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THE COMPARATIVE ADVANTAGE OF EDUCATED WORKERS IN IMPLEMENTING NEW TECHNOLOGY

Ann P. Bartel and Frank R. Lichtenberg*

Abstract—We estimate labor demand equations derived from a (restricted variable) cost function in which "experience" on a technology (proxied by the mean age of the capital stock) enters "non-neutrally." Our specification of the underlying cost function is based on the hypothesis that highly educated workers have a comparative advantage with respect to the adjustment to and implementation of new technologies. Our empirical results are consistent with the implication of this hypothesis, that the relative demand for educated workers declines as the ages of plant and (particularly) of equipment increase, especially in R & D-intensive industries

I. Introduction

THE notion of the "learning curve," which was evidently first formalized about half a century ago, has turned out to be a useful and widely applicable concept in the analysis of production behavior.[1] The general acceptance of the learning curve hypothesis reflects a consensus, as expressed by Kaplan (1982, p. 98), that "the cost of doing most tasks of a repetitive nature decrease[s] as experience at doing these tasks accumulate[s]." According to the standard learning curve model, costs decline with accumulated experience, but at a diminishing rate. In his seminal article on "learning by doing," Arrow noted that

> A . generalization that can be gleaned from many of the classic learning experiments is that learning associated with repetition of essentially the same problem is subject to sharply diminishing returns. There is an equilibrium response pattern for any given stimulus, towards which the behavior of the learner tends with repetition. To have steadily increasing performance, then, implies that the stimulus situations must themselves be steady evolving rather than merely repeating. (1962, pp 155–156)

The hypothesis that there is a learning curve associated with a production activity implies that the duration of experience with the technology is an argument of the cost and production functions, and that the first and second partial derivatives of cost (output) with respect to experience are negative (positive) and positive (negative), respectively.

Despite the recognition that experience "matters" in cost functions, it has, virtually without exception, been ignored in modern econometric analysis of cost and production. Although most such models include a "technology" variable as an argument, that variable is supposed to represent the "level" or "state" of technology (and changes in it the extent of technical progress) rather than experience with technology.

The primary objective of most econometric studies of cost and production is to analyze the structure and determinants of factor demand. Factor demand equations are obtained by partially differentiating the cost function with respect to factor prices, and setting the derivatives equal to zero, to satisfy the necessary conditions of producer equilibrium. For this reason, whether or not experience is included in the cost function will affect the specification of factor demand equations only if experience affects costs "non-neutrally," that is, only if it has other than a purely first-order effect on costs.

The major hypothesis to be developed and tested in this paper is that experience does *not* enter the cost function "neutrally," and thus (from a geometric perspective), that ceteris paribus increases in experience do not result in "parallel" shifts in the cost function. Consequently, equilibrium shares of factors in production costs are a function of the amount of experience with the technology, as well as of the conventional determinants (e.g., relative factor prices).

More specifically, we postulate that highly-educated workers have a comparative advantage with respect to learning and implementing new technologies, and hence that the demand for these workers relative to the demand for less-educated

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* Columbia University.

[1] For example, see Dudley (1972), Preston and Keachie (1964) and Rapping (1965).

workers is a declining function of experience.[2] Nelson and Phelps (1966) incorporated a similar proposition as an assumption in a simple neoclassical model of economic growth; Nelson, Peck, and Kalachek (1967) provided some interesting anecdotal evidence; in the only econometric study of the subject, Welch (1970) estimated a model of relative earnings of workers by education category on cross-sectional U.S. farm data. His analysis refers only to agriculture, and evidence from other sectors is clearly needed to determine the validity and applicability of the hypothesis. The purpose of our paper is to provide such evidence, using what we believe are superior measures of experience on a technology.

In the next section of the paper the previous literature is reviewed. In section III we formulate an econometric model of the demand for highly-educated workers, derived from a cost function in which experience enters non-neutrally. The model is estimated on a panel of 61 U.S. manufacturing industries observed in 1960, 1970, and 1980; the results are given in section IV. A brief summary and conclusions follow.

II. Theoretical Perspectives and Literature Review

This section has three main objectives. We begin by attempting to provide a theoretical justification for the hypothesis that the demand for educated, relative to uneducated, workers declines with experience on a technology. We then distinguish this proposition from others concerning the relationship between education and technical change. Finally, we review existing evidence apposite to our hypothesis.

