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The Demand for Human Capital: A Microeconomic Approach

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Abstract

We propose a model for explaining the demand for human capital based on a CES production function with human capital as an explicit argument in the function. The resulting factor demand model is tested with data on roughly 6,000 plants from the Census Bureau's Longitudinal Research Database. The results show strong complementarity between physical and human capital. Moreover, the complementarity is greater in high than in low technology industries. The results also show that physical capital of more recent vintage is associated with a higher demand for human capital. While the age of a plant as a reflection of learning-by-doing is positively related to the accumulation of human capital, this relation is more pronounced in low technology industries.

Key words: Human capital, productivity, technical change, complementarity.

JEL Classification: D20, O30, J30

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In recent years, there has been considerable discussion of the skill premium reflected in wages. In this paper, we pose a complementary question. Given the distribution of wages associated with differing skills, what explains the quantity of skills—that is, human capital—that will be chosen for a production process?

In a way, all technical change involves a change in knowledge. It is, however, convenient for analytic uses to distinguish knowledge that is embodied in physical capital and, hence, requires investment in physical assets, from knowledge that takes other forms. Similarly, it is convenient to distinguish knowledge the returns to which are captured by labor through sellable labor skills, and which we define as human capital, from knowledge the returns to which are captured by the firm and, hence, may be called organizational capital. Human capital consists of, or is embodied in, labor skills. In contrast, organizational capital is firm specific knowledge. It facilitates the efficient use of all other inputs. Residual changes in knowledge not reflected in physical or human or organizational capital as defined above, are changes in industry-wide or economy-wide knowledge which, in turn, are primarily a function of chronological time.

I. The Model

We assume competitive labor markets and, hence, that wage differences measure the differences in the marginal products of labor of various skills. Hence, the market prices for labor of various levels and types of skills permit us to measure the quantity of skills per unit of labor, or human capital per unit of labor, in common efficiency units. Within this framework, variations across firms or plants in the average wage reflect differences in the amount of human capital used in the production process, given the market price of such capital. A discussion of the empirical basis that makes it reasonable to invoke these assumptions, at least as an approximation, appears in section II.

No doubt there are unique attributes to each industry's production process that constrain the choice of inputs. Our objective, however, is to identify the common elements that define that choice. Some of these elements explain mainly the variations across plants in the same industries. Some hopefully also explain, at least in part, the variation across industry averages. We start with a simple production function with three inputs: pure labor L, human capital H and physical capital K.

$$Y_t = F(L_t, H_t, K_t), \tag{1}$$

where subscript t denotes chronological time in years. Pure labor is defined simply as human effort which varies mainly in quantity, and can therefore be approximated in homogeneous units such as number of employees or person hours of work. All skills are therefore reflected in human capital. We could, alternatively, introduce a quality index modifying the labor input instead of introducing human capital as a separate argument in the production function.

The approach we take, while somewhat artificial, is however analytically convenient in that it permits us to examine explicitly complementarity and substitution among skills, physical capital and number of employees. We assume that human and physical capital are measured in efficiency units. That is, they are adjusted for input-augmenting skills and for technical change. Workers' skills in specific tasks are partly a function of the initial endowments and training they bring to the job and partly a function of experience on the job. These skills are expressed in common units through prices which are assumed to reflect the marginal products of labor. The measurement of physical capital in homogeneous units is more complex.

Since physical capital of different vintages is not priced concurrently and merely reflects historical valuations, some alternative must be used to convert it to common efficiency units. We assume that each vintage is associated with a unique best practice technology, and the efficiency of a plant's stock of capital q_K is a function of the average vintage of the stock, that is $q_{Kit} = q_K(v_{it})$ where v denotes the average vintage of the stock of plant i at time t. We therefore specify the following:

$$q_{Kit} = e^{\lambda_K v_{it}}, \qquad (2)$$

where $\lambda_K > 0$ is a parameter that reflects productivity enhancement attributable to vintage and is used to convert capital into common efficiency units. For our present purpose, it does not matter if, for any given vintage, what is best practice capital may depend scale of output. Since for each vintage, regardless of scale, we have the concurrent prices of all capital goods, the relative prices of these capital goods will reflect their marginal products just as relative wages reflect the marginal products of alternative labor skills.

We have yet to consider disembodied technical change that is not input-augmenting. We further decompose such change into its two principal components. One component is associated with industry-wide or economy-wide changes in knowledge or in institutional arrangements. For want of a better proxy it is assumed to be dependent on chronological time. The other component captures organizational learning and can be labeled organizational capital. Within a cross-sectional context it may be proxied, as proposed by Oi (1967) and Fellner (1969), by the age of the organization.[1] Organizational learning or capital affects the productivity of all inputs. For example, experience improves the matching of employees with specific tasks, while the routinization of tasks that experience permits reduces, as pointed out by Penrose (1959), the level of managerial skills required for a given output. More recently, Bahk and Gort (1993) identified learning in the use of physical capital that raises the productivity of capital goods.

In principle, there is no compelling reason to assume a symmetrical shift in the productivity of all inputs as organizational capital accumulates. As a simplifying assumption, however, we model it as a symmetrical shift parameter on the premise that such simplification is acceptable as an approximation. Since an explicit variable is used to capture organizational capital, the scope of shifts in productivity attributed to unidentified time dependent changes in knowledge or institutional arrangements is greatly reduced.

