the age of technology.

---

[14]This is the percent of variation of the dependent variable explained by the indicator, *holding constant* the other regressors, and is calculated by the formula $t^2/(t^2 + \text{residual degrees of freedom})$.

[15]Since the R&D variable is only measured in 1974 one would expect its coefficient to be lower in 1960 than in the other two years. When we estimated the equation separately for each year, we indeed found that the coefficient on R&D was larger in 1970 and 1980; for 1980, its coefficient (t-value) was .146 (6.19), as opposed to .046 (3.71) from the pooled regression. In addition, in the 1980 equation the coefficient on COMPUTERS fell to 1.03 ($t = 2.07$), perhaps because in 1980, this variable was a poorer indicator of the age of technology than it was in earlier years.

Table 3. The Effects of the Age of Technology on Wages By Age and Education from Equations without Fixed Effects

A.	*AGEEQ*	Total	Educ ≦ 15	Educ ≧ 16
	Total	−.041	−.038	−.056
		(−12.19)	(−10.62)	(−6.67)
	Ages 18–34	−.032	−.028	−.066
		(−6.19)	(−5.45)	(−7.02)
	Ages 35–64	−.046	−.044	−.053
		(−11.10)	(−10.19)	(−6.05)
B.	*COMPUTERS*	Total	Educ ≦ 15	Educ ≧ 16
	Total	3.31	3.20	3.78
		(14.25)	(12.54)	(7.25)
	Ages 18–34	3.24	3.17	4.14
		(9.35)	(8.28)	(5.51)
	Ages 35–64	3.37	3.23	3.77
		(11.15)	(9.85)	(5.35)
C.	*OWNRD*	Total	Educ ≦ 15	Educ ≧ 16
	Total	.119	.119	.117
		(12.28)	(11.85)	(6.17)
	Ages 18–34	.123	.123	.141
		(9.83)	(9.40)	(5.05)
	Ages 35–64	.118	.118	.106
		(10.67)	(10.35)	(4.50)

Note: The AGE, EDUC, 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.

Even though these findings cast doubt on the alternative interpretations of our estimates, we can further assess their validity by including two additional regressors in the wage model, the growth rate of output (which is highly correlated with the growth rate of employment, and more likely to be exogenous with respect to wages), and the capital labor ratio. These variables are added in column (5), and all three of our technology variables remain significant, although the sizes of the coefficients do change. The coefficient on CAPLAB is negative in column (5) but was positive and very significant when the technology variables were excluded. Previous studies that reported 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 age of the industry's technology. Our analysis implies that it is the age of the technology, not the capital/labor ratio, that determines the wage premium.

Table 2 reports the results of estimating equation (1) with fixed effects.[16] 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 the age of technology.

The analysis so far has assumed that the impact of the age of technology on wages is the same for all workers in the industry. We discussed in Section II how and why

[16]The R^2 values in Table 2 differ from those in Table 1 because those in Table 2 measure the fraction of *within-industry* variation in wages that is explained and those in Table 1 measure the fraction of *total* (within- and between-industry) variation that is explained.

its impacts on highly educated vs. less educated, and young vs. older workers might differ. We now allow for unequal effects of the age of technology on different demographic groups by creating interaction variables between the technology measure and several age by education categories. The interaction effects were estimated initially with six age groups and five education groups.[17] After reviewing these results, we decided to aggregate the cells into two age categories ((1) ages 18–34 and (2) ages 35–64) and two education categories ((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 the age of technology 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. We also allow the effect on wages of the variable GROWTH to vary by 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 the age of technology on the structure of wages, it is not due to a correlation between the age of technology and output growth.

In panel A of Table 3, the effect of the age of technology on relative wages is estimated with AGEEQ as the technology indicator. We see that *all* workers in industries with new technology (i.e., lower values of AGEEQ) have higher wages, ceteris paribus.[18] 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

Table 4. The Effects of the Age of Technology on Wages By Age and Education from Equations with Fixed Effects

A.	*AGEEQ*	Total	Educ ≦ 15	Educ ≧ 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 ≦ 15	Educ ≧ 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, EDUC, 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.

[17]Using AGEEQ as the technology indicator, the interaction effects for the six age groups were: Age 18–24: −.039; Ages 25–34: −.045; Ages 35–44: −.048; Ages 45–54: −.051; and Ages 55–64: −.051. The interaction effects for the education groups were: 0-8 Years: −.043; 9–11 Years: −.037; 12 Years: −.041; 13–15 Years: −.046 and 16 or more years: −.063.