A. Hypotheses Regarding Education and Technology

Two premises—one about the impact of the introduction of new technology on the production environment, the second about differences in the way educated and uneducated workers function in that environment—are sufficient to justify our hypothesis about the effect of experience on a technology on the structure of labor demand. The first premise is that the degree of uncertainty as to what constitutes effective task performance declines with experience on a technology. 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 second premise underlying our hypothesis is that the productivity of highly-educated relative to less-educated workers is greater, the more uncertainty characterizing the production environment. Nelson and Phelps (1966, p. 69) argue that "education enhances one's ability to receive, decode, and understand information." Presumably this is why, according to Welch (1970, p. 47), "educated persons... can distinguish more quickly between the systematic and random elements of productivity responses." When a new product or process has recently been introduced, there is "more (remaining) to be learned" about the technology, and there is a greater premium on the superior "signal-extraction" capability of educated labor.

Before considering the existing empirical evidence and our own new results, it behooves us to contrast the hypothesis developed above to two other propositions about the relationship between education and the introduction of new technology, or technical change. These contrasts involve two distinctions, one between the *adoption* and the *implementation* of new technology, and the other between the *short-run* and *long-run* impact of technical change on skill or educational requirements.

There is abundant evidence, from studies of both consumer and producer (entrepreneur) behavior, that more highly-educated individuals tend to adopt innovations sooner than less-educated

[2] We are agnostic as to the extent to which this advantage derives from skills conferred by education as opposed to an alternative (selection) function of education—in other words, how much school *produces* "learning ability," versus how much (exogenously) better learners choose to attend school

individuals.[3] Our hypothesis, however, is that educated workers have a comparative advantage with respect to the *implementation* of innovations, which occurs following, and conditional on, adoption. (The learning curve depicts the improvement in performance following adoption of a new technology.) Under the hypothesis about the relationships between education and adoption, on the one hand, and education and implementation, on the other hand, the directions of causality between education and innovation are opposite. Education "causes" individuals to adopt (earlier); the adoption of an innovation (which requires implementation for full realization of benefits) "causes" increased relative demand for educated workers. While there is, then, a kind of "simultaneity" with respect to the relationship between education and innovation, we argue below that the (single) equation we estimate is part of a *recursive* simultaneous equations system that can be consistently estimated by ordinary least squares (OLS).

The second hypothesis from which we wish to distinguish our story might be referred to as the "biased technical change hypothesis." If technical change is biased or nonneutral, the transition from an old to a new technology will result in *permanent* changes in equilibrium factor shares, holding output and relative factor prices constant.[4] Models incorporating biased technical change abstract from the process of implementing new technologies (which is precisely our concern); the implicit assumption is that the structure of factor demand does not vary after adoption. Our hypothesis is that the process of *adjustment* to (implementation of) the new technology is educated-labor-using. We do not venture to speculate as to whether in long-run equilibrium, new technologies are more educated-labor using than the technologies which they replace.[5] It *is* an implication of our hypothesis, however, that sectors or industries characterized by high rates of innovation, which are, as a result, continuously implementing new technologies, will tend to create the most opportunities (demand) for highly-educated workers.

B. Previous Work on "Experience on a Technology" and Labor Demand

We turn now to a brief summary of the existing evidence concerning the relationship between "experience" on a technology and the education-structure of labor demand. Bright (1961) observed that the skill requirements of jobs in several industries first increased and then decreased sharply as the degree of mechanization grew. This finding is consistent with the hypothesis that the process of adjustment to new technology is skilled-labor-using, and that technical change is biased in favor of unskilled labor.

Nelson et al. provide some anecdotal evidence on the tendency of the average educational attainment of workers to decline as a technology matures:

> The early ranks of computer programmers included a high proportion of Ph.D mathematicians; today, high school graduates are being hired. During the early stage of transistors chemical engineers were required to constantly supervise the vats where crystals were grown. As processes were perfected, they were replaced by workers with less education. (1967, p 144–145)

Welch (1970) investigated the relationship between the demand for labor by education category and an indicator of experience (actually, an indicator of the "newness" of inputs, or of the *lack* of experience) using 1959 cross-sectional (state) farm data. Welch implicitly assumed that workers (at least in some educational categories) were immobile across states, so that wages were not equalized across states. In his model relative wages by education class are endogenous, determined by (exogenous) *quantities* of labor by education class, nonlabor inputs, and the "newness" indicator, in addition to other variables. The measure that he uses to proxy the rate of flow of new inputs (hence the degree of *in*experience with the technology) is a weighted average of expenditures per farm for research over the past nine years. Welch found that the wage rate of college graduates relative to

[3] See Wells (1972), p 9, and Nelson and Phelps (1966), pp. 70 and 72. Wozniak (1984) found that farm operators with more education are more likely to be adopters of innovations than operators with less education, but that education did not affect the utilization of an innovative input several periods after its introduction.

