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THE COMPARATIVE ADVANTAGE OF EDUCATED WORKERS IN IMPLEMENTING NEW TECHNOLOGY: SOME EMPIRICAL EVIDENCE

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ABSTRACT

In this paper we estimate 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 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 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.

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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. The general acceptance of the learning curve hypothesis reflects a consensus, as expressed by Kaplan, that "the cost of doing most tasks of a repetitive nature decrease[s] as experience at doing these tasks accumulate[s]."[1] 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.[2]

The hypothesis that there is a learning curve associated with a production activity has implications for the (dual) cost and production functions which characterize that activity, or technology. In particular, the hypothesis 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.

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[1]Kaplan (1982), p. 98.

[2]Arrow (1962), pp. 155-156.

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. By analogy, the levels of technology and of output, respectively, appear in factor demand equations only if technological change is "biased" and production is nonhomothetic.

The major hypothesis to be developed and tested in this paper is that experience does <u>not</u> enter the cost function "neutrally," and thus (from a geometric perspective), that <u>ceteris paribus</u> 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 workers is a declining function of experience.[3] We are not the first authors either to propose or to attempt to rigorously test this hypothesis -- 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 empirical 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 only refers 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.

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[3] 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.

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 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 <u>different</u> but, in the short run at least, less well-defined. Wells (1972) 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."[4] Nelson et al also observe that

> the introduction and early operation of new processes [creates] an environment of uncertainty and imperfect knowledge. But the growth of understanding about particular processes, and the learning experiences of early use, ultimately lead to specialization of function and subdivision of labor. As knowledge progresses, it results in routinized and mechanized processes capable of being easily operated.[5]

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 argue that "education enhances one's ability to receive, decode, and understand information."[6] Presumably this is why, according to Welch "educated persons ... can distinguish more quickly between the systematic and random elements of productivity responses."[7] 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

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[4]Wells, pp. 8-9.

[5]Nelson, et al.

[6]Nelson and Phelps, op. cit., p. 69.

[7]Welch, op. cit., p. 47.

involve two distinctions, one between the adoption and the implementation of new technology, 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 individuals. Wells, for example, cites evidence from the marketing literature that "early [consumer] purchasers of a new product ... are generally found to be ... more educated."[8] And Nelson and Phelps, citing Rogers' work on the diffusion of innovations in U.S. agriculture, assert that "it is clear that the farmer with a relatively high level of education has tended to adopt productive innovations earlier than the farmer with relatively little education."[9] Such evidence motivates Nelson and Phelps to analyze a theoretical model of the process of technological diffusion and the role of education predicated on the assumption that "the time lag between the creation of a new technique and its adoption is a decreasing function of some index of average educational attainment ... of those in a position to innovate" [emphasis added].[10]

Our hypothesis 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

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[8]Wells, op. cit., p. 9.

[9]Nelson and Phelps, op. cit., p. 70.

[10]Nelson and Phelps, op. cit., p. 72.

adoption, on the one hand, and education and implementation, on the other hand, the direction 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. In our empirical work we analyze the relationship between the education-structure of labor cost (or employment) and an indicator of the "presence" of new technologies, and we implicitly assume the latter to be exogenous. This assumption might appear to be of questionable validity in view of the preceding discussion. But because our education data refer to total employment in an industry, and individuals responsible for making adoption decisions account for a very small fraction of total employment, we believe we are primarily capturing the effect of (previous) adoption on educational demand rather than the effect of education on the propensity to adopt.