Based on the above discussion our new production function is:

$$Y_{it} = A_t G(a_{it}) F(L_{it}, H_{it}, q_{Kit} K_{it}), \tag{3}$$

where A_t refers to industry-wide or economy-wide technical change and institutional arrangements, a_{it} to the age of a plant and q_{Kit} to the quality of physical capital of plant i at time t.

We next specify the production function in CES form. As pointed out by Arrow, Chenery, Minhas and Solow (1961) and McFadden (1963), the CES form allows for

[1] Bahk and Gort (1993) proxied it by the cumulative output of the plant since birth.

different elasticities of substitution among inputs and such substitution is relatively simple to quantify.

Following the hypothesis of capital-skill complementarity formalized by Griliches (1969), most authors, e.g. Fallon and Layard (1975), Stokey (1996), and Krusell, Ohanian, Rios-Rull and Violante (2000), analyzed skill premium using a homothetic CES production function. The question we pose however differs from that of these authors. Rather than examining what determines the skill premium at the macroeconomic level, we take the skill premium as given and seek to explain the microeconomic (plant level) demand for human capital. Such demand, as we show, depends on complementarities and substitution among inputs.

Using a CES specification, plant i has the following production function at time t, within a cross-section and time-series framework:

$$Y_{it} = A_t G(a_{it})\left[\alpha_L L_{it}^{\mu} + \alpha_H \left[\beta(q_{Kit} K_{it})^{\rho} + (1-\beta) H_{it}^{\rho}\right]^{\mu/\rho}\right]^{1/\mu}, \qquad (4)$$

where q_{Kit} is specified as in equation (2). In this production function, the parameters α and β, for $0 < \beta < 1$, are distributional weights to indicate the relative significance of the inputs. The parameters μ and ρ, for $\mu, \rho < 1$, represent the elasticities of substitution between inputs. That is, the substitution elasticity between labor and physical capital (or human capital) is $1/(1-\mu)$ and the substitution elasticity between human and physical capital is $1/(1-\rho)$.

Griliches (1969) argued that human capital is more complementary with physical capital than with labor while Hamermesh (1993) and Krusell et al (2000) suggested that the substitution elasticity between labor and physical capital (or human capital) is higher than the substitution elasticity between human and physical capital. This, if correct, implies that within the range of observed variations, complementarity between human and physical capital will be higher than that between labor and physical capital and, in the context of equation (4), we have $\mu > \rho$. Indeed, much technical change has taken the form of substitution of physical capital for labor while the demand for both human and physical capital has risen along with increases in the complexity of production processes. Even apart from essential technological links between skills and physical capital, as investment in capital goods rises, a greater attempt will be made to protect such investment from misuse by employing a higher level of labor skills. Hence complementarity between human and physical capital follows.

As previously noted, in a competitive market where all factor prices are given, profit maximization yields the following ratio of input demands as a function of these prices. That is, the marginal products of inputs are equal to given factor prices:

$$\frac{H_{it}}{L_{it}} = \left\{ \frac{\alpha_H (1-\beta)}{\alpha_L} \frac{r_L}{r_H} \left[\beta \left(\frac{q_{Kit} K_{it} / L_{it}}{H_{it} / L_{it}} \right)^{\rho} + (1-\beta) \right]^{(\mu-\rho)/\rho} \right\}^{1/(1-\mu)}, \tag{5}$$

where r_L is the baseline price of unskilled labor (the minimum wage) and r_H is the price of human capital.

We simply assume that the price of human capital converts it to common units across all plants and industries. Accordingly, equation (5) yields a first order (linear) Taylor series approximation around the point $\rho = 0$:

$$\ln \frac{H_{it}}{L_{it}} \cong \frac{1}{(1-\mu)+\beta(\mu-\rho)} \ln \left(\frac{\alpha_H (1-\beta)}{\alpha_L} \frac{r_L}{r_H} \right) + \frac{\beta(\mu-\rho)\lambda_K}{(1-\mu)+\beta(\mu-\rho)} v_{it}$$

$$+ \frac{\beta(\mu-\rho)}{(1-\mu)+\beta(\mu-\rho)} \ln \frac{K_{it}}{L_{it}}. \tag{6}$$

This equation allows us to examine the effects of the average vintage of the capital stock and of capital intensiveness on the demand for human capital. With $\mu > \rho$, the younger the average vintage of the capital stock and the greater the capital intensiveness, the greater will be the demand for human capital.

We have thus far considered only organizational learning. We now introduce the concept of labor learning and hence the effect of such learning on human capital. Learning-by-doing by employees, that is the acquisition of skills through experience, can be expected in each successive time period from the birth of a plant. However, does it follow that while labor skills grow with job experience, older firms or plants will have more experienced workers (hence, will use more human capital)? If labor is perfectly mobile and there are no informational asymmetries, the answer is no. However, these conditions are implausible. Current employers know what skills their employees have better than do outsiders. Asymmetric information renders it possible for current employers to outbid outsiders for the services of their experienced workers. And this is reinforced by seniority privileges that provide incentives for immobility on the part of their employees.

