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EDUCATION AND SCREENING

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I. INTRODUCTION

Since the formulation of the human capital concept, much attention has been devoted to the relationship between income and schooling. Numerous studies have demonstrated a substantial positive association between them, a finding which has not appreciably been altered by standardization for "ability" and family background. The conventional view is that schooling enhances earnings via the production of marketable skills, the productivity augmenting view. But, recent theoretical arguments have demonstrated the possibility that schooling's private return may be informationally based.[1] In the polar view schooling serves only to identify those individuals who are more productive in the market, the proposition being that an individual's productivity is unaffected by the schooling experience, i.e., the pure screening view.

A brief outline of the paper will serve to demonstrate its aims. In section II a model is developed which explores the impact of input-quality uncertainty on factor demand from which is derived a rationale for the use of devices which segment the population into classes differing in their "skill" distribution parameters.[2] The model, however, ignores the motivation of individuals to acquire the characteristics upon which firms screen, in particular, the greater incentive for the more productive to purchase the screen. This aspect has been explored by Spence (1973) and Stiglitz (1973) and will not be explicitly considered here. In section III the social value of schooling's informational context is derived within the preceeding framework. Section IV describes some empirical attempts to isolate the productivity and identification effects. The last section summarizes the paper.

II. THE MODEL

The stimulus for job market screening is derived from imperfect information about the quality of prospective employees. Workers must be selected from a population composed of individuals possessing a diverse set of productive attributes, most, or even all, of which cannot be observed by firms prior to employment and possibly for some time after.

To begin, consider the set of productive attributes to consist of all those skills (technical knowledge, motivation, responsibility) which are perceived by firms as contributing to an individual's productivity. Since schooling can be viewed as either augmenting some of the elements in an individual's vector of skills or as a predictor of these elements, or both, it is not considered as belonging to the set. Similarly, race, sex, experience, marital status and other characteristics which (may) serve as possible information sources to the firm are excluded. To clarify the distinction, the attributes themselves will be referred to as elements of an individual's human capital stock and the characteristics as screening devices. Note that a screening device is not necessarily passive, but, as with experience, may augment an individual's stock of marketable skills. In this general sense, there is no presumption that screening devices are only associatively rather than causally related to human capital stocks. All potential information sources are similarly classified regardless of the nature of their relationship to actual productivities.

More concretely, let $k_i = (k_{i1}, k_{i2}, \ldots, k_{in})$ be the i^{th} individual's skill vector where the total potential set consists of n different types; thus, for any single individual some of the elements may be zero. Corresponding to a job task or "occupation" there is assumed to exist a transformation which maps each individual's combination of elementary attributes into a unique skill index.

The i^{th} individual's skill index for the j^{th} occupation is given by $s_{ij} = f_j(k_{i1}, k_{i2}, \ldots, k_{in})$.[4] Since the f_j's are assumed to vary across job tasks with respect to both the number of elements affecting the skill index and their marginal contributions to the skill index, individuals will be assinged a different skill index for each occupation.

The production process within the firm is assumed to take the following form:

(1) $Y = F(S_1, S_2, \ldots, S_v, K)$[5]

where

$$S_j = \sum_{i=1}^{L_j} s_{ij} = \text{aggregate skill for the } j^{th} \text{ job task}$$

L_j = the number of individuals employed in the j^{th} tasks

and

K = a non-labor input.

Notice that in this formulation workers substitute perfectly within occupations but not necessarily between occupations.

Suppose that firms have no a priori estimates of individual human capital vectors. Instead, let the j^{th} skill index be distributed over the population with mean μ_j and variance σ^2_j, both of which are known with certainty by the firm. Each firm is seen as drawing a random sample from the population for each occupation with $\bar{s}_j$ being the obtained sample skill mean for the j^{th} occupation. The first two moments of the sample mean are μ_j and σ^2_j/L_j where L_j is the size of the sample drawn (the number of workers employed). The firm receives $S_j = \bar{s}_j L_j$ aggregate units of the j^{th} skill index which is itself distributed with mean $\bar{S}_j = \mu_j L_j$ and variance $\sigma^2_j L_j$. Upon taking a second-order approximation of the production function around the point $(\bar{S}_1, \bar{S}_2, \ldots, \bar{S}_v, K)$, expected output is given by

$$(2) \quad \bar{Y} = F(\bar{S}_1, \bar{S}_2, \ldots, \bar{S}_v, K) + \frac{1}{2}\sum_{j=1}^{v} \sigma_j^2 L_j F_{\bar{S}_j \bar{S}_j}$$

$$= F(\bar{S}_1, \bar{S}_2, \ldots, \bar{S}_v, K) + \frac{1}{2}\sum_{j=1}^{v} R_j \bar{S}_j F_{\bar{S}_j \bar{S}_j}$$

$$= \phi(\bar{S}_1, \bar{S}_2, \ldots, \bar{S}_v, R_1, R_2, \ldots, R_v, K)$$

where it is assumed that sampling is independent over the v occupations and where $R_j = \sigma_j^2/\mu_j$ (the variance-mean ratio for the jth occupation) and $F_{\bar{S}_j \bar{S}_j} = \frac{\partial^2 F}{\partial S_j^2}$ evaluated at $(\bar{S}_1, \bar{S}_2, \ldots, \bar{S}_v, K)$. Thus, expected output is that level of output obtained with certainty if labor were homogeneous plus a variance correction.

The basic predictions of the model can be illustrated most easily with a single aggregate skill input.[6] Equation (2) reduces to

$$(3) \quad \bar{Y} = F(\bar{S}, K) + \frac{1}{2} R\bar{S} F_{\bar{S}\bar{S}}$$

$$= \phi(\bar{S}, R, K)$$

where $\bar{S} = \mu L$, $R = \sigma^2/\mu$ and μ and σ^2 are as previously defined.

The variance-mean ratio (R) can be interpreted as a measure of uncertainty attached to the labor input in the following sense. If individuals possessed identical skill vectors so that $\sigma^2 = 0$, the profit-maximizing level of aggregate skill could be obtained without error. For example, denoting S^* as the optimal skill input and μ as the number of skill units embodied in each individual, $L^* = S^*/\mu$ would be the optimal labor input. However, if human capital vectors differ $(\sigma^2 > 0)$ the firm can never be assured of obtaining L* regardless of its sampling decision. The question is whether the firm will alter its employment decision in response to the introduction of skill variance.

The first effect attributable to the introduction of uncertainty is a reduction in expected output at the original equilibrium input levels. Since $\phi_R = \frac{1}{2} \bar{S} F_{\bar{S}\bar{S}} < 0$ under the concavity assumption,

$$(4) \quad \frac{\partial \bar{Y}}{\partial \sigma^2} = \phi_R \frac{\partial R}{\partial \sigma^2} = \frac{1}{\mu} \phi_R < 0.$$ [7]

Firms will, therefore, always prefer to sample from a population characterized by lower variance.[8]

The equilibrium conditions for the profit-maximizing competitive firm are:

$$(5) \quad \bar{Y} = \phi (\bar{S}, R, K)$$

$$(6) \quad P_L = \lambda \phi_L$$

$$(7) \quad P_K = \lambda \phi_K$$

$$(8) \quad \lambda = P_Y = \text{MEC (marginal expected cost)},$$

where P_L is the wage rate (identical for each individual as they are indistinguishable prior to hiring), P_K is the rental rate per unit of capital, and P_Y is the product price.

