The Introduction of New Technology and the Demand for Educated Workers

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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.

Despite the recognition that experience "matters" in cost functions, it has, virtually without exception, been ignored in modern econometric

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1 Kaplan (1982), p. 98.
2 Arrow (1962), pp. 155-156.

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 it as an assumption in a simple neoclassical model of economic growth; Nelson, Peck, and Kalachek (1967) provided some interesting anecdotal evidence; and Welch (1970) estimated a model of relative earnings of workers by education category on cross-sectional U.S. farm data based on, and providing some support for, the hypothesis. This previous literature is reviewed in the next section of the paper. In section III we formulate and present estimates of variants of a 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. 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 a possible (selection) function of education -- in other words, how much school <u>produces</u> "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. Hypothesis 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 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 involve two distinctions, one between the _adoption_ and the _implementation_

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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.

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 adoption, on the one hand, and education and implementation, on the other hand, the direction of causality between education and innovation are

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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.

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 analyse 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 econometric cost functions.[12] Most studies of biased technical change

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11 A general framework for analyzing technical change biases was developed by H. Biswanger (1974), Binswanger. "The Measurement of Technical Change Biases With Many Factors of Production," American Economic Review, December, 1974.

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

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 technologies, will tend to create the most opportunities (demand) for highly-educated workers.

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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 perceptually influence the biases."

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 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]

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 <u>lack</u> of experience) using

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15 Nelson et al., op. cit., p. 144-5.
16 Nelson et al., op. cit., p. 16.

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.

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

III. ECONOMETRIC SPECIFICATION

In order to test the hypothesis discussed in Section II we begin with the following cost function for each industry:

(1) $C = F(W,Q,T,AGE)$

where C = Total cost of primary inputs[18]

W = Vector of exogeneous primary input prices

Q = level of real output

T = technology level

AGE = age of the technology

Alternatively we can specify the industry's restricted variable cost function as:

(2) $VC = F(W', Q, T, AGE, K)$

where VC = variable cost

W' = vector of exogeneous prices of the variable inputs[19]

K = the industry's stock of capital

This approach has become more popular in the literature on production and cost because of the recognition that at least some factors of

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18 We are assuming, for convenience, separability of raw materials from other inputs in the cost function.

19 We assume that the supply of labor to all industries is infinitely elastic at exogenous wage rates. Relative prices are believed to be constant across industries, at least in the long run, because of mobility between industries. Welch's 1970 study of technical change and the demand for educated workers in agriculture treated quantities as exogeneous. Since he studied one industry across 49 states, this assumption is reasonable if inter-area migration is unlikely. The likelihood of inter-area migration suggests that, data permit-

production, are "quasi-fixed." According to the specification in (2), the industry chooses its cost-minimizing variable inputs needed to produce output Q, conditional on the stock of its quasi-fixed factor, the capital stock.[20] In addition to its being consistent with notions about the variability of different kinds of inputs, this specification is also particularly useful to us because it enables us to focus on the composition of variable (labor) cost, rather than that of total cost.

We approximate equation (2) with a translog variable cost function for each industry i:[21]

$$
\begin{aligned}
(3)\quad \ln VC_i = {} & \alpha_{i0} + \alpha_{iQ} \ln Q_i + \sum_j \alpha_{ij} \ln W'_j + \tfrac{1}{2}\sum_{jk}\sum \beta_{ijk} \ln W'_j \ln W'_k \\
& + \alpha_{iT} \ln T_i + \sum_j \alpha_{ijT} (\ln W'_j) T_i + \alpha_{iAGE} \cdot AGE_i \\
& + \sum \alpha_{ijQ} (\ln W'_j) \cdot \ln Q_i + \sum_j \alpha_{ijAGE} (\ln W'_j) \cdot AGE_i \\
& + \sum_j \alpha_{ijK} (\ln W'_j) \cdot \ln K_i + \mu_{it}
\end{aligned}
$$

This specification allows for non-neutral technological change, as measured by the parameters α_{ijT}, nonhomotheticity as measured by α_{ijQ} and differential abilities to adjust to new technologies, as measured by α_{ijAGE}. The parameters in equation (3) are specific to each industry but are assumed not to vary over time within an industry. By Shepard's lemma:

$$
(4)\quad \partial \ln VC_i / \partial \ln W'_j = (\partial VC_i / \partial W'_j)(W'_j / VC_i) = S_{ij} \qquad j = 1 \ldots m
$$

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ting, it would have been preferable for him to use some instrumental variables for factor quantities.