Accordingly, experienced workers are not distributed evenly across plants of varying age even though the acquired skills are sellable. Hence, older plants can be expected to employ more human capital. In the context of our model, this is reflected in the distributional weights of labor and human capital which are a function of labor learning as proxied by plant age. However, learning is bounded in a given technology since the stock of knowledge and skills to be acquired through experience is finite.

Therefore, the effect of plant age on productivity and human capital increases at a decreasing rate. Hence, we have

$$\alpha_H / \alpha_L = e^{\lambda_{H1} a_{it} + \lambda_{H2} a_{it}^2}, \tag{7}$$

where a denotes the learning-by-doing measured by plant age, and $\lambda_{H1} > 0$ and $\lambda_{H2} < 0$ are parameters that reflect the effect of labor learning on productivity. The parameter λ_{H1} captures the positive effect of labor learning on productivity while the negative value of λ_{H2} captures the bounded learning effect. With this elaboration for labor learning, equation (6) can be rewritten as:

$$\ln \frac{H_{it}}{L_{it}} \cong \frac{\lambda_{H1}}{1-\mu+\beta(\mu-\rho)} a_{it} + \frac{\lambda_{H2}}{1-\mu+\beta(\mu-\rho)} a_{it}^2 + \frac{\beta(\mu-\rho)\lambda_K}{(1-\mu)+\beta(\mu-\rho)} v_{it}$$

$$+ \frac{\beta(\mu-\rho)}{(1-\mu)+\beta(\mu-\rho)} \ln \frac{K_{it}}{L_{it}}. \tag{8}$$

So far, we have analyzed the demand for human capital without distinguishing plants in high technology industries from those in low technology industries. The behavior of the demand for human capital by plants in high technology industries is, however, likely to differ from that in low technology industries. Advanced technology requires better matching of machines and skills, which reinforces complementarity between human and physical capital. Moreover, newer technologies require scarcer and, hence, more valued skills as the supply of those skills adjusts with a lag to new demand. Low technology, on the other hand, favors substitution of baseline labor for human capital.

In the light of this, we hypothesize that complementarity of human capital with physical capital is higher in high technology industries than in low technology industries.

This implies $\rho_l > \rho_h$, where we specify $\rho = \rho_h$ if a plant belongs to a high technology industry and $\rho = \rho_l$ if it belongs to a low technology industry. With this hypothesis, we examine the effects of learning, vintage and capital intensiveness of plants on the demand for human capital by comparing the separate estimates for plants in high and low technology industries.

If $\rho_1 > \rho_h$, the effects of learning by doing, the average vintage of the capital stock and capital intensiveness on the demand for human capital should show the following:

$$\left.\frac{\partial H_{it}}{\partial a_{it}}\right|_{\rho=\rho_h} < \left.\frac{\partial H_{it}}{\partial a_{it}}\right|_{\rho=\rho_l},\ \left.\frac{\partial H_{it}}{\partial v_{it}}\right|_{\rho=\rho_h} > \left.\frac{\partial H_{it}}{\partial v_{it}}\right|_{\rho=\rho_l},\ \left.\frac{\partial H_{it}}{\partial (K_{it}/L_{it})}\right|_{\rho=\rho_h} > \left.\frac{\partial H_{it}}{\partial (K_{it}/L_{it})}\right|_{\rho=\rho_l}. \quad (9)$$

That is, the effects of younger average vintage and of capital intensiveness on the demand for human capital should be positive and larger for high than for low technology industries. The intuition for this, as previously indicated, is that advanced technologies lead to greater dependence on skills in the use of physical capital. An equivalent difference in vintage entails a greater change in technology in high technology sectors and, hence, more demand for human capital. Similarly, an equivalent change in capital intensiveness leads to more demand for human capital per unit of physical capital.

While more rapid technical change imposes higher requirements for skills, the requisite skills are harder to acquire through experience. This is because past experience is less relevant to new technology the faster the rate of technical change. For this reason, learning-by-doing and experience should contribute less to the accumulation of human capital in high technology industries. An alternative hypothesis is that the more complex the technology, the longer it takes to learn to use it. In the context of equation (7), this would mean a larger positive value for λ_{H1} and a larger negative value for λ_{H2}.

Our model requires a final step. We have thus far assumed a homothetic production function. However, what constitutes best practice technology may vary according to scale of the production process. For example, as scale increases, coordination problems may arise that require more managerial controls and, hence, more human capital. Moreover, larger scale permits greater specialization of functions and this, in turn, may require different configurations of skills. Consequently, a homothetic production function cannot be assumed.