Totally differentiating the first-order conditions with respect to skill variance, allowing inputs to vary but maintaining a constant mean skill index, and solving for input and marginal cost adjustment, yields

$$(9) \quad \frac{d\lambda/\lambda}{d\sigma^2} = \frac{1}{\Delta} [(\frac{d\bar{Y}}{d\sigma^2} - \phi_{\sigma^2}) \Delta_0 - \phi_{L\sigma^2} \Delta_L - \phi_{K\sigma^2} \Delta_K]$$

$$(10)\quad \frac{dL}{d\sigma^2} = \frac{1}{\Delta}\ [(\frac{d\bar{Y}}{d\sigma^2} - \phi_{\sigma}2)\ \Delta_L - \phi_{L\sigma}2\ \ \Delta_{LL} - \phi_{K\sigma}2\ \ \Delta_{KL}]$$

$$(11)\quad \frac{dK}{d\ \ 2} = \frac{1}{\Delta}\ [(\frac{d\bar{Y}}{d_{\sigma}2} - \phi_{\sigma}2)\ \Delta_K - \phi_{L\sigma}2\ \ \Delta_{LK} - \phi_{K\sigma}2\ \ \Delta_{KK}]$$

where Δ is the usual bordered Hessian determinant and subscripted Δ's are the relevant cofactors.[9]

The first effect of skill variance has been shown to be a reduction in expected output at the original input levels. The second effect entails a movement away from the previous optimal factor ratio at the new lower level of expected output. This substitution effect can be isolated by setting $\frac{d\bar{Y}}{d\sigma^2} - \phi_{\sigma}2$ equal to zero in (9) and (10). This, after some manipulation, yields

$$(12)\quad \frac{1}{L}\ \frac{dL}{d\sigma^2} - \frac{1}{K}\ \frac{dK}{d\sigma^2} = \varepsilon_{LK}\ \left(\frac{\phi_{L\sigma}2}{\phi_L} - \frac{\phi_{K\sigma}2}{\phi_K}\right)$$ [10]

where ε_{LK} is the elasticity of substitution between K and L, the latter being evaluated at μ.

Upon expanding (12) it is found that the substitution effect is related to third partial derivatives.

$$(13)\quad \frac{\phi_{L\sigma}2}{\phi_L} - \frac{\phi_{K\sigma}2}{\phi_K} \sim (F_K\ F_{\bar{S}\bar{S}} + \bar{S}\ F_K\ F_{\bar{S}\bar{S}\bar{S}} - \bar{S}\ F_{\bar{S}}\ \ F_{\bar{S}\bar{S}K})$$

The signs of $F_{\bar{S}\bar{S}\bar{S}}$ and $F_{\bar{S}\bar{S}K}$ indicate the rate at which the marginal product of skill declines with increased usage of labor and capital respectively.[11] If $F_{\bar{S}\bar{S}K} > 0$, an increase in the quantity of capital retards the rate of decline in labor's marginal product (and raises its own marginal expect product for any increase in variance, $\phi_{K\sigma^2} > 0$), while a negative value implies an acceleration in the rate of decline in labor's marginal product (in which case $\phi_{K\sigma^2} < 0$).[12] A similar set of conditions applies to the own third partial, $F_{\bar{S}\bar{S}\bar{S}}$. In a sense these third partials can be considered as indexes of similarity with a positive sign implying complementarity and a negative sign competitiveness.

Although one might expect firms to substitute away from the risky input (labor), this is not necessarily the case. It is possible for an increase in the labor input to reduce the adverse effect of variance on expected output if the rate of decline of labor's marginal product is sufficiently slow, i.e., if $F_{\bar{S}\bar{S}\bar{S}}$ is sufficiently positive. The sign of the substitution effect is determined by the relative effect of the two inputs in reducing the impact of variance on expected output.[13]

Figure 1 illustrates the case of a negative substitution effect where A corresponds to the position prior to the introduction of quality uncertainty and B corresponds to the new equilibrium factor ratio established at the lower level of expected output, $\bar{Y}_1$, after introducing uncertainty. There are, however, two further effects. First, there is a direct production effect corresponding to a northward movement along the new expansion path in order to restore output to its previous level($\bar{Y}_0$). This, together with the substitution effect, corresponds to the usual output constant substitution adjustment. Second, there is an induced production effect in response to a change in marginal expected cost after regaining the original output level. In Figure 1 the direct effect is shown as a movement from B to C and the induced effect from C to D.

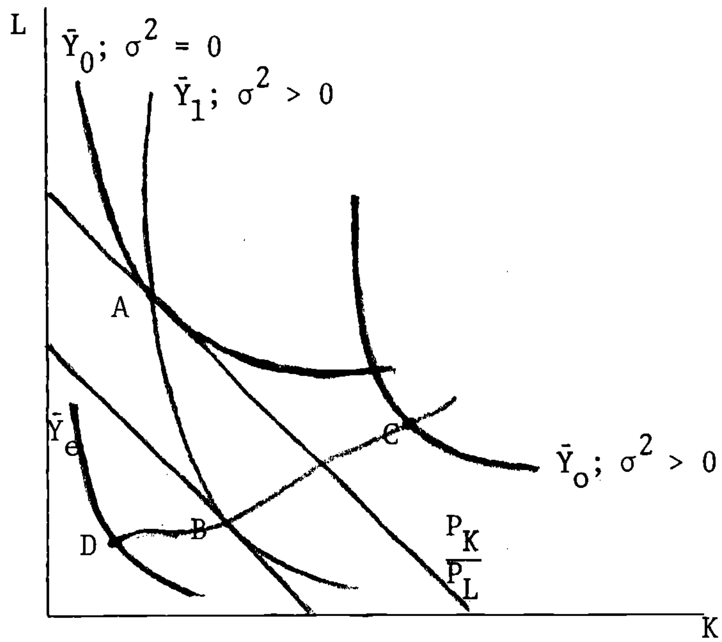


Figure 1. The Effect of Skill Variance on Factor Demand

Both the direct and induced effects are movements along the same expansion path and must be in opposite directions. The question concerns the dominant one. The net scale effect is found by setting $\frac{d\bar{Y}}{d\sigma^2} - \phi_{\sigma}2 = 0$ in equation (9) and is given by

$$(14) \quad - \frac{d\lambda/\lambda}{d\sigma^2} = \left(\frac{\phi_{L\sigma^2}}{\phi_L} \frac{E\lambda}{EP_L} + \frac{\phi_{K\sigma^2}}{\phi_K} \frac{E\lambda}{EP_K} \right)$$

where $\frac{E\lambda}{EP_L}$ and $\frac{E\lambda}{EP_K}$ are the elasticities of marginal cost with respect to factor prices. The percentage change in marginal cost is a weighted sum of percentage changes in marginal expected products, where the sign of the weights depend upon the normality or inferiority of the factors. Figure 1 illustrates a negative net scale effect ($- \frac{d\lambda/\lambda}{d\sigma^2} < 0$), a further reduction in expected output from $\bar{Y}_1$ to $\bar{Y}_e$.[14]

Although the results of the previous analysis are somewhat ambiguous as to the effect of introducing a risky input on factor demand, the important point to note is that firms are definitionally "risk" averse; quality uncertainty must lead to a reduction in expected output. The following extension makes use of this proposition to show how the firm may use screening devices to reduce uncertainty. Although schooling is used throughout as the device analyzed, the model is perfectly general for any screen as previously defined.

Suppose there to be only two schooling classes denoted as E_C and E_H with the former being the higher level. Let the corresponding parameters of the skill distributions associated with these classes be μ_C, σ^2_C and μ_H, σ^2_H respectively. Awareness by the firm of individual schooling levels would enable it to sample independently from within each schooling class. The firm's obtained aggregate skill would be $S = \bar{s}_H L_H + \bar{s}_C L_C$ with expectation $\bar{S} = \mu_H L_H + \mu_C L_C$ and variance $\sigma^2_H L_H + \sigma^2_C L_C$ where L_H and L_C are the numbers of individuals sampled from each group.