20 See Mohnen et al. (1984) for a thorough development of this approach.

21 We suppress time subscripts on the variables.

where S_{ij} = the share of input j in variable cost in industry i.

The factor share equations can be written as follows:

$$(5)\quad S_{ij} = \alpha_{ij} + \sum_k \beta_{ijk} \ln W'_k + \alpha_{ijT} T_i + \alpha_{ijQ} \ln Q_i + \alpha_{ijAGE} \cdot AGE_i + \alpha_{ijK} \ln K_i + \mu_{it} \qquad j = 1 \ldots n$$

Since we estimate equations (5) on panel data rather than on a time-series database for each industry, we are only able to estimate the mean of each parameter. We rewrite equation (5) to reflect this:

$$(6)\quad S_{ij} = \bar{\alpha}_j + \sum_k \bar{\beta}_{jk} \ln W'_k + \bar{\alpha}_{jT} T_i + \bar{\alpha}_{jQ} \ln Q_i + \bar{\alpha}_{jAGE} \cdot AGE_i + \bar{\alpha}_{jk} \ln K_i + \varepsilon_i \qquad j = 1 \ldots n$$

where $\varepsilon_i = \mu_i + (\alpha_{ij} - \bar{\alpha}_j) + (\sum_k(\beta_{ijk} - \bar{\beta}_{jk}) \ln W'_k) + (\alpha_{ijT} - \bar{\alpha}_{jT}) \cdot T_i + (\alpha_{ijQ} - \bar{\alpha}_{jQ}) \ln Q_i + (\alpha_{ijAGE} - \bar{\alpha}_{jAGE}) \cdot AGE_i + (\alpha_{ijK} - \bar{\alpha}_{jK}) \ln K_i$

Data limitations require us to impose two other restrictions on equations (6). First, since we are unable to adequately measure the variation across industries in T_i, the technology index, we delete it from the equation and assume that α_{ijT} is uncorrelated with AGE.[22] Second, we proxy the age of the industry's technology by the age of its capital stock. If one accepts the notion of embodied technological change, then the age of the capital stock equals 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 strength of the relationship may vary

22 The mean of T_i is, of course, captured in our time dummies.

across industries, as we show below. The link between the age of capital and the age of technology results from the assumption that innovations are cost-reducing. Then, output increases, thereby producing an increase in investment and a younger capital stock.[23] The link can also be interpreted as consistent with the product life cycle approach (Wells, 1972). This approach argues that 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.

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

IV EMPIRICAL RESULTS

A. Data

Equation (6) is estimated on a pooled cross-section time-series data set containing 61 manufacturing industries in each of the years 1960, 1970 and 1980.[24] 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 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,[25] and finally, information on the R&D intensity of each industry is obtained from the technology matrix constructed by F.M. Scherer (1984). All of the equations that we estimate include time and industry dummies, thereby controlling for permanent differences across industries and changes common to all industries, such as secular and aggregate business cycle effects. Our equations should therefore be interpreted as being estimated on deviations from industry means.

B. Results

Table 1 presents our findings. The dependent variable is the share of labor cost attributed to highly educated workers, defined as 13+ years

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24 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

25 See Griliches and Lichtenberg 1984b for a complete description.

of 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 $W = W_2/W_1$, 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[26]

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

We have information on ℓ from the BIE and we can obtain an estimate of W from the Current Population Reports. Since we assume W is constant across industries, equation (7) is simply a nonlinear transformation of the employment shares[27]

Columns (1) and (2) of Table 1 try alternative measures of the age of the capital stock; the first column uses the average age of the plant and equipment while the second column uses the average age of equipment. Both have the hypothesized signs but equipment age is more significant. In fact, in a regression not shown here plant age did not matter at all. This is not surprising since technology is more likely to be embodied in the industry's equipment. Hence, the remainder of Table 1 uses equipment age to measure the age of technology in the industry.

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26 Since $S_1 = W_1L_1/(W_1L_1 + W_2L_2) = 1/(1 + W(L_2/L_1))$.

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

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)
$AGECAP^{-1}$	0.555 (2.47)						
$AGEEQ^{-1}$		0.445 (2.80)	0.386 (2.49)	0.312 (1.94)	0.319 (1.98)		
$AGEEQ^{-1}$* OWNRD						2.073 (3.14)	
$AGEEQ^{-1}$* IMPRTRD							43.727 (1.87)
Log(CAPITAL)			0.036 (3.00)		0.009 (0.51)	0.018 (0.98)	0.018 (0.95)
Log(OUTPUT)				0.041 (3.66)	0.035 (2.14)	0.026 (1.58)	0.035 (2.20)
R^2	0.9625	0.9630	0.9656	0.9666	0.9667	0.9683	0.9666
N	183	183	183	174	174	174	174

*All equations include year and industry dummies.