A simplifying modification for a non-homothetic production function is obtained by rewriting equation (7) as $\alpha_H / \alpha_L = e^{\lambda_{H1} a_{it} + \lambda_{H2} a_{it}^2} Y_{it}^{\delta}$, where $\delta > 0$ is a parameter that reflects the scale effect on the production function. This specification with plant size measured by output is similar to an "almost homogenous" non-homothetic production function as shown by Sato (1977) in the sense that the factor demand ratio is a function of output. With this modification that captures the relationship between wages and plant size, the relevant demand for human capital becomes

$$\ln\frac{H_{it}}{L_{it}} \cong \frac{\lambda_{H1}}{1-\mu+\beta(\mu-\rho)} a_{it} + \frac{\lambda_{H2}}{1-\mu+\beta(\mu-\rho)} a_{it}^{2} + \frac{\beta(\mu-\rho)\lambda_K}{(1-\mu)+\beta(\mu-\rho)} v_{it}$$

$$+ \frac{\beta(\mu-\rho)}{(1-\mu)+\beta(\mu-\rho)} \ln\frac{K_{it}}{L_{it}} + \frac{\delta}{(1-\mu)+\beta(\mu-\rho)} \ln Y_{it}. \qquad (10)$$

This equation allows for a positive effect of scale measured by output on the demand for human capital. Such an effect is consistent with the empirical literature that shows a strong relationship between wages and plant (or firm) size. For example, Brown and Medoff (1989) examined six possible explanations for the possible association of wages and employer size. Of the six explanations, only one was supported, namely that larger firms (or plants) employ higher quality labor (that is, in our terminology, more human capital). Dunne and Schmitz (1995) also found a positive association between wages and plant size. Oi (2000) attributes the phenomenon to a higher work pace in larger firms. This raises labor productivity and workers are compensated for higher effort with a higher wage.

II. Data and Descriptive Statistics

Our data are drawn from the U.S. Census Bureau's Longitudinal Research Database for manufacturing plants. We selected plants that were coded as new in the period 1973-87 subject to two restrictions. First, all so-called new plants were excluded from our sample if the cumulative capital expenditures for the first three years of the plant's life were less than 75 percent of total assets at the end of the third year. This procedure was followed to exclude plants that, in fact, were born prior to the first year of their recorded life or that may have had a prior incarnation and were miscoded as completely new. Moreover, where the 75 percent criterion was not met, we did not have sufficient information for our analysis of the role of capital in the early life of the plant. The second restriction involved inclusion of plants in our sample only if there were continuous data for them.[2]

The resulting sample left us with a non-balanced panel of 5,979 plants with 42,194 observations for these plants in the pooled time-series and cross-section for the period 1973-96. Thus, the average interval for which we had continuous data for a plant was roughly 7 years but ranged to a maximum of 24 years for some plants.

[2] Plants with only one year of missing data were, however, retained in the sample.

Assuming there were no coding errors, the fact that a plant remained in our record for less than 24 years is attributable to one of three factors: (a) it died prior to 1996, (b) it was still alive in 1996 but was born after 1973 (some as late as 1987), (c) the plant was not in the certainty sample. The third reason requires a brief explanation. The certainty of inclusion sample for inter-census years consists of plants with 250 and more employees plus some plants needed for adequate representation for selected product lines. It accounts for roughly two-thirds of the total sample in the Annual Survey of Manufactures. The remainder is sampled subject, however, to the further condition that the composition of this portion of the sample shall change one year following each five-year census.

Clearly then, factors (b) and (c) above account for most of the cases of short plant histories in our sample. That is, our data do not encompass for most plants the entire life cycle of the plant.

Our next task is to examine data on average wages to see if our assumption that they reflect differences in the marginal products of labor rather than market imperfections is valid. Implicitly, we have questioned the practice of measuring the elasticity of substitution between capital and labor using reported wage data to capture differences in the price of equivalent classes of labor.

Table 1 shows (a) average annual wages for all employees in selected industries and the standard deviations of these wages and (b) the average hourly earnings of production workers in the same industries and the corresponding standard deviations. All data are restricted to the Northeast region to eliminate any effect of geographical differences in prices and wages. The industries were selected to obtain broad