Expected output is

$$(15)\quad \bar{Y} = \phi(\mu_H L_H + \mu_C L_C,\ \frac{\sigma^2_H L_H + \sigma^2_C L_C}{\mu_H L_H + \mu_C L_C},\ K)$$

The marginal rate of substitution between the two worker classes is, with a fixed stock of capital, given by

$$(16)\quad -\frac{dL_C}{dL_H} = \frac{\mu_H}{\mu_C}\left[\frac{\bar{S}\phi_{\bar{S}} - R\phi_R + R_H\phi_R}{\bar{S}\phi_{\bar{S}} - R\phi_R + R_C\phi_R}\right]$$

where $R_H = \sigma^2_H/\mu_H$ and $R_C = \sigma^2_C/\mu_C$.

Suppose that education acts as a perfect screen so that individuals within schooling classes are homogeneous, $\sigma^2_H = \sigma^2_C = 0$. The use of schooling as a screen eradicates the uncertainty previously associated with the labor input. Since $R_H = R_C = 0$, the MRS is independent of the ratio of workers sampled from the two classes. Workers substitute perfectly at the rate given by the ratio of their average levels of skill, μ_H/μ_C.

Since in the absence of screening all individuals are equally compensated, any single firm would perceive itself as being in a better position when the information is utilized. For any given total labor input, $\bar{L}$, the expected gain from screening is

(17) $F(\mu_C\bar{L}, K) - [F(\mu\bar{L}, K) + 1/2\, R\mu\bar{L}F_{\bar{S}\bar{S}}]$

and is composed of two components, the output effect of the increased aggregate skill level ($\mu_C\bar{L}$ as opposed to $\mu\bar{L}$) and the output gain due to variance reduction (in this case to zero).[15]

When education is an imperfect screen, $\sigma^2_C, \sigma^2_H \neq 0$, and there are many reasons why this will be the case, workers from the two schooling classes are no longer perfect substitutes. The MRS will be less than unity at all input ratios if $\mu_C > \mu_H$ and $R_C < R_H$. Neither condition is, in itself, sufficient. In the example that follows strict preference for the more schooled, i.e., $-\frac{dL_C}{dL_H} < 1$ for all labor ratios, is assumed.[16] It can be demonstrated that a necessary condition for isoquants to be convex is that $\phi_{\bar{S}\bar{S}} < 0$, i.e., the marginal expected product of skill declines.[17]

Figure 2 illustrates the employment decision when schooling is an imperfect screen and there is strict preference for the more schooled. With equal wage rates, profit maximization would entail the employment of individuals from a single schooling class. If AB is a representative isoquant and AC the unit sloped iso-cost line, a corner solution is obtained at A, where only the more schooled are employed. For a fixed labor input, the gain from screening (the loss from ignoring schooling's screening potential) is given by the difference in revenue associated with any point along AC and that corresponding to AB.[18]

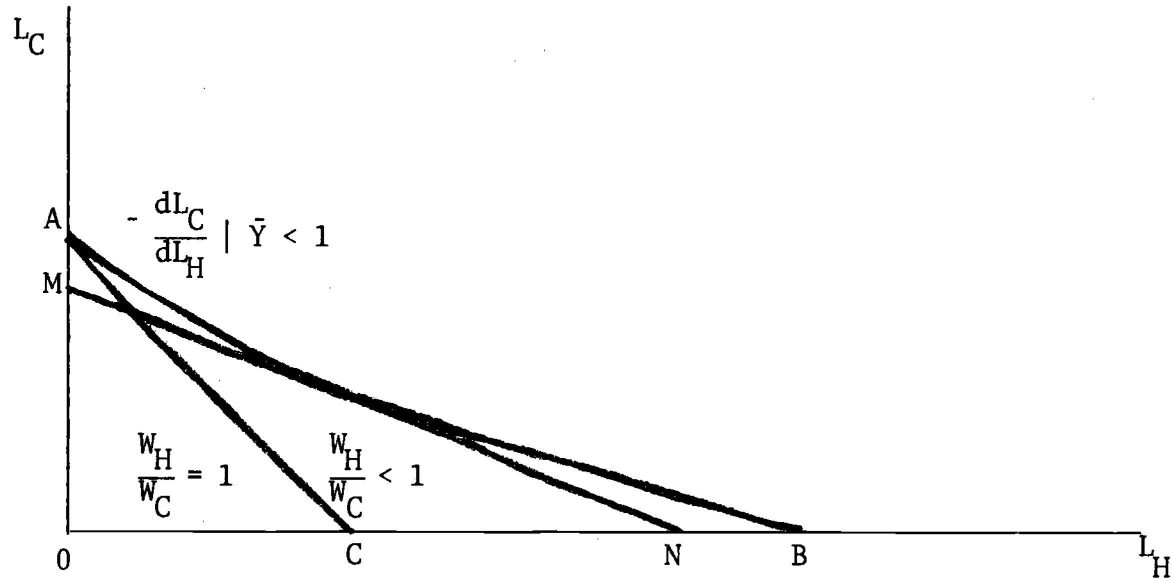


Figure 2.

The gain from utilizing the screen is a function of the degree to which skill parameters diverge. For a fixed labor input, $\bar{L}$, the return to employing an additional E_C worker (thus, one fewer E_H worker) is given by

$$(18) \quad \frac{d\bar{Y}}{dL_C} \Big|_{\bar{L}} = \phi_{\bar{S}} (\mu_C - \mu_H) + \phi_R \frac{\mu_C \mu_H \bar{L}}{\bar{S}} (R_C - R_H).$$

The marginal return to employing an extra preferred worker is a positive function of $\mu_C - \mu_H$ and $R_H - R_C$.[19,20]

Competitive bidding for the more schooled will cause W_C to rise relative to W_H.[21] For example, in Figure 2 the new isocost line, MN, reflects the increased relative demand for E_C workers. As shown, a new equilibrium position is established at D where workers from both schooling classes are employed by the firm.[22]

Since schooling's sorting efficiency can be expected to vary with occupation, in general, occupations will be characterized by different proportions of schooled labor. The factor intensities of occupations with respect to schooling classes will depend upon comparative advantages. Even if the more schooled have an absolute advantage in many occupations, those occupations for which skill parameters most diverge (in combination with the output cost of variance and the level of marginal expected skill products) will be more schooled-labor intensive.

To summarize, several components of schooling's private return have been identified. The first is attributable to differences in average skill levels which may or may not bear any other than an associative relationship to the educational process. The second component is a function of skill variances, the demand for labor of a given class being negatively associated with its variance - mean ratio.[23,24]

III. THE SOCIAL RETURN TO SCREENING

The major point of screening models is that the empirically observed private return to schooling can be generated within a framework of incomplete information without relying on human capital augmentation.[25] The importance of this interpretation hinges upon the magnitude of schooling's social return, ie., the social value of schooling's informational content.

In a strict sense, in both Spence (1973) and Stiglitz (1973), the information itself has no social value - the social return to schooling is, in fact, negative. If education imparts no marketable skills, from a social perspective the resources used in the acquisition of schooling are social wastes. The reason is simply that in these models constant marginal products are assumed. To illustrate, if k is the constant marginal product of skill, μ the average skill level and L the labor stock, gross social product is $k\mu L$. Net social output is $k\mu L - gL_C$ where g is the output cost per schooled individual and L_C the number of such individuals. The optimal social investment in education is zero since gross social output is unaffected by the number of schooled individuals.

Consider the following example. Suppose there are two productivity types of individuals (A and B) and two schooling classes (E_C and E_H). Assume that the distribution of skill within the two schooling groups have as their respective means and variance (μ_C, σ^2_C) and (μ_H, σ^2_H) with $\mu_C > \mu_H$. In particular, consider the case where education is a perfect screen so that $\sigma^2_H = \sigma^2_C = 0$. Let s_A be the skill endowment of all type A individuals and s_B that of all type B with L_A and L_B being their respective numbers and $s_A > s_B$. With a perfect screen $\mu_C = s_A$, $\mu_H = s_B$, $L_C = L_A$ and $L_H = L_B$. Gross social product with constant marginal products is simply $k(\mu_C L_C + \mu_H L_H) = kS$ where S is aggregate skill.