[4] A general framework for analyzing technical change biases was developed by Binswanger (1974). Examples of studies that tested the biased technical change hypothesis are Levy et al. (1983) and Denny and Fuss (1983).

[5] We agree with Binswanger (1974) p. 975, however, that long-run technical change biases may be endogenous, determined by relative factor prices, although his evidence suggests that "it takes very substantial changes in factor prices in order to perceptibly influence the biases."

that of "laborers with conventional skill" was positively and significantly related to research expenditures. But because, as he argues, "agriculture is probably atypical inasmuch as a larger share of the productive value of education may refer to allocative ability than in most industries" (1970, p. 47), evidence from other sectors (and perhaps based on different assumptions and methodology) is needed to determine the validity and applicability of the hypothesis.

III. Econometric Specification

In this section we specify a cost function in which the age of the technology enters non-neutrally with respect to labor input classified by education, and derive from it a labor demand equation to be estimated below.

In view of the issues we wish to explore, it is convenient and, we think, reasonable to specify a model of *total labor cost* rather than a model of total cost of production (the sum of labor, capital, and materials costs). Abstracting from materials cost is acceptable if raw materials are separable from primary inputs in the total-cost function. Although there is evidence against such separability, the failure of this assumption to hold is unlikely to affect our estimates or hypothesis tests regarding the effect of "age" on the structure of labor demand. If one hypothesizes that capital is a "quasi-fixed" input that producers cannot adjust freely in response to relative price changes, it is appropriate to specify a *restricted variable* cost function, according to which minimum variable-input cost is determined by variable input prices, the stock of capital, output, and perhaps other variables.[6] Since we are excluding materials inputs from consideration, total variable cost reduces to total labor cost.

To keep the model as simple as possible, we postulate there to be only two categories of labor ("highly educated" and "less educated"), and specify the following general form for the restricted variable or total labor cost function:

$$TLC = f(W_1, W_2, AGE, K, Q, T) \tag{1}$$

[6] See Mohnen et al. (1986) for a detailed discussion of restricted variable cost functions.

where

TLC = total labor cost
W_1 = wage rate of highly-educated workers
W_2 = wage rate of less-educated workers
AGE = age of the technology
K = stock of quasi-fixed capital (plant and equipment)
Q = real output
T = index of the state of technology.

The minimum total labor cost of producing a level of output Q using a capital stock K and a technology of state T and age AGE, given wage rates W_1 and W_2, is determined by equation (1). It is convenient to define a four-element (row) vector Z, where

$$Z_1 = AGE$$
$$Z_2 = \ln K$$
$$Z_3 = \ln Q$$
$$Z_4 = T,$$

so that we can rewrite (1) as

$$TLC = f(W_1, W_2, Z). \tag{2}$$

We assume that equation (2) can be approximated by the translog function

$$\begin{aligned} \ln TLC = {} & \alpha_0 + \alpha_1 \ln W_1 + \alpha_2 \ln W_2 \\ & + \tfrac{1}{2}\left[\alpha_{11}(\ln W_1)^2 + \alpha_{12}(\ln W_1)(\ln W_2)\right. \\ & \left. + \alpha_{21}(\ln W_2)(\ln W_1) + \alpha_{22}(\ln W_2)^2\right] \\ & + \sum_{j=1}^{4}\left[\beta_j Z_j + \beta_{1j}(\ln W_1)(Z_j)\right. \\ & \left. + \beta_{2j}(\ln W_2)(Z_j)\right]. \end{aligned} \tag{3}$$