Table 1
Wage Variations within Industries in the Northeast Region, 1997*

IND	N	Annual Wage of All Employees ($1,000)			Hourly Wage per Production Workers ($)		
		W	S	CV	W	S	CV
2051	911	18.08	8.95	0.50	9.39	4.20	0.45
2099	298	22.59	13.63	0.60	11.38	6.22	0.55
2253	359	19.86	12.52	0.63	9.49	5.21	0.55
2273	53	20.18	8.56	0.42	9.43	3.72	0.39
2339	1,303	15.48	12.03	0.78	8.14	4.41	0.54
2396	735	19.64	9.92	0.51	9.04	3.49	0.39
2411	2,446	18.57	9.96	0.54	12.34	3.95	0.32
2421	1002	20.34	9.78	0.48	11.15	3.43	0.31
2511	622	19.24	9.08	0.47	9.92	3.80	0.38
2541	606	27.66	11.42	0.41	12.95	4.03	0.31
2653	356	32.84	11.30	0.34	13.28	3.24	0.24
2679	182	28.83	12.43	0.43	12.57	4.36	0.35
2711	1,561	21.68	11.23	0.52	12.27	5.19	0.42
2752	5,879	26.65	13.71	0.51	14.39	5.80	0.40
2851	306	34.95	15.72	0.45	14.77	4.80	0.32
2899	248	37.02	14.04	0.38	15.69	5.94	0.38
2951	358	42.54	17.04	0.40	19.10	9.38	0.49
2992	70	40.70	18.71	0.46	17.02	5.36	0.31
3086	182	29.05	11.97	0.41	12.60	4.15	0.33
3089	1,765	26.93	12.10	0.45	11.87	4.55	0.38
3111	141	25.05	9.84	0.39	11.15	3.40	0.30
3199	80	16.30	7.10	0.44	7.84	3.73	0.48
3272	522	27.13	11.49	0.42	12.51	4.04	0.32
3273	684	33.15	12.82	0.39	16.44	6.19	0.38
3321	149	30.28	10.92	0.36	13.99	4.44	0.32
3398	157	34.96	11.79	0.34	14.46	3.51	0.24
3444	1,046	32.47	13.09	0.40	14.89	7.01	0.47
3471	725	27.31	13.01	0.48	12.32	4.15	0.34
3544	1,471	34.50	15.46	0.45	17.22	5.29	0.31
3599	5,012	28.91	15.01	0.52	14.89	5.72	0.38
3672	295	27.65	13.33	0.48	11.87	3.81	0.32
3679	779	30.78	15.67	0.51	12.37	7.02	0.57
3714	427	27.11	14.37	0.53	13.79	5.42	0.39
3728	158	36.94	13.95	0.38	17.23	5.72	0.33
3841	420	33.99	16.77	0.49	13.51	5.33	0.39
3842	378	31.61	15.72	0.50	13.43	5.43	0.40
3993	1,168	25.36	12.44	0.49	11.47	4.76	0.41
3999	660	22.52	11.45	0.51	10.87	4.23	0.39

* Estimates are based on data from the 1997 Census of Manufactures at the U.S. Bureau of the Census. The two 4-digit industries in the Northeast region that have the largest number of plants within each 2-digit industry were selected. IND refers to industry; N to number of plants; W to mean wage; S to standard deviation; CV to coefficient of variation.

representation of the manufacturing universe and to include only industries with large numbers of plants so as to reduce the chance that a misleading conclusion may result from the idiosyncrasies of a few outliers. Specifically, we chose two 4-digit industries that had the largest number of plants in each of 19 2-digit categories in the 1997 Census.[3]

Table 1 reveals an enormous dispersion in wages within each industry even though all plants were limited to the same Northeast region. For annual wages of all employees, the median coefficient of variation reveals a standard deviation that is 47 percent of the mean. Even when we restrict the data to the more homogenous category of production workers' hourly wages, the median value shows a standard deviation that is 38 percent of the mean.

In short, is it plausible to assume that roughly 31 percent of all plants (that is assuming a normal distribution) are either able to pay a wage 47 percent less than the mean of their industries or, alternatively, are forced to pay a wage 47 percent higher than the mean? Does that not assume an implausible degree of imperfection in labor markets? When we further compared the average wage for the twenty plants that have the highest wages in each industry with the means for the relevant industries, the former were often several times larger than the latter. The data for the twenty highest wage plants in each industry cannot be shown because of possible disclosure of confidential information. However, the reported result is generally consistent with the spread in wages in many industries as shown in Table 1 if we consider values beyond two standard deviations from the mean. Given the typically high fraction of total costs in manufacturing accounted for by wages, how could the high wage plants survive? The most credible explanation is that

[3] One 2-digit industry was left out because it did dot have any 4-digit industries with a sufficient number of plants to assure the results would not be unduly influenced by outliers.

the labor varies greatly in quality across plants within industries and that the differences in wages measure primarily differences in human capital.

III. Empirical Methodology and Estimates

Our empirical work on the demand for human capital is based on equations (6) and (10). We have shown that a plant's demand for human capital is a function of age, age^2, vintage, capital intensiveness of the plant and plant scale. The age and age^2 variables capture the effects on the demand for human capital of, respectively, learning-by-doing and the limits on knowledge accumulation arising from the finite quantity of existing knowledge. While the input-augmenting effect of learning-by-doing raises the quantity of human capital employed by the plant, a concurrent process of organizational learning may, as discussed earlier, reduce the need for human capital thereby offsetting, at least partially, the positive impact of plant age on the quantity of human capital employed. The vintage and capital intensiveness variables are relevant because of the complementarity of physical with human capital. The hypothesis that human capital is complementary with physical capital leads, for reasons given earlier, to the further conclusion that the demand for human capital increases both with younger vintage and with greater capital intensiveness.

The homothetic specification of a production function rules out the effect of plant size on the demand for human capital. However, while each vintage is assumed to have a unique best practice technology for a given size of plant, as a plant grows what is best practice may change. Thus best practice may be a function of scale. For example, larger plants may use more complex production technologies and, hence, require workers with more specialized skills. Accordingly, a homothetic production function cannot be assumed and we therefore introduce plant size as a variable.

As a further explanation of the relevant relationships, we add three control variables to the model to capture possible influences extraneous to the model specified thus far. First, a plant's unique characteristics, although partly a function of variables discussed above, is also partly a function of other unidentified attributes that may govern the relative numbers of production and non-production workers.[4] For example, some plants engage in research or have their own sales force and their own engineering staff for planning plant additions; others do not. The evidence shows that non-production workers, on the average, earn substantially higher wages and, within our analytical framework, are presumed to embody more human capital than production workers. One control variable, therefore, is the ratio of the plant's non-production workers to the total number of employees.