Now suppose that production is characterized by equation (2), Section II and that there are N firms each employing L workers. For the i^{th} firm, actual output is

$$(19) \quad Y_i = F(S_i, K) = F(\bar{s}_i L, K)$$

where $\bar{s}_i$ is the mean skill level obtained by the i^{th} firm from a random sample of L workers. Taking a second-order approximation around $\bar{S} = \mu L (= \frac{S}{N})$, the expected aggregate skill input, yields

$$(20) \quad Y_i = F(\mu L, K) + (\bar{s}_i - \mu) L F_{\bar{S}} + \frac{1}{2} (\bar{s}_1 - \mu)^2 L^2 F_{\bar{S}\bar{S}}.$$

Aggregate output is

$$(21) \quad \Sigma Y_i = NF(\mu L, K) + \frac{1}{2} L^2 F_{\bar{S}\bar{S}} \Sigma(\bar{s}_i - \mu)^2$$

since $\Sigma(\bar{s}_i - \mu) = 0$, as total skill must be exhausted. Since $F_{\bar{S}\bar{S}} < 0$, total product is maximized where $\Sigma(\bar{s}_i - \mu)^2 = 0$, i.e. where each firm obtains the identical mean skill level. Maintaining the assumption of a perfect screen, it can easily be demonstrated that

$$(22)\quad \Sigma Y_i = NF + \frac{1}{2} F_{\bar{S}\bar{S}}(\mu_C - \mu_H)^2 \sum_{i=1}^{N} (L_{Ci} - \frac{L_C}{N})^2$$

$$= NF + \frac{1}{2} F_{\bar{S}\bar{S}}(s_A - s_B)^2 \sum_{i=1}^{N} (L_{Ci} - \frac{L_C}{N})^2$$

where L_{Ci} is the i^{th} firm's labor input obtained from the E_C schooling class and L_C/N is the number of E_C workers the i^{th} firm would obtain if the L_C workers were equally distributed over firms. But, it was demonstrated in Section II that in utilizing the screen each firm samples the same number of workers from within a schooling class so that $L_{Ci} = \frac{L_C}{N}$ for all i and aggregate output is, therefore maximized.

It can further be demonstrated that as education becomes a less perfect screen (σ^2_C, $\sigma^2_H > 0$), its social benefit declines. In this case, even as firms employ the same factor proportions (L_C/L_H), variations in aggregate skill will persist since within-group skill variances are not zero. The return to screening is due to the elimination of between-group variance; it is as if each firm samples from a population with smaller skill variance. Regardless of screening efficiency, the output loss from ignoring the information is a rising function of the difference in skill endowments, i.e., a positive function of $(s_A - s_B)$.[26]

In the above analysis, schooling's only function is as an identification device given fixed skill endowments. But, suppose that schooling creates productivity differences. This effect can be demonstrated by differentiating equation (21) with respect to μ, yielding

$$(23)\quad \frac{d\Sigma\, Y_i}{d\mu} = NL\, F_{\bar{S}} + \frac{1}{2} L^2\, F_{\bar{S}\bar{S}\bar{S}}\ \Sigma\, (\bar{s}_i - \mu)^2 + \frac{1}{2} L^2\, F_{\bar{S}\bar{S}}\ \frac{d(\Sigma(\bar{s}_i - \mu)^2)}{d\mu}$$

The first term reflects the direct output effect of the increase in aggregate skill. The second term shows the impact of the rise in aggregate skill on schooling's informational return for a given screening efficiency. If $F_{\bar{S}\bar{S}\bar{S}} > 0$, the output cost of skill dispersion between firms falls while the opposite is true if $F_{\bar{S}\bar{S}\bar{S}} < 0$. When schooling is a perfect screen this term is zero; the more imperfect the screen initially, the more important is this effect. The last term reflects the change in screening efficiency accompanying the rise in average skill. In general, a rise in within-group variances will increase variation in aggregate skill between firms and, thus, reduce aggregate output. Therefore, schooling induced increases in the average skill level of a population will have its greatest positive impact on aggregate output the higher is the marginal product of skill, the more slowly it declines and the more homogeneous schooling groups become.[27]

With the introduction of a second "occupation" or type of skill, schooling's informational return may be further enhanced. As before, the social return to identification is related to reductions in aggregate skill variation between firms. However, there is also a social gain to allocating individuals to their most productive uses which will be operative if schooling's sorting efficiency differs by occupation or if the output cost of uncertainty varies by occupation.[28]

IV. EMPIRICAL TESTS OF THE SCREENING HYPOTHESIS

Although a wide range of studies exist on the schooling-income relationship few empirical attempts have been directed toward discovering the generating mechanism. Much of the work has been concerned with assessing the bias in schooling's private return which results from ignoring measures of ability. The results have consistently found a minimal reduction in schooling's incremental effect on earnings.[29] However, it would be erroneous to conclude from this that schooling directly produces human capital rather than serving an identification function. The reason is that screening arises solely as a consequence of imperfect information. Schooling is simply a proxy for earnings producing skills. Even if ability measures were perfectly correlated with productive skills, but firms were unaware of each individual's ability (measure), schooling might still have a larger impact on earnings over the life cycle. That these ability measures only imperfectly correlate with job success may actually be only a peripheral consideration for the applicability of these studies to the screening hypothesis.[30]

Consider some of the previous attempts to isolate the identification and productivity effects. There is only one published empirical study of which I am aware, that by Taubman and Wales (1973), which purports to isolate a significant identification role. According to the authors, screening is said to occur when individuals, due to their lack of education, are restricted from entering occupations in which their marginal products are greatest. In other words, if individuals could freely choose their occupations, a greater proportion of those with lower schooling levels would be found in higher paying occupations.[31]

Their screening test involves a comparison of the actual and expected fractions of people with different educational attainment in various occupations. To derive the expected distribution under free entry, within-occupation earnings regressions were estimated from which the potential incomes of individuals in other occupations were obtained.[32] Their occupational regressions included schooling, ability, age, and several other socio-economic variables. Occupations were grouped into three categories with separate dummies for individual occupations. The groupings were (1) professional, sales, and technical; (2) blue-collar, white-collar, and service;

(3) managerial. No interactions were used so that earnings merely shift up or down for occupations within each broad classification.

The problem with this method, ignoring the assumptions made in calculating the expected distribution, is that individuals with the same observed characteristics are, by definition, equally productive; yet, observed characteristics account for only part of the variance in earnings. If these unmeasured skills are correlated with schooling and more important in some occupations than others, potential earnings will be overestimated for the less schooled in those occupations.[33] Although Taubman and Wales realize that this problem exists, they state that they cannot determine its importance. However, one can see from their results that the effect is swamping all others. Table 1 duplicates their findings although it is rearranged in a more revealing manner.

The authors conclude from this table that: "In general, then, under the assumption of free entry and income maximization, very few people at any educational level would choose the blue collar, white collar, or service occupations."[34] The fact that the high school and some college groups predominate in these occupations is taken as evidence of educational credentialism. Notice that when the occupations are grouped as they were in the regressions, the expected fractions in the three broad occupational categories are almost identical for the three schooling classes. Taubman and Wales have merely made people look more alike than they really are. Thus, the problem they have in explaining the result that the expected proportion of college graduates in the highest paying occupations exceeds the actual proportion (after all, they are the preferred group), is easily resolved. The interpretation of their results as due to entry barriers is not warranted. Moreover, even if the actual distributions are those which would

TABLE 1*

ACTUAL AND EXPECTED OCCUPATIONAL DISTRIBUTIONS

	High School				Some College				College Graduate			
	Actual	(bracket)	Expected	(bracket)	Actual	(bracket)	Expected	(bracket)	Actual	(bracket)	Expected	(bracket)
Prof	1.5		9.5		5.8		14.8		25.0		17.8	
Tech	11.5	20.6	21.0	52.5	9.6	24.8	19.1	55.7	2.8	36.6	14.1	55.7
Sales	7.6		22.0		9.4		21.8		3.8		25.5	
Blue Collar	28.6		1.3		10.2		.8		1.8		.9	
Service	6.8	38.7	1.4	3.2	3.8	26.5	1.2	2.6	1.1	4.0	.9	2.2
White Collar	3.3		.5		2.5		.6		1.1		.4	
Managerial	40.6		42.4		58.8		39.8		59.4		38.3	

*Brackets are my own.