(We suppress quadratic and interaction terms among the Z_j which would vanish in the first-order conditions.) Shephard's lemma implies the following necessary condition for cost-minimization:

$$\frac{\partial \ln TLC}{\partial \ln W_i} = S_i \qquad (i = 1, 2) \tag{4}$$

where S_i = share of i^{th} labor category in total labor cost. Differentiating equation (3) with respect to $\ln W_1$, imposing the usual symmetry and homogeneity restrictions, and using the equilibrium condition (4), we obtain

$$S_1 = \alpha_1 + \alpha_{11}\ln(W_1/W_2) + \sum_j \beta_{1j}Z_j \qquad (5)$$

where S_1 = share of cost of highly-educated labor in total labor cost. Equation (5) implies that, in general, the equilibrium share of educated-labor's cost in TLC is determined by relative wages and by AGE, K, Q, and T. The central hypothesis we wish to test is that $\beta_{11} < 0$, i.e., that increases in experience with, or in the age of, the technology lead to reductions in S_1. We allow for nonzero β_{1j} ($j = 2, 3, 4$) because it is plausible that K, Q, and T also determine S_1 and because (as we discuss in detail below) these variables are potentially correlated with AGE. According to the "capital-skill complementarity" hypothesis, for example, $\beta_{12} > 0$, and if the TLC function is nonhomothetic and characterized by nonneutral technical change, β_{13} and β_{14} will also be nonzero.

Factor-share equations are conventionally estimated on time-series data for a given industry or sector, which is reasonable under the hypothesis that cost-function parameters are invariant over time (but not necessarily across industries). In our empirical work, however, we estimate S_1-equations on a *panel* of 61 industries each observed in the (Census of Population) years 1960, 1970, and 1980. There are several reasons for taking this approach. First, reasonably good estimates of the distribution of employment and labor cost by education and industry are available only in Census years. One could, of course, estimate equation (5) on *aggregate* time-series data, but even at the aggregate level, *annual* data on S_1 would be subject to substantial measurement error. Moreover, it is much less reasonable to maintain the convenient assumption that (relative) wage rates are exogenous at the aggregate level than it is at the industry level.

The equations which we actually estimate on our panel are variants of the following "fixed effects" or "analysis of covariance" model:

$$S_{1kt} = \gamma_k + \zeta_t + \beta_{11}AGE_{kt} + \beta_{12}\ln K_{kt} + \beta_{13}\ln Q_{kt} + \epsilon_{kt} \qquad (6)$$

where the double kt-subscript refers to the value of the variable for industry k in year t, and ϵ is a disturbance term. By including the industry effects γ_k we control for the effects of any permanent differences across industries in unmeasured determinants of S_1; the time dummies, ζ_t, control for the effects of changes over time in unmeasured determinants which are common to all industries. Within this econometric framework the coefficients on the covariates AGE, K and Q capture the partial relationships between *deviations* of these variables from their respective industry means and deviations of S_{1kt} from its respective industry mean. A heuristic interpretation of our estimation procedure is that it reveals whether an industry which experienced an increase in AGE above the average experienced by all industries between, say, 1960 and 1970, had a (significantly) below-average increase in S_1 during that period.

The reader will note that whereas equation (5) includes the relative-wage variable and the technology index T on the right hand side, these variables are absent from equation (6).[7] We can at least partially justify the omission of these variables from our estimating equations on the following grounds. In contrast to Welch, we assume that both types of labor are mobile across industries in the long run, so that (relative) wages are both equalized across industries and exogenous to any given industry in any particular year. Under this assumption all of the relative-wage variation in our sample is in the time-dimension, and this variation is controlled for by the presence of time dummies.[8]

T, the index of the state of technology, is excluded from equation (6) because we lack industry- and year-specific data on this variable. To the extent that the total sample variation in T is accounted for by permanent interindustry differences and by changes common to all industries, T is controlled for by the industry- and year-

[7] Data on relative wages are not available by industry. Even if such data were available, under the hypothesis of interindustry labor mobility, the observed variation in relative wages across industries would reflect variation in (relative) "labor quality" and other measurement error, rather than variation in the true user cost of labor.

[8] It is true that the effect on S_1 of a given change in relative wages will be different in industries with different elasticities of substitution between the two types of labor (and hence different values of α_{11}); we might think of the time dummies as capturing, inter alia, the product of the year-specific relative wage and the *mean* across industries of α_{11}. Indeed under suitable assumptions we can interpret all of our parameter estimates (e.g., β_{11}) as means of the respective distributions of parameters across industries.

effects.[9] We recognize, however, that industries experience different rates of technical change, so that not all of the variation in T will be captured by the fixed effects. Of course, if technical progress is, in reality, neutral with respect to the structure of labor demand, then we do not commit a specification error by omitting T from the share equation.