A second variable is intended to capture the unique technology of each industry that governs the need for human capital where, once again, uniqueness derives from sources other than the variables specified thus far. We therefore introduce the industry's average wage (measured at the 4-digit SIC level) as a control variable for all plants in that industry. This variable serves us in two other ways. It eliminates the need for the use of a price deflator to render plant wages of different years comparable in real terms. It further captures the role of industry-wide learning (see equations (3) and (4)) and renders the introduction of a chronological time variable redundant.

[4] Non-production workers are those who are engaged in factory supervision, sales, sales delivery, advertising, credit collection, installation and servicing of products, clerical and routine office functions, executive, purchasing, financing, legal, professional, and technical personnel.

Finally, we introduce regional dummies for four geographic regions (Northeast, Midwest, South and West) to control for regional differences that may produce differences across geographic regions in the relation of wages to the implied index of "real" human capital.

Our empirical model has key features distinct from those in the existing literature. First, complementarity between human and physical capital is estimated directly without having to estimate elasticities of substitution from unreliable input price data. Second, we explicitly measure the effect of plant size on the demand for human capital. Third, learning and vintage effects on the demand for human capital are explicitly measured consistently with our theoretical model. Fourth, we examine differences in the roles of all variables depending on whether the plant is in a high or low technology industry.

We now test the following specification based on equations (6) and (10), but with the three additional control variables discussed above:

$$\ln h_{it} = \gamma_0 + \gamma_a a_{it} + \gamma_{a2} a_{it}^{\ 2} + \gamma_v v_{it} + \gamma_k \ln k_{it} + \gamma_y \ln y_{it}$$

$$+ \gamma_l \ln l_{it} + \gamma_w \ln w_t + \Sigma_{r=1}^{3} \gamma_r D_{rit} + u_{it}\,, \qquad (11)$$

where h is human capital measured by the plant's average wage; a is the plant's age measured in years since birth; v is weighted average vintage of the capital stock with higher values for more recent vintage; k is capital intensiveness measured by $k = K / L$ where K stands for gross stock of physical capital and L for the number of employees; y is output measured by shipments; l is non-production worker intensiveness measured by the ratio of non-production workers to total employment; w is average wage of the relevant 4-digit SIC industry; D_r are regional dummies. The subscripts i and t refer to the plant and chronological time in years, respectively. The measure of the industry's average wage is based on the NBER-CES Bartlesman-Becker-Gray database. The capital variable is measured by cumulative gross investment streams from the birth of a plant to t in 1987 dollars, deflated with a GDP deflator as shown in the NBER-CES Bartlesman-Becker-Gray database.

We first estimate equation (11) without non-production worker intensiveness and regional dummy variables. We then add variables in our estimation, one by one. With the plant size variable, equation (11) is estimated using two-stage least squares for the pooled time-series and cross-section data. This is because plant size measured by output is itself an endogenous variable. Shipments are estimated as a function of gross stock of physical capital and number of employees with a log-linear specification where shipments and capital are deflated with a GDP deflator. An alternative measure of plant size, the average total number of workers over the plant's life span, was also used. This alternative measure is, in one sense, less appropriate but avoids the problem of endogeneity.

The results for the two-stage least squares estimation of equation (11) are shown in Table 2. The tests for heteroskedasticity reject the null hypothesis of homoskedasticity. Accordingly, the results shown in Table 2 were estimated with the feasible generalized least squares (FGLS) specification and that t-values are heteroskedasticity-corrected. Because the data are predominantly cross-sectional and the panel of plants is highly unbalanced, serial correlation is most unlikely to be important and a Durbin-Watson statistic is not shown.

The results in Table 2 strongly support the predicted relations. They indicate that all the coefficients of the explanatory variables are associated with high t-values and

Table 2

Explanation of Demand for Human Capital*

Independent Variables	Demand for Human Capital				
	(i)	(ii)	(iii)	(iv)	(vi)
Intercept	2.1516	3.1457	2.2720	3.2284	3.1892
	(43.04)	(65.98)	(44.92)	(66.83)	(66.15)
Age	0.0098	0.0169	0.0100	0.0171	0.0175
	(6.71)	(12.97)	(6.87)	(13.19)	(13.59)
Age^2	-0.0001	-0.0002	-0.0001	-0.0002	-0.0002
	(-1.44)	(-3.00)	(-1.05)	(-2.78)	(-2.89)
Vintage	0.0245	0.0267	0.0243	0.0266	0.0263
	(33.92)	(41.14)	(33.39)	(40.87)	(40.55)
Log (k)	0.0739	0.0682	0.0779	0.0718	0.0797
	(65.17)	(58.66)	(69.08)	(61.88)	(69.94)
Log (w)	0.6552	0.5396	0.6473	0.5349	0.5375
	(89.79)	(78.61)	(87.83)	(77.33)	(78.19)
Log (y)	0.0359	0.0360	0.0387	0.0379	
	(29.47)	(27.33)	(31.98)	(28.91)	
Log (n)					0.0448
					(34.56)
Log (l)		0.1168		0.1097	0.1093
		(49.39)		(46.33)	(47.26)
Northeast			-0.0129	-0.0242	-0.0247
			(-2.14)	(-4.29)	(-4.39)
Midwest			-0.0822	-0.0711	-0.0711
			(-13.98)	(-12.72)	(-12.786
South			-0.1307	-0.1148	-0.1163
			(23.76)	(-22.25)	(-22.64)
R^2	0.65	0.69	0.66	0.69	0.70