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.[11] In order to test for the presence of nonneutral technical change, an indicator of technology -- either a time trend, or an index of diffusion of a new technology -- is sometimes included in aggregate or industry-level

[11] A general framework for analyzing technical change biases was developed by H. Binswanger (1974).

econometric cost functions.[12] Most studies of biased technical change have addressed the question of whether technical change is (aggregate-) labor-saving (non-labor using) -- the answer is generally affirmative -- not whether new technologies are biased towards particular types of labor. An exception is the study by Denny and Fuss, who found that "the labor-saving impact [of technical change in the Canadian telecommunications industry] was felt most severely by the least skilled occupations.[13]

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.[14] 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

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[12]For example, Levy et al's measure of technology for underground mining is the fraction of production carried out by what are considered relatively new methods: continuous, shortwall, and longwall mining, while Denny and Fuss' index of technology for the Canadian telecommunications industry is based on the percentage of telephones with access to direct distance dialing. See Levy et al (1983) and Denny and Fuss (1983).

[13]Denny and Fuss, op. cit., p. 161.

[14]We agree with Binswanger (op. cit., 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 perceptably influence the biases."

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 relationships between "experience" on a technology and the education-structure of labor demand. In the early 1960s, Bright (1961) studied the effects of automation on job-skill requirements in metal working, food and chemicals. He observed that the skill requirements of jobs first increased and then decreased sharply as the degree of mechanization grew. The conclusion of his study was that, in the long run, automated machinery would require less operator skill.

Nelson _et al_ (1967) 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.[15]
>
> The effect [of the introduction of new technology on the demand for education] is not just on the production work force. Technological advance changes the whole pattern of information that must flow between economic units.
>
> High remuneration of technically trained sales people in the electronics industry, for example, relates to their ability to communicate new developments to the potential market.[16]

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[15] Nelson et al., _op_. _cit_., p. 144-5.

[16] Nelson et al., _op_. _cit_., p. 16.

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 endogeneous, determined by (exogeneous) 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 inexperience 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 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,"[17] 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

[17] Welch, op. cit., p. 47.

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.[18] 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:

$$TLC = f(W_1, W_2, AGE, K, Q, T) \qquad (1)$$

where TLC = total labor cost

W_1 = wage rate of highly-educated workers

[18]See Mohnen et al. (1984) for a detailed discussion of restricted variable cost functions.

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 eq. (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 eq. (2) can be approximated by the translog function

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

(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:

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

where S_i = share of cost of highly-educated labor in total labor cost. Differentiating eq. (3) with respect to ln W_1, imposing the usual symmetry and homogeneity restrictions, and using the equilibrium condition (4), we obtain

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

Eq. (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 only available in Census years. One could, of course, estimate eq. (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:

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

where the double kt-subscript refers to the value of the variable for industry k in year t. 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 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 <u>deviations</u> 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 eq. (5) includes the relative-wage variable and the technology index T on the RHS, these variables are absent from eq. (6). 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.[19]

T, the index of the state of technology, is excluded from eq. (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-effects.[20] 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

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[19]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.

[20]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 and Jondrow (1983).

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. 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.[21] 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 two econometric points regarding our proxy for AGE. First, the mean age of the capital stock is, like (the quantity of) the capital stock itself,

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

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 $\beta_{11} = 0$).

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.[22] Data on the demographic characteristics

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[22]The 61 industries and their SIC counterparts are listed in Appendix A. These are the industry sectors used by the BIE for their labor demographic matrices. The industry codes in the other datasets that we use are all matched to the 61 BIE codes.

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,[23] and finally, information on the R&D intensity of each industry is obtained from the technology matrix constructed by F.M. Scherer (1984). Table 1 presents some summary statistics from our database.

B. Results

The results of estimating variants of equation (6) are shown in Table 2. 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 approximate 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 ($\ell = L_1/(L_1 + L_2)$) 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[24]

$$(7) \quad S_1 = (1 + \omega(\ell^{-1} - 1))^{-1}$$

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

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

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.[25] Since we assume ω is constant across industries for any given year, the cost share is simply a nonlinear transformation of the employment share.[26]

Columns (1), (2) and (3) of Table 2 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 (AGECAP) while the second column uses the average age of equipment only (AGEEQ) and the third uses the average age of the plant (AGEPL). 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 2, we use equipment age to measure the age of the technology in the industry.