We turn now to an issue of obviously critical importance in our research design—the measurement of "age of the technology." The age or "newness" of the technology is for us, as it was for Welch, not directly observable. As noted above, Welch used R & D expenditure as a proxy for "newness" of inputs. We also find industries' R & D spending to contribute to the explanation of the observed variation in S_1, but in a way different from that hypothesized or investigated by Welch. Our proxy for the age of an industry's technology is the age of its capital stock (or the ages of its two components, plant and equipment).

If one accepts the notion of embodied technological change, then the age of the capital stock is identical to the age of the technology.[10] Even if technological change is not completely embodied, we expect there to be a strong relationship between the age of the capital stock and the age of the technology. The link between the age of capital and the age of technology results from the assumption that the introduction of new technology increases equilibrium industry output, due to both demand increases arising from product innovations and cost reductions arising from process innovations. Output increases in turn lead to a higher rate of investment and a younger capital stock.[11] The link can also be interpreted as consistent with the product life cycle approach (Wells, 1972), according to which early in a product's life, a low capital to labor ratio is used because of frequent design changes. 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.

Before turning to our empirical analysis, we wish to make several econometric points. First, two comments regarding our proxy for AGE. The mean age of the capital stock is, like (the quantity of) the capital stock itself, determined by the past history of investment. Thus one can view an equation including the mean age variable as a specification including a very restricted distributed lag on past investment. In principle, it might be desirable to relax this restriction, and to include an unconstrained distributed lag, but this would be likely to introduce severe multicollinearity and render the interpretation of our estimates difficult. Second, we recognize that a significant fraction of investment may involve simply replacing old capital with capital of similar design, as opposed to the installation of capital embodying new technology. We try to take account of this by allowing the effect of changes in capital age on S_1 to depend on an industry's own and "embodied" R & D-intensity. In any case, however, the fact that some or even most investment is merely "replacement" investment implies that the mean age of capital is a "noisy" (error-ridden) indicator of the age of the technology, which should render our hypothesis tests on β_{11} strong tests (i.e., biased towards acceptance of the hypothesis that $\beta_{11} = 0$).[12]

Finally, a comment regarding "simultaneity." While we noted above that there is a sense in which the relationship between AGE and education is "simultaneous," we submit that equation (6) can be viewed as part of the following *recursive* two-equation system:

$$\textit{relative employment} = f(AGE, \textit{relative wages}, Z)$$
$$AGE = f(\textit{relative wages}, X)$$

where X represents such factors as technological opportunities and growth in product demand, and

[9] In fact, specifying time dummies is somewhat less restrictive than specifying a time trend, the proxy for T frequently employed in previous econometric factor-demand studies, such as Binswanger (1974) and Levy, Bowes, and Jondrow (1983)

[10] Much of the neoclassical growth literature on embodied technical change is predicated on the assumption that "technological progress must be embodied in design changes built into new machines alone." (See Burmeister and Dobell (1970), p 90.) We do not need to assume that machines purchased at time t embody technology of vintage t. We require only the weaker assumption that the technology embodied in new machines is newer, on average, than the technology embodied in existing machines.

[11] Jorgenson's 1971 survey of the literature on investment concluded that output was clearly the major determinant of investment in fixed capital

[12] Griliches (1984) has shown that the well-known measurement-error-induced bias-towards-zero result of the bivariate regression model generalizes, under suitable conditions, to the multivariate case.

Z reflects determinants of relative employment. Because, under our assumptions, labor is perfectly mobile across industries, there is no reason for decisions by producers in an industry to introduce new technology to be based on relative *quantities* of labor employed in the industry; as we suggest in the conclusion, however, they *will* be based on relative *wages*. Labor mobility, as observed above, implies that relative wages would be equalized across industries, and thus controlled for by the time dummies. Since the above system is recursive, the first equation can be consistently estimated by OLS.

IV. Empirical Analysis

A. Data

Variants of equation (6) are estimated on a pooled cross-section time-series data set containing 61 manufacturing industries in each of the years 1960, 1970 and 1980.[13] Data on the demographic characteristics of the workers in these industries were obtained from the Labor Demographics Matrices of the Bureau of Industrial Economics (BIE). Information on the age and the quantity of the industry's capital stock is taken from the Bureau of Industrial Economics' Capital Stocks Data Base. Data on real output are from the Census/SRI/Penn Data Base which is derived primarily from the Annual Survey of Manufactures and the Census of Manufactures,[14] and finally, information on the R & D intensity of each industry is obtained from the technology matrix constructed by Scherer (1984).