* Estimates are based on data from the LRD at the U.S. Bureau of the Census.
Heteroskedasticity-corrected t-values are in parentheses.
Dependant variable is log (average wage). The sample consists of 5,979 plants for the periods 1973-96 that were born after 1973. For the independent variables, k is capital intensiveness measured by capital stock over total employment; w is average wage of the relevant 4-digit SIC industry; y is plant size measured by predicted value of shipments; n is alternative size variable measured by the average total number of workers over the plant's life span; l is non-production worker intensiveness measured by the ratio of non-production workers to total employment. West is used as a base for regional dummies.

significant at the one percent level. Most coefficients are quite stable and consistent across alternative specifications. The results of Table 2 may be summarized as follows:

(a) Learning-by-doing, measured by the number of years from the birth of plants, shows a positive effect on the demand for human capital in all five equations in Table 2. The results point to a one to two percent rise in human capital per year of plant life. Learning-by-doing, however, increases the demand for human capital at a decreasing rate as can be seen from the negative coefficient of age^2.

(b) Vintage and capital intensiveness have a positive effect on the demand for human capital. A one percent change in the average vintage of the capital stock is associated with about a 0.025 percent change in the demand for human capital. The highly significant coefficient of capital intensiveness strongly supports the conclusion of complementarity between human and physical capital.

(c) The coefficient of plant size, whether measured by output or by the average number of workers over the plant's life, was consistently positive. The appropriate production function appears to be non-homothetic.

(d) The average wage of the relevant 4-digit SIC industry is positively related to human capital at the plant level – a result that is hardly surprising. Excluding this variable and, instead, deflating the dependant variable by the GDP deflator reduces the R^2 but leaves the signs and approximate coefficient values for the other variables largely unchanged. Similarly, the regional dummies are generally significant and point to somewhat higher wages in the West.

We next test equation (11) with decomposition of plants into high and low technology industries, based on equations (9) and (10). The results of two-stage least squares estimation for equation (11), with decomposition of plants into high and low technology industries, are shown in Table 3. Two methods were used for distinguishing between high and low technology industries. First, we used an index based on Hadlock, Hecker and Gannon (1991). This classification is based on 3-digit SIC data on the proportion of total employment in R&D. Plants classified as being in low technology industries consisted of 4,317 plants and those in high technology industries 1,787 plants. The results with this classification of high and low technology industry are designated as equation (i) in Table 3.

An alternative measure of the industry technology index was based on the coefficient of the time variable for the following specification:

$$V_{jt} = \Psi(P_{jt}, t)\,, \tag{12}$$

where V_{jt} refers to total value-added in industry j at time t; P_{jt} to production worker hours in industry j at time t; t to chronological time in years. The information is derived from the NBER-CES Bartlesman-Becker-Gray database. The regression estimates use time-series data for each U.S. manufacturing industry, at the 4-digit SIC level, for the periods 1965-1996. Plants are labeled as being in high technology industries if the coefficient of the time variable is in the highest 20 percent of all industry estimates and otherwise in low technology industries. The number of plants so classified is 3,965 in low and 2,451 in high technology industries. The results with this classification are designated as equation (ii) in Table 3.

Table 3 strongly supports our hypothesis that complementarity of human and physical capital is higher in high technology industries than in low technology industries. The results in Table 3 indicate that all the coefficients of the explanatory variables are

Table 3

Technological Intensiveness and The Explanation of Demand for Human Capital*

Independent Variables	Demand for Human Capital			
	(i)		(ii)	
	Low Tech	High Tech	Low Tech	High Tech
Intercept	2.8188	3.0521	3.0616	3.1891
	(45.70)	(26.69)	(47.65)	(35.09)
Age	0.0194	0.0053	0.0208	0.0095
	(11.68)	(2.38)	(12.60)	(4.43)
Age^2	-0.0003	0.0002	-0.0004	0.0001
	(-3.48)	(1.61)	(-4.07)	(0.90)
Vintage	0.0239	0.0257	0.0264	0.0248
	(29.43)	(20.37)	(32.26)	(21.40)
Log (k)	0.0667	0.0741	0.0582	0.0884
	(45.70)	(37.79)	(39.31)	(45.86)
Log (w)	0.5933	0.5622	0.5599	0.5400
	(66.58)	(34.65)	(60.57)	(41.59)
Log (y)	0.0376	0.0434	0.0338	0.0449
	(20.82)	(22.85)	(18.98)	(22.37)
Log (l)	0.1024	0.1469	0.1230	0.0962
	(34.70)	(35.04)	(41.13)	(24.62)
Northeast	-0.0213	-0.0408	-0.0232	-0.0268
	(-3.01)	(-4.40)	(-3.30)	(-2.89)
Midwest	-0.0746	-0.0684	-0.0595	-0.0921
	(-10.28)	(-7.75)	(-8.26)	(-10.34)
South	-0.1309	-0.0960	-0.1143	-0.1201
	(-19.98)	(-11.33)	(-17.40)	(-14.41)
R^2	0.68	0.68	0.69	0.67