Source: Taubman and Wales (1973), Table 5.

obtain under strict income maximization, the question would still remain as to whether schooling produced those occupational skills or merely signalled their endowment.

The empirical work presented here is confined to two issues approximating the mean and variance components of schooling's return previously discussed. In all cases, an attempt is made to discern the existence of a significant identification component to schooling's return.

A general description of the data base employed follows. The NBER-Thorndike sample consists of approximately 5000 men who were air force pilot, navigator and bombadier candidates in 1943. The population was obtained from a subsample of 17,000 men from whom Thorndike collected information in 1955 on earnings, job experience and other socioeconomic variables including numerical scores on seventeen tests administered by the air force in 1943 which purport to measure various capabilities ranging from manual dexterity to abstract problem solving capabilities. The NBER resampled a subset of these men in 1969 and again in 1971 updating data on job histories and socioeconomic characteristics. Specifically, the data includes information on jobs held in five separate time intervals: 1945-1952, 1953-1957, 1958-1962, 1963-1966, and 1967-1970.[35] Information on jobs held in years other than those corresponding to the interview years are retrospective. All individuals are at least high school graduates and a majority have an undergraduate degree or some graduate training. Ages, as of 1969, range from 42 to 55.

Since, for many, employment was interrupted by the war, accurate estimates of market experience were obtained by restricting attention to those individuals whose initial job occurred after military service and, in particular, within the 1945-1952 interval. Experience is calculated simply as the difference between a reported job year lying within any of the five periods and the initial job year; it is thus, by definition, zero for the initial job. Further exclusions were those individuals with extended military service, those who were civilian pilots, the disabled and the unemployed. The constructed longitudinal sample consists of 9,799 separate experience-earnings points.

Earnings profiles were estimated for both private wage workers and for the self-employed.[36] Table 2 reports the results for several specifications. The dependent variable in this and all other tables is the natural logarithm of earnings (in 1958 dollars), S is schooling completion level, P is experience, and A is an IQ-type ability measure.[37] Since it will be argued that the relevant hypotheses are concerned with coefficient equality as between the two groups, the regressions in Table 2 (and all others except where noted) are from a pooled sample in which each coefficient represents the partial effect of a given variable for one or the other group.[38] Descriptive statistics for selected variables are found in Table 1 of Appendix B.

If a major portion of schooling's private return is merely informational, it should manifest itself in a smaller earnings increment to the self-employed and/or a lower average schooling level. Clearly, there is less incentive for the more productive among the self-employed to use schooling as an identification device.[39] Moreover, lacking Spence's self-selection mechanism, the sorting of more productive types by schooling should be less clear and since the self-employed can earn at most only the market's valuation of their marginal product, the incremental effect of schooling on earnings should be lower for this group. However, when one looks at the schooling effect in Table 2, equations 1 and 2, it is seen that schooling has a differentially larger impact on earnings among the self-employed.[40] Moreover, average

TABLE 2

EARNINGS REGRESSIONS FOR PRIVATE WAGE AND SELF-EMPLOYED WORKERS

Coefficients (t-values in parentheses)

	(1)		(2)		(3)	
	Private	Self-Employed	Private	Self-Employed	Private	Self-Employed
S	0.029 (12.7)	0.040 (9.5)	0.023 (9.9)	0.040 (9.2)	-0.023 (6.4)	-0.014 (2.2)
P	0.078 (38.5)	0.074 (18.2)	0.078 (38.6)	0.074 (18.2)	0.008 (1.7)	-0.01 (1.2)
P^2	-0.0014 (15.8)	-0.0010 (5.5)	-0.0014 (15.9)	-0.0010 (5.5)	-0.0012 (14.0)	-0.0008 (4.3)
SP	-	-	-	-	0.0043 (16.1)	0.0053 (10.8)
A	-	-	0.027 (9.8)	0.004 (0.7)	0.006 (1.3)	-0.008 (.09)
AP	-	-	-	-	0.002 (6.1)	0.001 (1.7)
Intercept (a)	7.9 (221.1)	-0.01 (0.1)	7.99 (218.4)	-0.09 (1.1)	8.71 (153.9)	.029 (0.2)
R^2	.4927		.4977		.5225	

(a) The self-employed intercept is the difference between the actual self-employed intercept and the private wage intercept given to the left. Insignificance of the coefficient implies equality of the constant term in the two samples.

schooling levels are very similar with private wage workers obtaining 15.6 years of schooling and the self-employed 15.3.[41] A major screening role is not indicated by these results.

One obvious modification is to delete the professional class (doctors, lawyers, teachers, etc.) since it is, in many instances, subject to public screening through occupational licensure. Table 3 reports the results for all individuals who were not professional on either their first or their last reported job.[42] As seen, the overall schooling coefficient is, in magnitude, somewhat smaller for the self-employed. These differences are not "significant" in a statistical sense.[43] Moreover, when "ability" is controlled for, as one should if this measure is known by the firm, the difference is less pronounced. Further average schooling levels again do not diverge significantly (see Table 3 of Appendix B).

Similar reasoning applies to the effect of college quality on earnings as between the two groups. If the quality of college attended is used as a screen and merely serves a classificatory function, its effect should be less pronounced on the earnings of the self-employed. To facilitate the comparison, the subsample of college graduate non-professionals (only those with exactly 16 years of schooling) was chosen. The regression equations are presented in Table 4 where Q represents the college quality variable and other symbols are as previously defined.[44] It is seen that the overall quality effect is larger for the self-employed. If the quality variable can be interpreted as a measure of accrued knowledge, it appears that these acquired skills are indeed productive in the market. Furthermore, the incentive for the self-employed to obtain higher quality schooling seems not to be dampened as average qualities are almost identical (see Table 5, Appendix B).

TABLE 3

EARNINGS REGRESSIONS FOR PRIVATE WAGE AND SELF-EMPLOYED NON-PROFESSIONALS

Coefficients (t-values in parentheses)

	(1)		(2)		(3)	
	Private	Self-Employed	Private	Self-Employed	Private	Self-Employed
S	0.050 (13.2)	0.042 (5.6)	0.048 (12.3)	0.043 (5.5)	-0.011 (1.3)	-0.018 (1.6)
P	0.065 (22.1)	0.063 (11.5)	0.065 (22.1)	0.063 (11.5)	0.017 (2.3)	-0.020 (1.4)
P^2	-0.0011 (8.2)	-0.0007 (2.8)	-0.0011 (8.2)	-0.0007 (2.8)	-0.0009 (6.9)	-0.0005 (2.2)
SP	-	-	-	-	0.0055 (12.2)	0.0056 (6.6)
A	-	-	0.008 (1.9)	-0.004 (0.5)	-0.017 (2.5)	-0.016 (1.3)
AP	-	-	-	-	0.0023 (4.6)	0.0011 (1.2)
Intercept[a]	-0.28 (2.2)	7.95 (72.0)	-0.24 (1.8)	7.94 (70.1)	-0.25 (1.3)	8.82 (51.0)
R^2	.426		.427		.454	

[a] The private intercept given in the table is the difference between the actual private intercept and the self-employed intercept to the right. Insignificance of the coefficient implies equality of the constant term in the two samples.