B. Basic Results

The results of estimating variants of equation (6) by OLS are shown in table 1.[15] The dependent variable is the share of labor cost attributed to highly educated workers, defined as those with greater than a high school education. Since our data set does not report labor cost, we approxi-

[13] The 61 industries are the industry sectors used by the BIE for their labor demographic matrices.

[14] See Griliches and Lichtenberg (1984b) for a complete description.

[15] We tested for first-order serial correlation of the residuals by estimating a version of equation (6) that included lagged dependent and independent variables; the coefficient on the lagged dependent variable may be interpreted as an estimate of ρ, the autocorrelation coefficient. The point estimate and t-ratio of ρ were, respectively, 0.044 and 0.33, so we could not reject the null hypothesis of serially uncorrelated residuals. Since the frequency of our data is decennial, the low estimated value of ρ is not surprising. (The *quarterly* autocorrelation coefficient implied by our estimate, $\hat{\rho}^{1/40} = .044^{.025} = .925$, is, however, quite high.) Because $\hat{\rho}$ was estimated to be very small and insignificant, and also because, as Brown (1985) observes, GLS (generalized least squares) does not necessarily yield smaller true standard errors than OLS when ρ is estimated, we did not pursue estimation by GLS.

TABLE 1.—DEPENDENT VARIABLE: LABOR COST SHARE OF EMPLOYEES WITH 13 + YEARS OF EDUCATION
(t-statistics in parentheses)

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGECAP	−0.0074							
	(−2.66)							
AGEEQ		−0.0086		−0 0078	−0.0063	−0.0065		
		(−2.60)		(−2 42)	(−1.90)	(−1.93)		
AGEPL			−0.0017					
			(−0.88)					
AGEEQ * *OWNRD*							−0 4821	
							(−2.86)	
AGEEQ * *IMPRTRD*								−0.6954
								(−1.71)
Log (*REAL CAPITAL STOCK*)				0.0321		0.0069	0.0161	0 0143
				(2.67)		(0.38)	(0 87)	(0.73)
Log (*REAL OUTPUT*)					0.0360	0.0315	0.0227	0.0325
					(3.24)	(1.94)	(1.38)	(2.00)
R^2	0.962	0 962	0.961	0.964	0.964	0.964	0.966	0.964
N	183	183	183	183	174	174	174	174

Note All equations include year and industry dummies, which are in all cases jointly highly statistically significant The independent variables are defined in the text The employment share of workers with 13+ years of education was 0 158 in 1960, 0 190 in 1970 and 0 271 in 1980 The mean age of the capital stock was 9 25 years in 1960, 9 18 in 1970 and 9 45 in 1980 mate it by using the information on employment in the following way. We have two classes of workers: highly educated (L_1) and less educated (L_2). Define ($l = L_1/(L_1 + L_2)$) which is L_1's share in total employment; and $\omega = W_2/W_1$, the ratio of less educated to highly educated wages. Then it can be shown that L_1's share in labor cost is given by[16]

$$S_1 = \left(1 + \omega(l^{-1} - 1)\right)^{-1}. \tag{7}$$

We have information on l from the BIE and we can obtain an estimate of ω in each of the years 1960, 1970 and 1980 from the Current Population Reports.[17] Since we assume ω is constant across industries for any given year, the cost share is simply a nonlinear transformation of the employment share.[18]

Columns (1), (2) and (3) of table 1 report regressions using alternative measures of the age of the capital stock and omitting ln K and ln Q; the first column uses the average age of the plant and equipment combined ($AGECAP$) while the second column uses the average age of equipment only ($AGEEQ$) and the third uses the average age of plant only ($AGEPL$).[19] While $AGECAP$ and $AGEEQ$ both have the hypothesized signs and are significant, $AGEPL$ does not have a significant effect. This is not surprising since technology is more likely to be embodied in the industry's equipment. The insignificance of $AGEPL$ is also important because it casts doubt upon an alternative interpretation of the negative effect of $AGECAP$. The alternative argument is that industries that are relocating their plants to developing regions such as the South are more likely to increase their share of educated workers because they will be hiring new labor force entrants who, on average, have more education. If this argument were correct, $AGEPL$ would have a negative and significant coefficient. In the remainder of table 1, we use equipment age to measure the age of the technology in the industry.