* Estimates are based on data from the LRD at the U.S. Bureau of the Census.
Heteroskedasticity-corrected t-values are in parentheses.
Dependant variable is log (average wage). The classification of high and low technology in equation (i) is based on 3-digit SIC data on the proportion of total employment in R&D, as shown in Hadlock, Hecker and Gannon (1991). The sample consists of 4,317 and 1,787 plants, respectively, for low and high technology industries. The classification of high and low technology in equation (ii) is based on the coefficient of the time variable for equation (12). Plants are classified in high technology industries if the coefficient is in the highest 20 percent of all industry estimates and otherwise in low technology industries. The sample consists of 3,965 and 2,451 plants, respectively, for low and high technology industries. All the independent variables are as defined in Table 2.

associated with high t-values and are quite stable across alternative specifications. These results may be summarized as follows:

(a) Plants in high technology industries are associated with greater complementarity between human and physical capital than those in low technology industries. When the technology index is proxied by the coefficient of the time variable (equation (ii) in Table 3), complementarity of human and physical capital appears even stronger for the high technology and vise-versa for the low technology industries than when it is proxied by proportion of total employment in R&D.

(b) Learning-by-doing and experience contribute more to the accumulation of human capital in low technology industries. This is consistent with the intuition that there is more to be gained from experience when technology is stable than when changes in technology render past experience obsolete.

(c) The effect of vintage of physical capital on the demand for human capital seems to be very similar across the two sets of industries, contrary to our prediction.

(d) The impact of plant size on the demand for human capital is stronger in high technology industries. This is consistent with the findings of Dunne and Schmitz (1995) of a positive relation among the three variables (wages, plant size and technology use), and of Oi (2000) who says, "The adoption of advanced technologies allegedly prompted big firms to hire more skilled workers which contributed to the size-wage effect" (p.10).

IV. Conclusions

We have proposed a model for explaining the demand for human capital based on a production function with human capital as an explicit argument in the function. The resulting estimates show there is strong complementarity between human and physical capital. Moreover, the complementarity is greater in high technology than in low technology industries. The results indicate that plants with physical capital of more recent vintage are associated with a higher demand for human capital. These conclusions generally support the view that technical change leads to a skill bias in the demand for labor.

The age and experience of a plant contribute to a plant's accumulation of human capital. However, input augmentation through learning-by-doing is more pronounced in low technology industries. It is in these industries that experience raises wages most. This is consistent with the intuition that the past has greater relevance for the future when technology changes more slowly.

References

Arrow, Kenneth J.; Chenery, Hollis B.; Minhas, Bagicha S.; and Solow, Robert M. "Capital-Labor Substitution and Economic Efficiency." *Review of Economics and Statistics* 43(3) (August 1961): 225-250.

Bahk, Byong-Hyong, and Gort, Michael. "Decomposing Learning by Doing in New Plants." *Journal of Political Economy* 101(4) (August 1993): 561-583.

Brown, Charles, and Medoff, James. "The Employer Size-Wage Effect." *Journal of Political Economy* 97(5) (October 1989): 1027-1059.

Dunne, Timothy, and Schmitz, James, Jr. "Wages, Employment Structure, and Employer Size Wage Premia: Their Relationship to Advanced Technology Usage at U.S. Manufacturing Establishments." *Economica* 62 (March 1995): 89-105.

Fallon, P. R. and Layard, P. R. G. "Capital-Skill Complementarity, Income Distribution, and Output Accounting." *Journal of Political Economics* 83(2) (April 1975): 279-302.

Fellner, William. "Specific Interpretations of Learning by Doing." *Journal of Economic Theory* 1 (August 1969): 119-140.

Griliches, Zvi. "Capital-Skill Complementarity." *Review of Economics and Stastistics* 51(4) (November 1969): 465-468.

Hamermesh, Daniel S. *Labor Demand*. Princeton, NJ: Princeton University Press, 1993.

Krusell, Per; Ohanian, Lee E.; Rios-Rull, Jose-Victor; and Violante, Giovanni L. "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis." *Econometrica* 68(5) (September 2000): 1029-1053.

McFadden, Daniel. “Constant Elasticity of Substitution Production Functions.” *Review of Economic Studies* 30(2) (June 1963): 73-83.

Oi, Walter Y. “The Neoclassical Foundations of Progress Functions.” *Economic Journal* 77 (September 1967): 579-594.

Oi, Walter Y. “The Pace of Work and Pay.” Working Paper (December 2000).

Penrose, Edith T. *The Theory of the Growth of the Firm*. New York: John Wiley, 1959.

Sato, Ryuzo. “Homothetic and Non-Homothetic CES Production Functions.” *American Economic Review* 67(4) (September 1977): 559-569.

Stokey, Nancy L. “Free Trade, Factor Returns, and Factor Accumulation.” *Journal of Economic Growth* 1(4) (December 1996): 421-447.