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[25] 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 .59 in 1960, .62 in 1970 and .68 in 1980.

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

Table 1

Summary Statistics

	1960	1970	1980
Total Employment (millions)	18.6	21.1	22.2
Employment Share of Workers with 13+ Years of Education (percent)	15.8	19.01	27.1
Mean Age of Capital Stock (years)	9.25	9.18	9.45
Mean Age of Equipment (years)	7.25	6.66	6.83
Mean Age of Plant (years)	11.59	12.21	13.73

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 2 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 col. (5) has a coefficient similar to the capital term in col. (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 (col. (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 .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 .433. According to the estimated parameter on AGEEQ in column 6, 18 percent 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.

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 of 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.[27] 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 $\partial S_1/\partial AGE$ 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.[28] Further, when AGEEQ and AGEEQ * OWNRD are

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[27]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.

[28]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.

Table 2
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	-.0074 (-2.66)							
AGEEQ		-.0086 (-2.60)		-.0078 (-2.42)	-.0063 (-1.90)	-.0065 (-1.93)		
AGEPL			-.0017 (-0.88)					
AGEEQ* OWNRD							-.4821 (-2.86)	
AGEEQ* IMPRTRD								-.6954 (-1.71)
Log (REAL CAPITAL STOCK)				.0321 (2.67)		.0069 (.38)	.0161 (.87)	.0143 (.73)
Log (REAL OUTPUT)					.0360 (3.24)	.0315 (1.94)	.0227 (1.38)	.0325 (2.00)
R^2	.962	.962	.961	.964	.964	.964	.966	.964
N	183	183	183	183	174	174	174	174

*All equations include year and industry dummies. The independent variables are defined in the text.

used together, the coefficient on AGEEQ is not significant, while the interaction term is.[29] These findings demonstrate that the effect of the age of technology on the labor cost share of highly educated workers is heavily dependent on the R&D intensity of the industry.

C. Additional Findings

Although the significant negative effects of AGEEQ in Table 2 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, then the experienced workers in the industry. Since average educational attainment has been increasing over the period we are studying,[30] it is possible that the coefficients observed in Table 2 are simply due to 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.[31] 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 3, where we tried two specifications. In column (1) we assumed that the

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[29]The t-value of AGEEQ is -.37 and the t-value on AGEEQ * OWNRD is -2.11.

[30]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.

[31]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.

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 2 that the latter specification produced much stronger results. In Column (2) of Table 3, 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 3 imply 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-structures_ of an industry's workforce and of its capital stock. But although we can apparently dispose of this potential explanation of our results, a problem of interpretation remains. This is because the age of the equipment is defined as the date at which the industry is observed (e.g., 1960) minus the date at which the equipment was acquired. Since all industries are observed at the same dates, in our sample equipment age is perfectly collinear with equipment acquisition date. Hence one could interpret our results as indicating that the cost-share of highly-educated workers is determined by the calendar date at which the equipment was acquired (biased technical change), rather than, or in addition to, by the time elapsed since

Table 3

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**	b	t	b	t
1. 14-17	-.0021	(-1.08)	-.0189	(-1.94)
2. 18-24	-.0071	(-1.72)	-.0400	(-1.90)
3. 25-34	-.0074	(-1.85)	-.0781	(-4.06)
4. 35-44	-.0024	(-.66)	-.0352	(-1.88)
5. 45-54	-.0033	(-.74)	-.0241	(-1.07)
6. 55+	-.0030	(-.71)	-.0024	(-.11)

*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.

**The means of the employment shares of workers with 13+ years of education are as follows:

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

acquiring, or "experience with," the equipment. For this reason, it is not possible to determine the extent to which the increase in educated labor's share resulting from a reduction in equipment age is transitory versus permanent. The coefficient on equipment age may be regarded as capturing the sum of the transitory and permanent effects of the introduction of new technology on the structure of labor demand. In our opinion, while technical change may be biased in favor of highly-educated workers, our results are primarily a reflection of the comparative advantage enjoyed by these workers at learning and implementing new technologies. Although this issue cannot be definitively resolved here, we believe that our results, summarized in the next section, will be of interest to economists and policymakers.