While the negative and significant effect of $AGEEQ$ in column (2) strongly supports our hypothesis regarding the superior ability of educated workers to adapt to new technology, it is likely that changes in $AGEEQ$ are highly correlated with the growth rates of the capital stock and of output in the industry; i.e., growing industries have newer equipment. In order to control for this, columns (4), (5) and (6) in table 1 add the logarithms of the real capital stock and real output to the cost share equation. When only the log capital stock is added to the equation, its coefficient is positive and significant (and the coefficient on $AGEEQ$ remains negative and significant), a finding consistent with the "capital-skill complementarity" hypothesis. Because growth in the capital stock and in real output tend to be highly correlated across industries, the output term in column (5) has a coefficient similar to the capital term in column (4) and a similar effect on the $AGEEQ$ coefficient, although it reduces its significance somewhat more. When both the capital and output variables are included (column (6)), only the output variable is significant, and $AGEEQ$ remains significant.

These estimates appear to provide rather strong support for our hypothesis about the effect of the introduction of new technology on the relative demand for educated workers. We can gauge the magnitude of this impact in the following way. Consider the two industries with maximum and minimum sample values of $AGEEQ$: (1) Wood Containers, in which, in 1980, the mean age of the equipment is 8.66 years and the labor cost share of highly educated workers is 0.307 and (2) Electronic Components and Accessories in which, in 1980, the mean age of equipment is 5.19 years and the labor cost share of highly educated workers is 0.433. According to the estimated parameter on $AGEEQ$ in column 6, 18% of the observed difference in the labor cost share of highly educated workers between these two industries is due to the difference in the ages of their equipment.

[16] Since $S_1 = W_1L_1/(W_1L_1 + W_2L_2) = 1/(1 + \omega(L_2/L_1))$.

[17] From the Current Population Reports, we calculate the ratio of mean total earnings of year-round full-time workers with 13+ years of education to the comparable mean for workers with less than 13 years of education. The values of the ratio are 0.59 in 1960, 0.62 in 1970 and 0.68 in 1980.

[18] The results we present below are virtually identical to those that use the employment share.

[19] According to Arrow (see quote in introduction), we should expect diminishing returns to learning. This implies that a nonlinear specification of the age variable is appropriate. In regressions not reported here, we tried the logarithm of AGE and the inverse of AGE and found that the t-statistics on these variables were virtually identical to the t-statistics on AGE reported in table 1. Since the linear version fits equally well and is considerably easier to interpret, we only report the linear results in this paper.

TABLE 2.—EFFECTS OF AGE OF TECHNOLOGY ON EMPLOYMENT SHARES OF WORKERS WITH 13+ YEARS OF EDUCATION, WITHIN SPECIFIED AGE GROUPS

	(1) *AGEEQ*		(2) *AGEEQ * OWNRD*	
Age Group[a]	*b*	*t*	*b*	*t*
1. 14–17	−0.0021	(−1.08)	−0.0189	(−1 94)
2. 18–24	−0.0071	(−1.72)	−0.0400	(−1.90)
3. 25–34	−0.0074	(−1.85)	−0.0781	(−4.06)
4. 35–44	−0.0024	(−0.66)	−0.0352	(−1.88)
5. 45–54	−0.0033	(−0.74)	−0.0241	(−1.07)
6. 55 +	−0.0030	(−0 71)	−0.0024	(−0.11)

Note Each parameter shown here comes from a separate regression equation Every equation also includes the log of the real capital stock, the log of real output, a vector of industry dummy variables and a set of time dummy variables

[a] The means of the employment shares of workers with 13+ years of education are as follows

	1960	1970	1980
1 14–17	0 004	0 005	0 009
2 18–24	0 149	0 190	0 218
3 25–34	0 214	0 236	0 354
4 35–44	0 166	0 210	0 290
5 45–54	0 127	0 170	0 235
6 55 +	0 107	0 132	0 204

C. *The Role of R & D*

Up to this point, we have been assuming that the effect of *AGE* on the distribution of labor cost is constant across industries. It is reasonable to hypothesize, however, that the impact on S_1 of a change in *AGE* will be greater in more R & D-intensive industries. This is because new capital is most likely to embody new technology in R & D-intensive industries. In order to test this hypothesis, we replaced *AGEEQ* by the interaction of *AGEEQ* with the industry's 1974 R & D-intensity.[20] We use two different measures of R & D-intensity. The first is *OWNRD* which equals the ratio of the industry's 1974 R & D expenditures to its 1974 nominal output. The second is *IMPRTRD* which is the ratio of 1974 R & D "imported" from other industries, i.e., embodied in products purchased from other industries, to 1974 nominal output. In principle, we might expect $\partial S_t/\partial AGE$ to depend more on *IMPRTRD* than on *OWNRD* because *IMPRTRD* measures the R & D that is embodied in the industry's capital stock. However, as can be seen in columns (7) and (8), the effect of *AGEEQ* is more significant when we use *OWNRD* rather than *IMPRTRD*, probably because of the large amount of error in measuring *IMPRTRD*.[21] Further, when *AGEEQ* and *AGEEQ* * *OWNRD* are used together, the coefficient on *AGEEQ* is not significant, while the interaction term is.[22] These findings demonstrate that the effect of the age of technology on the labor cost share of highly educated workers depends upon the R & D intensity of the industry.