TABLE 4

COLLEGE QUALITY REGRESSIONS FOR NON-PROFESSIONAL PRIVATE WAGE AND SELF-EMPLOYED WORKERS

Coefficients (t-values in parentheses)

	(1)		(2)		(3)	
	Private	Self-Employed	Private	Self-Employed	Private	Self-Employed
P	0.083 (15.0)	0.092 (9.2)	0.083 (15.0)	0.092 (9.2)	0.072 (7.9)	0.068 (3.8)
P^2	-0.0014 (5.5)	-0.0013 (2.9)	-0.0014 (5.5)	-0.0013 (2.9)	-0.0014 (5.5)	-0.0013 (2.9)
Q	0.051 (4.3)	0.053 (2.2)	0.051 (4.3)	0.055 (2.2)	0.025 (1.3)	0.004 (0.09)
QP	-	-	-	-	0.0023 (1.6)	0.0049 (1.6)
A	-	-	0.002 (0.3)	-0.006 (0.4)	-0.011 (0.9)	0.006 (0.3)
AP	-	-	-	-	0.0013 (1.3)	-0.0012 (0.8)
Intercept	-0.05 (0.38)	8.16 (64.4)	-0.04 (0.3)	8.15 (63.5)	-0.17 (0.8)	8.40 (42.1)
R^2	.505		.506		.508	

A comparison of average incomes of rural farm workers and urban workers at alternative schooling levels found in Welch (1971) also supports the human capital view. The argument is basically the same as that with respect to the self-employed and private wage comparison made above, since the rural farm class is predominantly composed of self-employed individuals. As Table 5 illustrates, the percentage increase in earnings with increased schooling is larger for the rural farm class. The absence of a screening motive would preclude such a result if schooling did not augment productivities. There is no reason for the more able among rural farmers to be more prone to obtain schooling unless they perceive some benefit which, for them, must result from skill augmentation rather than identification.

TABLE 5[a]

INCOME IN 1959 FOR URBAN AND RURAL FARM MALES, 45-54 YEARS OLD, BY YEARS OF SCHOOLING

Comparison for the	1-4 Years	12 Years	16 Years
(1) Urban Average	4,370	6,900	10,130
(2) Rural Average	2,780	4,900	7,600
(3) 2 ÷ 1	0.64	0.71	0.75

[a] Source: Welch (1971), Table 2; computed from U.S. Census of Population.

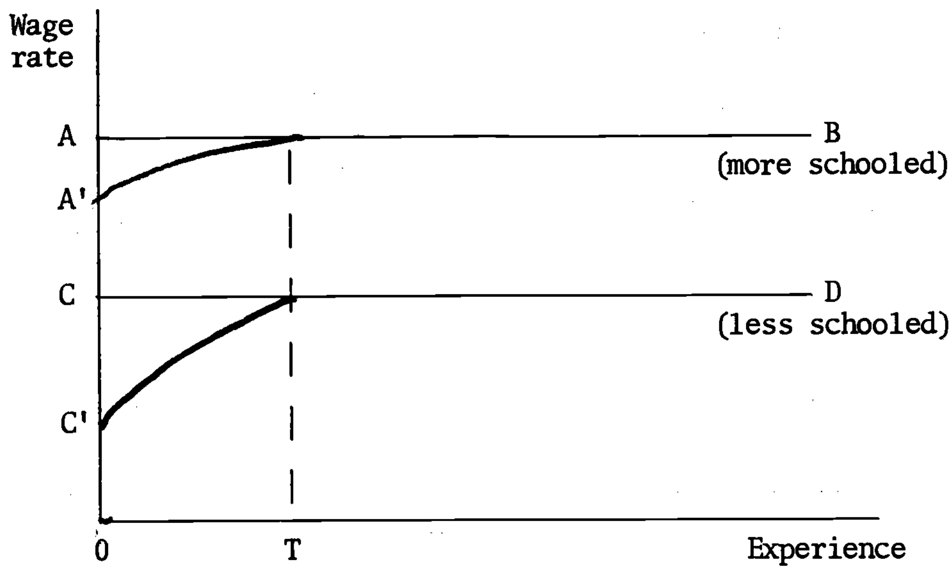
Further independent evidence is supplied by Pencavel (1974) in a study of piece rate and time rate payment schemes. The male (female) segment of the sample consisted of 183 (120) punch press operators in

12 (8) firms, 84 (51) of whom worked on time-rates and 99 (69) on piece-rates. According to our previous discussion, a dominant identification function of schooling would imply substantially lower schooling levels for piece-rate workers.[45] In fact, Pencavel finds for males that the average level of schooling is 9.16 for those in piece-rate and 9.71 for those on an hourly rate and for females 9.57 and 9.22 respectively, results which are not supportive of a major screening role.

A test for the variance component of the screening return postulated in section II can be made explicit under the assumption that post-schooling investments are zero. If the variance effects are operative, the private return to schooling may be larger than that which is warranted by actual productivity differences. However, as firms learn about productivities, wage rates will adjust to reflect performance. Wages should, thus, regress to their certainty levels over time.

Recall that ambiguous theoretical results were obtained with respect to the effect of uncertainty on labor demand. Initial wages might be above or below that which would prevail under uncertainty. With perfect information and the absence of human capital accumulation after the schooling period, mean wage profiles for the two schooling classes would be horizontal as depicted in Figure 3. Those with more schooling would earn AC more at all levels of experience. However, with variance effects favoring the more educated and assuming a negative impact of uncertainty on labor demand, wage profiles would be given by A'B and C'D where full learning is assumed to occur T years after initial work experience. Wage profiles would, thus, converge with experience.[46]

FIGURE 3



Complications arise when there are opportunities for on-the-job training. If post-school investment behavior is systematically related to educational attainment, any degree of convergence or divergence can be elicited. If there is a positive association, earnings profiles will fan out over time. In this case, variance effects will be discernable only if they outweigh training effects.

Since convergence implies declining earnings differentials between schooling classes with experience, a negative coefficient on a schooling-experience interaction term (SP) would be consistent with a positive bias in schooling's private return due to imperfect information. However, a positive interaction term results (Equation 3, Tables 2 and 3) for private wage workers, those who would be subject to uncertainty effects. If such a bias exists, it is swamped by further training investments. For the self-employed, there should be no relative certainty return so that earnings profiles should diverge to a greater extent for this group if investment patterns are identical for the two groups. There is no strong confirmation of this effect.

It could be argued that the positive ability-experience interaction observed for the private class of workers is confirmation of schooling's informational role. If the ability measure reflects productivity endowments, its impact should rise with experience as firm learning occurs. Moreoever, the fact that this interaction is insignificant for self-employed workers should strengthen the argument. However, the ability measure is never relevant for the self-employed; indeed, a larger ability effect would be expected for this group at initial experience (P = 0) than for those privately employed since, if the latter are subject to a screening process, individuals of different ability would be more equally compensated. This, however, is not the case.

V. SUMMARY

Recently, questions have been raised concerning the underlying nature of the observed relationship between income and schooling. The issue revolves around the extent to which formal schooling serves to augment worker productivity and, thus, social product, as opposed to conveying information to employers about the probable productive capabilities of prospective workers without, in itself, affecting those capabilities.

This paper first explored a theoretical model of this latter "screening" role and then attempted an empirical investigation of its relative importance. The basis for the model was that individual productivities are unknown to the firm prior to hiring and are neither instantaneously nor costlessly determinable from direct observation of on-the-job performance. The information available to the firm was restricted to knowledge (a subjective notion was also treated) of the first two moments of the population's skill distribution with output a function of occupation-specific aggregate skill levels and capital. Within an expected profit maximization framework, uncertainty in the form of skill variance was shown to lead to a reduction in expected profits at the previous input scales and to substitution and production effects on factor employment. It was further demonstrated that the demand for workers associated with a given schooling group depended upon both the average skill level and the variance-mean skill ratio of the group. Thus, schooling's private return could be viewed as a reflection of its informational content, i.e., its sorting function. Further, eliminating between group skill variance through the use of identification or screening devices was shown to lead to a more efficient allocation of workers both within and across firms. Therefore, even if the higher average skill levels associated with the more schooled were not produced in the schooling process, schooling's social benefit would be positive.