AGEEQ is entered into the equation in inverse form, so that the effect of increases in AGEEQ on the labor cost share of highly educated workers is given by:

$$(8) \quad \frac{\partial S_1}{\partial AGEEQ} = -\beta_1/AGEEQ^2$$

where β_1 is the estimated parameter shown in Table 1. This specification reflects our hypothesis that the effect of AGEEQ on S_1 is nonlinear, with bigger effects occurring at younger equipment ages.[28] Recall from our discussion in Part II that this is precisely the prediction from the learning curve approach.

Columns (3), (4) and (5) in Table 1 add the logarithms of the real capital stock and real output to the cost share equation. Note that the capital stock is not significant, once we control for the level of real output.[29] We find no evidence that the labor cost share of highly educated workers is related to the overall stock of capital; rather it is the mean age of that capital that is important. Real output, however, is significant, indicating either that the production function in the industries we are studying is non-homothetic or that there are cyclical factors affecting labor demand.[30]

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28 This specification fit the data marginally better than a linear or log functional form

29 This is an important finding because, one might have argued that the observed relationship between the age of the capital stock and the labor cost share was due to a correlation between age of the capital stock and the amount of the stock, i.e. industries with more capital would have, by definition, younger capital.

30 An alternative way to examine the impact of output is to use information on changes in output over the last decade. We tried a vector of annual differences in output and found no significant relationships.

Note that β_1 is statistically significant in all columns of Table 1, confirming 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 two very different industries: (1) Wood Containers, in which, in 1980, the mean age of the equipment is 8.66 years (the inverse of the mean age is .118) 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 (the inverse of the mean age is .195) and the labor cost share of highly educated workers is .433.[31] According to the estimated parameter on $AGEEQ^{-1}$ in column 5, 20 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 age of their technologies.

Up to this point, we have been assuming that α_{ijAGE}, the effect of AGE in the i^{th} industry, is constant across industries. It seems reasonable to argue that α_{ijAGE} varies across industries in some systematic way. In particular, α_{ijAGE} is likely to be a function of the R&D-intensity of the industry. Our argument that the age of the industry's capital stock is a proxy for the age of the industry's technology is better suited to R&D-intensive industries, where new capital is most likely to embody new technology. Hence, we allow the following specification for $\alpha_{i,j,AGE}$:

(9) $\alpha_{i,j,AGE} = \bar{\alpha}_{j,AGE} * RD_i$

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31 These two industries are chosen because they have, respectively, the highest and lowest mean equipment ages in the sample.

We use two different measures for RD_i. 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, relative to the industry's 1974 nominal output. In principle, we might expect $\partial S_i/\partial AGE$ 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 (6) and (7), the effect of AGEEQ is more significant when we use OWNRD rather than IMPRTED, probably because of the large amount of error in measuring IMPRTRD.[32] Further, when $AGEEQ^{-1}$ and $AGEEQ^{-1} * OWNRD$ are used together, the coefficient on $AGEEQ^{-1}$ is not significant, while the interaction term is (these coefficients are not shown on Table 1). 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 industries.

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32 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!

IV CONCLUSIONS

As we stated in the introduction, the purpose of this paper was to develop and test the hypothesis that experience on a technology is an important determinant of the equilibrium shares of inputs in production costs. Specifically, we have argued 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. The hypothesis was tested on a pooled cross-section time series data set containing 61 manufacturing industries in each of the years 1960, 1970 and 1980; the findings strongly support our argument.

We have shown the importance of distinguishing the process of _implementing_ new technologies from the concept of technological change as a once-and-for-all transformation of the production function. While the latter assumes that the structure of factor demand does not vary after adoption, our evidence suggests that the _process of adjusting_ to a new technology is educated-labor-using. The implication of this is that sectors or industries characterized by continually high rates of innovation will tend to create the most opportunities for highly-educated workers. Further, the comparative advantage of educated workers in implementing new technologies also implies that economies with a ready availability of educated workers will be more innovative, _ceteris paribus_, than economies without this labor pool. Hence, policies that encourage the acquisition of education can facilitate an economy's international competitiveness.

We have focused on the increase in the employment and cost shares of educated workers that results from the introduction of new technology. Further work should consider the extent to which these increases are due to increases in education within versus between occupations. We plan to examine whether the increase in the demand for educated workers has resulted in an increase in the share of high level occupations in addition to, or in lieu of, an increase in the average level of education within occupational categories.

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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