[18]It might be argued that the steeper age-earnings profiles in high-tech industries result from the negative correlation between innovation and percent unionized in the industry. Connolly *et al.* (1986) and Hirsh 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.

particular, the wages of college graduates increase more from new technology than those of the less educated employees, but this difference is not significant when older workers are compared. The higher relative wage of college graduates, especially younger ones, is consistent with the comparative advantage theory proposed in our 1987 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 will be higher if the supply of labor to particular industries is less than perfectly elastic.

Regarding the impact of the age of technology on the age-wage profile, the results in panel A are ambiguous. When we do not disaggregate by education, we find that the profile is steeper in industries using young technology. But disaggregation reveals that the profile is steeper only for the less-educated workers in these industries. The fact that this does not hold for the college 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 on-the-job training that has been observed in other studies.[19] One possible explanation is that skill obsolescence is much stronger for the college graduates; thus, a decrease in the age of technology 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 the introduction of new technology increased the cost to the employer of monitoring less-educated employees relative to the cost of monitoring highly-educated employees. 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 the age of technology. 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. When AGEEQ is used as the technology indicator, the *relative* magnitudes of the coefficients are virtually identical to those reported in Table 3, although as before inclusion of fixed effects reduces the absolute magnitudes and significance of the coefficients.[20] 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-wage profile for the less-educated workers.

[19]See Tan (1988).

[20]Recall from Table 2 that COMPUTERS had an insignificant coefficient in the fixed effects model so it is not surprising that no effect is observed in Table 4.

VI. CONCLUSIONS

This paper examined the relationship between the age of technology and wages using pooled cross-sectional industry-level data and several alternative indicators of the age, or rate of introduction, of new technology. Our main finding is that industries with young technologies pay higher wages to workers of given age and education, compared to industries with more mature technologies. 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) are higher relative to those of less educated workers in industries utilizing young technology; this is consistent with the notion that educated workers are better learners.

The evidence presented in this paper is important for several reasons. First, our results suggest that observed industry wage differentials may 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 the age of technology in an industry suggests that they may not be a consequence of market imperfections, but instead may reflect differential demand for ability and effort. A second implication of our results is that the ability of U.S. firms to implement new technology 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.

References

Akerlof, G. and J. Yellen (1986) *Efficiency Wage Models of the Labor Market,* Orlando: Academic Press.

Akerlof, G. and J. Yellen (1988) "Fairness and Unemployment," *American Economic Review,* 78, No. 2, pp. 44–49.

Bartel, A.P. and F.R. Lichtenberg (1987a) "The Comparative Advantage of Educated Workers in Implementing New Technology," *The Review of Economics and Statistics,* 59, No. 1, pp. 1–11.

Bartel, A.P. and F.R. Lichtenberg (1987b) "The Skill Distribution and Competitive Trade Advantage of High-Technology Industries," in *Advances in Industrial and Labor Relations,* Volume 4, JAI Press, Inc.

Connolly, R.A., B.T. Hirsch and M.Hirschey (1986) "Union Rent Seeking, Intangible Capital, and Market Value of the Firm," *Review of Economics and Statistics,* 53, No. 4, pp. 562–577.

Conrad, K. and D. W. Jorgenson (1985) "Sectoral Productivity Gaps Between the United States, Japan and Germany, 1960–1979," in *Problems und Perspekteven der Weltwertschaflichen Entwecklung,* Berlin: Duncker and Humbolt.

Dickens, W.T. and L.F. Katz (1987) "Inter-Industry Wage Differences and Industry Characteristics," in Kevin Lang and Jonathan Leonard, eds., *Unemployment and the Structure of Labor Markets,* New York: Basil Blackwell, pp. 48–89.

Gollop, F.M. and D.W. Jorgenson (1980) "U.S. Productivity Growth by Industry: 1947-1973," in J.W. Kendrick and B.N. Vaccara, eds., *New Developments in Productivity Measurement and Analysis,* NBER Studies in Income and Wealth, Cambridge: NBER, Vol. 44.

Griliches, Z. and J. Hausman (1986) "Errors in Variables in Panel Data," *Journal of Econometrics,* Vol. 31 No. 1, February, pp. 93-118.