Several tests aimed at distinguishing between the two views were conducted. A comparison of self-employed and private wage workers with respect to their schooling decision and the life-cycle effects of schooling on earnings yielded results which are not consistent with the existence of a substantial identification or screening function.[47] Other independent evidence was also reported which support this view.

APPENDIX A

Consider the production function given by equation (1) in the text. First-order conditions for profit maximization are:

$$\text{(A.1)}\quad \bar{Y} = \phi(\bar{S}_1, \bar{S}_2, \ldots, \bar{S}_v, R_1, R_2, \ldots, R_v, K)$$

$$\text{(A.2)}\quad P_L = \lambda \phi_{L_j} \qquad j = 1, \ldots, v$$

$$\text{(A.3)}\quad P_K = \lambda \phi_K$$

$$\text{(A.4)}\quad \lambda = MC = P_Y.$$

Totally differentiating (A.1) to (A.4) with respect to σ_ℓ^2 and rewriting in matrix form yields

5)
$$\begin{pmatrix} 0 & \phi_{L_1} & \cdots & \phi_{L_v} & \phi_K \\ \phi_{L_1} & \phi_{L_1L_1} & \cdots & \phi_{L_1L_v} & \phi_{L_1K} \\ \vdots & \vdots & & \vdots & \vdots \\ \phi_{L_v} & \phi_{L_vL_1} & \cdots & \phi_{L_vL_v} & \phi_{L_vK} \\ \phi_K & \phi_{KL_1} & \cdots & \phi_{KL_v} & \phi_{KK} \end{pmatrix} \begin{pmatrix} \frac{d\lambda/\lambda}{d\sigma_\ell^2} \\ dL_1/d\sigma_\ell^2 \\ \vdots \\ dL_v/d\sigma_\ell^2 \\ dK/d\sigma_\ell^2 \end{pmatrix} = \begin{pmatrix} \frac{d\bar{Y}}{d\sigma_\ell^2} - \phi_{\sigma_\ell^2} \\ -\phi_{L_1\sigma_\ell^2} \\ \vdots \\ -\phi_{L_v\sigma_\ell^2} \\ -\phi_{K\sigma_\ell^2} \end{pmatrix}.$$

Solving for $dL_k/d\sigma_\ell^2$, the effect of skill variance in the ℓ^{th} labor input on the employment of the k^{th} labor input, yields

$$\text{(A.6)}\quad \frac{dL_k}{d\sigma_\ell^2} = [(\frac{d\bar{Y}}{d\sigma_\ell^2} - \phi_{\sigma_\ell^2})\ \Delta_{L_k} - \sum_{j=1}^{v} \phi_{L_j\sigma_\ell^2}\Delta_{L_jL_k} - \phi_{k\sigma_\ell^2}\ \Delta_{KL_k}]\ \frac{1}{\Delta} \quad .$$

where Δ is the determinant of the left-hand square matrix and the subscripted Δ's are the relevant co-factors.

The substitution effect is

$$\text{(A.7)}\quad \frac{1}{L_k}\frac{dL_k}{d\sigma_\ell^2} = - \sum_{j=1}^{v} \frac{\phi_{L_j\sigma_\ell^2}}{\phi_{L_j}} \frac{\phi_{L_j}\Delta_{L_jL_k}}{L_k\Delta} - \frac{\phi_{K\sigma_\ell^2}}{\phi_K} \frac{\phi_K\Delta_{KL_k}}{L_k\Delta} \quad .$$

But $\frac{\phi_{L_j}\Delta_{L_jL_k}}{L_k\Delta} = \alpha_j\sigma_{jk}$, where α_j is the cost share of L_j and σ_{jk} is the Allen-Uzawa partial elasticity of substitution. Therefore,

$$\text{(A.8)}\quad \frac{1}{L_k}\ \frac{dL_k}{d\sigma_\ell^2} = - \sum_{j=1}^{v} \alpha_j\sigma_{jk}\frac{\phi_{L_j\sigma_\ell^2}}{\phi_{L_j}} - \alpha_K\sigma_{Kk}\frac{\phi_{K\sigma_\ell^2}}{\phi_K} \ ,$$

where, also,

$$\phi_{L_j\sigma_\ell^2} = \frac{1}{2}\ \mu_j L_\ell F_{\bar{S}_\ell\bar{S}_\ell\bar{S}_j}, \qquad \phi_{L_\ell\sigma_\ell^2} = \frac{1}{2}\ \bar{S}_\ell F_{\bar{S}_\ell\bar{S}_\ell\bar{S}_\ell} + \frac{1}{2}\ F_{\bar{S}_\ell\bar{S}_\ell} \ ,$$

$$\phi_{K\sigma_\ell^2} = \frac{1}{2}\ L_\ell F_{\bar{S}_\ell\bar{S}_\ell K}\ , \quad \text{and} \quad \sum_j \alpha_j\sigma_{jk} + \alpha_K\sigma_{Kk} = 0.$$

The substitution effect due to an increase in variance associated with the ℓ^{th} labor input is, therefore, a weighted sum of percentage changes in marginal expected factor products, where the weights are products of factor cost shares and partial elasticities of substitution. The i^{th} term in (A.8) will be negative, where this implies a positive effect on the employment of L_k, if the increase in variance either reduces the marginal expected product of the i^{th} input and the i^{th} input is a substitute for the k^{th} ($\sigma_{ik} > 0$) or the i^{th} input's marginal expected product is enhanced and the i^{th} input is complementary to the k^{th} ($\sigma_{ik} < 0$). The marginal expected product of the i^{th} input will decline if $F_{\overline{S}_\ell \overline{S}_\ell \overline{S}_i} < 0$ and will rise if $F_{\overline{S}_\ell \overline{S}_\ell \overline{S}_i} > 0$. Opposite conditions hold for the i^{th} term to be positive.

Note that in the two-factor case (A.8) reduces to

$$\text{(A.9)} \qquad \frac{1}{L}\frac{dL}{d\sigma^2} = -\alpha_L \sigma_{LL} \frac{\phi_{L\sigma^2}}{\phi_L} - \alpha_K \sigma_{KL} \frac{\phi_{K\sigma^2}}{\phi_K} .$$

But $\alpha_L \sigma_{LL} = -\alpha_K \sigma_{KL}$ so that

$$\text{(A.10)} \qquad \frac{1}{L}\frac{dL}{d\sigma^2} = \alpha_K \sigma_{KL} \left[\frac{\phi_{L\sigma^2}}{\phi_L} - \frac{\phi_{K\sigma^2}}{\phi_K}\right].$$

Similarly

$$\text{(A.11)} \qquad \frac{1}{K}\frac{dK}{d\sigma^2} = -\alpha_L \sigma_{KL} \left[\frac{\phi_{L\sigma^2}}{\phi_L} - \frac{\phi_{K\sigma^2}}{\phi_K}\right] \quad \text{so}$$

$$\text{(A.12)} \qquad \frac{1}{L}\frac{dL}{d\sigma^2} - \frac{1}{K}\frac{dK}{d\sigma^2} = \sigma_{KL} \left[\frac{\phi_{L\sigma^2}}{\phi_L} - \frac{\phi_{K\sigma^2}}{\phi_K}\right]$$

which is the expression in the text.

APPENDIX B

TABLE 1

MEANS AND STANDARD DEVIATIONS OF SELECTED VARIABLES FOR PRIVATE WAGE AND SELF-EMPLOYED WORKERS*

	Private		Self-Employed	
	Mean	Standard Deviation	Mean	Standard Deviation
Earnings	8,832	5,897	11,860	10,420
Ln Earnings	8.921	0.5696	9.116	0.7027
Schooling	15.61	2.181	15.31	2.345
Ability	0.1555	1.809	0.117	1.769
Experience	10.62	8.332	10.60	8.692
No. of Observations	7,893		1,906	

*All tables of descriptive statistics pertain to all life-cycle points.