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 subsidies 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.

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APPENDIX A
Description of Industries

	Sector Title	1972 SIC Code
1.	Food and Kindred Products	20
2.	Tobacco Manufactures	21
3.	Broad and Narrow Fabrics, Yarn, and Thread Mills	221,222,223,224,226,228
4.	Miscellaneous Textile goods and Floor Coverings	227, 229
5.	Knitting Mills	225
6.	Apparel	231,232,233,234,235,236,237,238
7.	Miscellaneous Fabricated textile Products	239
8.	Lumber & Wood Products, Exc. Containers	241,242,243,249
9.	Wood Buildings & Mobile Homes	2451,2452
10.	Wood Containers	244
11.	Household Furniture	251
12.	Other Furniture & Fixtures	252,253,254,259
13.	Paper & allied products, exc. containers, Boxes & (Paper Mills, Exc. building paper)	261,263,264,266
14.	Paper mills, Exc. Building Paper	262
15.	Paperboard Containers & boxes	265
16.	Printing & Publishing	27
17.	Chemicals & Selected Chemical Products, exc. Nitrogenous & Phosphate Fertilizers, Fertilizers (mixing only), and Agricultural Chemicals	281, 286, 289
18.	Nitrogenous & Phosphatic fertilizers, Fertilizers (mixing only) & Agricultural chemicals, nec	287
19.	Plastic and synthetic materials	282
20.	Drugs, Cleaning & toilet preparations	283,284
21.	Paints & allied products	285
22.	Petroleum Refining	291
23.	Misc. Products of Petroleum & Coal	299
24.	Paving & Roofing Materials	295
25.	Rubber & misc. Plastics Products	30
26.	Leather Tanning & Finishing	311
27.	Footwear & Other Leather Products	313,314,315,316,317,319
28.	Glass & Glass Products	321,322,323
29.	Cement, Hydraulic	324
30.	Stone & Clay Products, exc. Hydraulic Cement	325,326,327,328,329
31.	Blast Furnaces, Steel Works, and Rolling and Finishing Mills	331
32.	Iron & Steel Foundries, Forgings, and Misc. Metal Products	332,339
33.	Primary Nonferrous Metals	33,334,335,336

34.	Metal Containers	341
35.	Heating, Plumbing, & Fabricated Structural Metal Products	343,344
36.	Screw Machine Products	345
37.	Metal Stampings.	346
38.	Other Fabricated Metal Products.	342,347,349
39.	Ordinance and Accessories, exc. Vehicles & guided missiles.	348
40.	Engines & Turbines	351
41.	Farm & Garden Machinery.	352
42.	Construction & Mining Machinery.	2531,3532,3533,3795
43.	Materials Handling Machinery & Equipment	3534,3535,3536,3537
44.	Metalworking Machinery & Equipment	354
45.	Special Industry Machinery and Equipment	355
46	General Industrial Machinery and Equipment	356
47.	Misc. Machinery, exc. electrical	359
48.	Office, Computing, and Accounting.	357
49.	Service Industry Machines.	358
50.	Electrical transmission & distribution equipment and industrial apparatus.	361,362
51.	Household appliances	363
52.	Electric Lighting & Wiring Equipment.	364
53.	Radio, T.V. and Communication equipment	365,366
54.	Electronic Components & Accessories	367
55.	Misc. electrical machinery, equipment, & supplies	369
56.	Motor vehicles & equipment	371
57.	Aircraft & Parts	372,376
58.	Other transportation equipment	373,374,375,379(exc.3795)
59.	Professional, scientific, and controlling instruments & supplies.	381,382,384,387
60.	Optical, ophthalmic and photographic equipment & supplies . . .	383,385,386
61.	Misc. Manufacturing Equipment.	39