Griliches, Z. and F. Lichtenberg (1984) "Interindustry Technology Flows and Productivity Growth: A Re-Examination," *Review of Economics and Statistics,* 66, No. 2, pp. 324–328.

Hirsch, B.T. and A.N. Link (1987) "Labor Union Effects on Innovative Activity," *Journal of Labor Research,* Vol. , No. , pp. 323-332.

Kokkelenberg, E.C. and D.R. Sockell (1985) "Union Membership in the United States, 1973-1981," *Industrial and Labor Relations Review*, 38, No. 4, pp. 497–543.
Lazear, E.P. (1981) "Agency, Earnings Profiles, Productivity, and Hour Restrictions," *American Economic Review*, 71, No. 4, pp. 606–20.
Lichtenberg, F. and Z. Griliches (1989) "Errors of Measurement in Output Deflators," *Journal of Business and Economic Statistics* 7, 1–9.
Mincer, J. and Y. Higuchi, (1988) "Wage Structures and Labor Turnover in the U.S. and in Japan," *Journal of the Japanese and International Economy*, Vol. 2, pp. 97–133.
Scherer, F.M. (1984) "Using Linked Patent and R&D Data to Measure Interindustry Technology Flows," in Z. Griliches (ed.), *R&D, Patents and Productivity*, Chicago: University of Chicago.
Tan, H.W. (1987) "Technical Change and Its Consequences for Training and Earnings," Santa Monica: Rand Corporation, mimeo.
Tan, H.W. (1988) "Private Sector Training in the United States: Who Gets It and Why," Santa Monica: Rand Corporations, mimeo.
U.S. Bureau of the Census (1977) *Current Population Reports*, Series P-60, No. 105, "Money Income in 1975 of Families and Persons in the United States," Washington, D.C.: U.S. Government Printing Office.
Wells, L.T., Jr. (ed.) (1972) *The Product Life Cycle and International Trade* Boston: Harvard Business School Division of Research.

Appendix A. Description of Industry Sectors*

Sector	*SIC Codes*	*Brief Description*
1.	20	Food and Kindred Products
2.	21	Tobacco Manufactures
3.	221-224, 226, 228	Fabrics, Yarn & Thread Mills
4.	227, 229	Misc. Textile Goods
5.	225	Knitting Mills
6.	231-238	Apparel
7.	239	Misc. Fabricated Textiles
8.	241-244, 249	Lumber & Wood Products
9.	25	Furniture
10.	261-264, 266	Paper & Allied Products
11.	265	Paperboard Containers & Boxes
12.	27	Printing & Publishing
13.	281, 286, 289	Chemicals & Selected Chemical Products
14.	287	Fertilizers
15.	282	Plastics
16.	283-284	Drugs, Cleaning & Toilet Preparations
17.	285	Paints
18.	291	Petroleum Refining
19.	295, 299	Misc. Petroleum Products, Paving & Roofing Materials
20.	30	Rubber & Misc. Plastic Products
21.	311	Leather Tanning & Finishing
22.	313-317, 319	Footwear & Other Leather Products
23.	321-323	Glass & Glass Products
24.	324-329	Stone & Clay Products, including Cement
25.	331	Blast Furnaces, Steel Works
26.	332-336, 339	Iron & Steel Foundries, Primary Nonferrous Metals
27.	341-344, 347, 349	Fabricated Metal Products
28.	345	Screw Machine Products
29.	346	Metal Stampings
30.	351	Engines and Turbines
31.	352	Farm and Garden Machinery
32.	353	Construction, Mining & Materials Handling Machinery
33.	354	Metalworking Machinery
34.	355-356, 358-359	Industrial Machinery
35.	357	Office, Computing & Accounting Machines
36.	361, 362, 364, 367, 369	Electrical Equipment
37.	363	Household Appliances
38.	365, 366	Radio, TV and Communication Equipment
39.	371	Motor Vehicles & Equipment
40.	372, 376	Aircraft and Parts
41.	373-375, 379	Other Transportation Equipment
42.	381-387	Professional, scientific, optical and photographic equipment
43.	39	Misc. Manufacturing Equipment

*Data are available for each of these industry sectors in 1980. In 1970 and 1960, however, the industrial classifications in the Census of Population were not as detailed and some sectors had to be merged together, resulting in fewer sectors in those years.