D. *Controlling for the Age of Employees*

Although the significant negative effects of *AGEEQ* in table 1 lend strong support to our guiding hypothesis, there is potentially an alternative interpretation of the results. The industries that have been most innovative are also likely to be hiring many new employees, and these new hires will be younger, on average, than the experienced workers in the industry. Since average educational attainment has been increasing over the period we are studying,[23] it is possible that the coefficients observed in table 1 are simply due to

[20] Time-series data on R & D-intensity by industry are not available for our industry classification. However, industries' relative R & D-intensities are generally thought to be very stable over time.

[21] See Scherer's (1984) discussion of the complicated algorithm in constructing imported R & D. Griliches and Lichtenberg (1984a) also found that the imported R & D variable had an insignificant effect on productivity growth, holding *OWNRD* constant, again suggesting the existence of substantial measurement error in this variable

[22] The t-value on *AGEEQ* is −0.37 and the t-value on *AGEEQ***OWNRD* is −2.11.

[23] The percentage of the civilian labor force aged 16 and over that had completed at least one year of college was 18.9 in 1960, 26.2 in 1970 and 35.1 in 1980.

the entrance of young educated workers into the labor market. We can address this problem by estimating the employment share equation separately for different age groups.[24] If the adjustment hypothesis is correct, then we should still observe a negative effect of the age of technology on the employment share of educated workers within age groups. The results are shown in table 2, where we tried two specifications. In column (1) we assumed that the effect of *AGEEQ* does not vary across industries and in column (2), we assumed that *AGEEQ's* effect is a function of the R & D intensity of the industry. Recall from table 1 that the latter specification produced much stronger results. In column (2) of table 2, we see that four out of the six parameters are negative and significant. The hypothesis regarding the superior ability of educated workers to adjust to new technology is borne out for employees under age 45. The insignificance of the parameters for workers over age 45 can be explained in one of two ways. First, firms may be unable to adjust the composition of their senior workers because of seniority rights regarding layoff and discharge. A second explanation is that the value of education depreciates such that individuals educated more than twenty-five years ago are no better able to adjust to new technology than their less educated peers. The estimates presented in table 2 show that our finding of a significant ceteris paribus relationship between the educated labor share and the average age of equipment is not merely reflecting a relationship between changes in the *age-structure* of an industry's workforce and of its capital stock.

V. Conclusions

In this paper we have estimated variants of a labor demand equation derived from a (restricted variable) cost function in which "experience" on a technology (proxied by the mean age of the capital stock) enters "non-neutrally." Our specification of the underlying cost function was based on the hypothesis that highly educated workers have a comparative advantage with respect to the adjustment to and implementation of new technologies. Our empirical results are consistent with the implication of this hypothesis, that the relative demand for educated workers declines as the capital stock (and presumably the technology embodied therein) ages. According to our estimates, the education-distribution of employment depends more strongly on the age of equipment than on the age of plant, and the effect of changes in equipment age on labor demand is magnified in R & D-intensive industries.

The evidence we have provided has several important policy implications. First, it suggests that macroeconomic policies which affect rates of innovation and investment (particularly in equipment) will affect the relative demand for workers classified by education, and hence the aggregate skill distribution of employment and earnings. Thus, policies such as the investment tax credit, accelerated depreciation, and liberalization of antitrust restraints on R & D joint ventures, will be expected to increase highly-educated workers' share in labor income. Our results may also have a bearing on the role of government education policy in promoting economic growth. In particular, government subsides and other policies which tend to encourage the acquisition of education and increase the relative supply of highly-educated workers, will be expected to accelerate the rate of diffusion of new industrial technologies by lowering the costs of adjustment and implementation.

[24] It is quite likely, however, that the employment share of educated workers by age group is subject to substantially greater measurement error than the overall educated employment share.

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