TABLE 2

MEANS AND STANDARD DEVIATIONS OF SELECTED VARIABLES FOR PRIVATE WAGE AND SELF-EMPLOYED WORKERS ON BOTH FIRST AND FIFTH JOB

	Private		Self-Employed	
	Mean	Standard Deviation	Mean	Standard Deviation
Earnings	8,833	5,840	12,920	10,670
Ln Earnings	8.921	0.5712	9.209	0.7088
Schooling	15.64	2.169	15.18	2.794
Ability	0.1596	1.822	-0.0091	1.688
Experience	10.59	8.321	10.86	9.072
No. of Observations	7,570		690	

TABLE 3

MEANS AND STANDARD DEIVATIONS OF SELECTED VARIABLES FOR PRIVATE WAGE AND SELF-EMPLOYED NON-PROFESSIONALS

	Private		Self-Employed	
	Mean	Standard Deviation	Mean	Standard Deviation
Earnings	8,832	6,700	11,837	10,411
Ln Earnings	8.92	0.559	9.117	0.695
Schooling	14.54	1.909	14.44	1.791
Ability	-0.184	1.709	-0.111	1.748
Experience	10.99	8.518	10.98	8.888
No. of Observations	4,038		1,182	

TABLE 4

MEANS AND STANDARD DEVIATIONS OF SELECTED VARIABLES FOR PRIVATE WAGE AND SELF-EMPLOYED NON-PROFESSIONALS ON FIRST AND FIFTH JOB

	Private		Self-Employed	
	Mean	Standard Deviation	Mean	Standard Deviation
Earnings	8,869	6,157	12,355	10,507
Ln Ear-ings	8.923	0.573	9.165	0.698
Schooling	14.55	1.921	13.95	1.809
Ability	-0.190	1.720	-0.234	1.676
Experience	10.976	8.517	11.227	9.314
No. of Observations	3,920		463	

TABLE 5

MEANS AND STANDARD DEVIATIONS FOR COLLEGE GRADUATE

PRIVATE WAGE AND SELF-EMPLOYED NON-PROFESSIONALS WORKERS

	Private		Self-Employed	
	Mean	Standard Deviation	Mean	Standard Deviation
Ln Earnings	8.987	0.646	9.148	0.750
Quality	4.964	1.105	4.915	0.972
Ability	0.165	1.686	0.140	1.786
Experience	10.421	8.124	10.399	8.414
No. of Observations	1,336		398	

TABLE 6

EARNINGS REGRESSIONS FOR ALL INDIVIDUALS WITH THE SAME WORKER CLASS

ON 1st AND 5th JOB

Coefficients (t-values in parentheses)

	(1)		(2)		(3)	
	Private	Self-Employed	Private	Self-Employed	Private	Self-Employed
S	-0.0233 (6.55)	-0.0016 (0.18)	0.0262 (11.79)	0.0460 (8.02)	0.0203 (8.01)	0.0476 (8.08)
P	0.0129 (2.76)	-0.0059 (0.48)	0.0803 (39.93)	0.0725 (10.97)	0.0800 (40.08)	0.0726 (11.06)
P^2	-0.0013 (14.94)	-0.0010 (3.35)	-0.0018 (16.73)	-0.0012 (4.25)	-0.0015 (16.74)	-0.0012 (4.29)
SP	0.0041 (15.58)	0.0048 (7.36)	-	-	-	-
A	0.0043 (1.01)	0.0001 (0.004)	- -	- -	0.0279 (10.34)	-0.0104 (1.08)
AP	0.0022 (6.85)	-0.009 (0.89)	-	-	-	-
Intercept	0.0134 (0.09)	8.6993 (63.51)	-0.037 (0.38)	7.9705 (87.62)	0.0757 (0.76)	7.9462 (85.32)
R^2	.5335		.5029		.5094	

TABLE 7

EARNINGS REGRESSION FOR NON-PROFESSIONALS WITH SAME WORKER CLASS

ON 1st AND 5th JOB

Coefficients (t-values in parentheses)

	(1) Private	(1) Self-Employed	(2) Private	(2) Self-Employed	(3) Private	(3) Self-Employed
S	0.0491 (12.9)	0.0384 (3.3)	0.0473 (12.0)	0.0455 (3.7)	-0.0118 (1.9)	0.0012 (0.1)
P	0.066 (22.5)	0.054 (6.3)	0.066 (22.5)	0.054 (6.3)	-0.016 (2.1)	-0.004 (0.2)
P^2	-0.0011 (8.4)	-0.0006 (1.7)	-0.0011 (8.4)	-0.0006 (1.7)	-0.0009 (7.2)	-0.0006 (1.5)
SP	-	-	-	-	0.0055 (12.2)	0.0040 (3.1)
A	-	-	0.008 (1.8)	-0.027 (2.1)	-0.019 (2.7)	-0.004 (0.2)
AP	-	-	-	-	0.0024 (4.8)	-0.002 (1.5)
Intercept	-0.47 (2.7)	8.16 (49.2)	-0.34 (1.8)	8.05 (46.4)	-0.10 (0.37)	8.68 (33.0)
R^2	.418		.419		.447	

FOOTNOTES

[1]For a formal presentation of the argument see Spence (1973), (1974).

[2]Spence's model is also concerned with input-quality uncertainty, but the model is constructed in such a way that expected output is unaffected by productivity variation except insofar as firms must decide on which jobs to assign to which individuals. Although this latter consideration is important and is explored here as well, it will be demonstrated that even in the absence of this specific allocation problem expected output (and social product) will be affected by the existence of a heterogenous labor pool. Moreover, the model presented in this paper explores the implications of skill variance on factor employment and develops criteria for the direction of substitution and output responses akin to those found in usual derived demand theory.

[3]In Spence's earlier published work (Spence (1973)) no explicit presentation of the information's social value was given and in a strict interpretation of the model the social benefit to schooling would, in a pure screening world, be zero. In his later work (Spence (1974)), the introduction of job assignment elicits a positive social product to schooling's sorting role, a possibility previously established under very restrictive assumptions by Arrow (1973). A more general specification of this proposition is advanced here which remains even in the absence of alternative occupational assignment.

[4]These transformation functions are assumed to be technologically given and, as such, fully determine occupational categories. For a linear specification, the weighting factors can be considered as fixed utilization rates (proportions of each skill utilized per unit time);

$$s_{ij} = \sum_{\ell=1}^{n} U_{j1} k_{i1}$$

where U_{j1} is the utilization rate for the ℓ^{th} productive attribute. If all such transformations are linear, occupations are characterized by the fixed manner in which attributes are utilized. In the more general case, utilization rates vary with the proportionate usage of attributes.

[5] $\frac{\partial F}{\partial S_j}, \frac{\partial F}{\partial K} > 0; \quad \frac{\partial^2 F}{\partial S_j 2}, \frac{\partial^2 F}{\partial K^2} < 0$ all j.

[6]Appendix A provides a full treatment of the general case along with explicit proofs of the propositions which follow.

[7]All subscripts refer to partial derivatives, e.g., $\phi_R = \frac{\partial \phi}{\partial R}$

[8]In reality, since only a second-order approximation is taken, this statement is only accurate if all moments of the skill distribution which positively affect the firm's expected output are unchanged in the comparison.

9

$$\Delta = \begin{vmatrix} 0 & \phi_L & \phi_K \\ \phi_L & \phi_{LL} & \phi_{KL} \\ \phi_K & \phi_{LK} & \phi_{KK} \end{vmatrix} > 0.$$

10 This formula is independent of the approximation and merely states that the percentage alteration in factor ratios depends on the variance induced percentage change in the marginal rate of substitution between the factors.

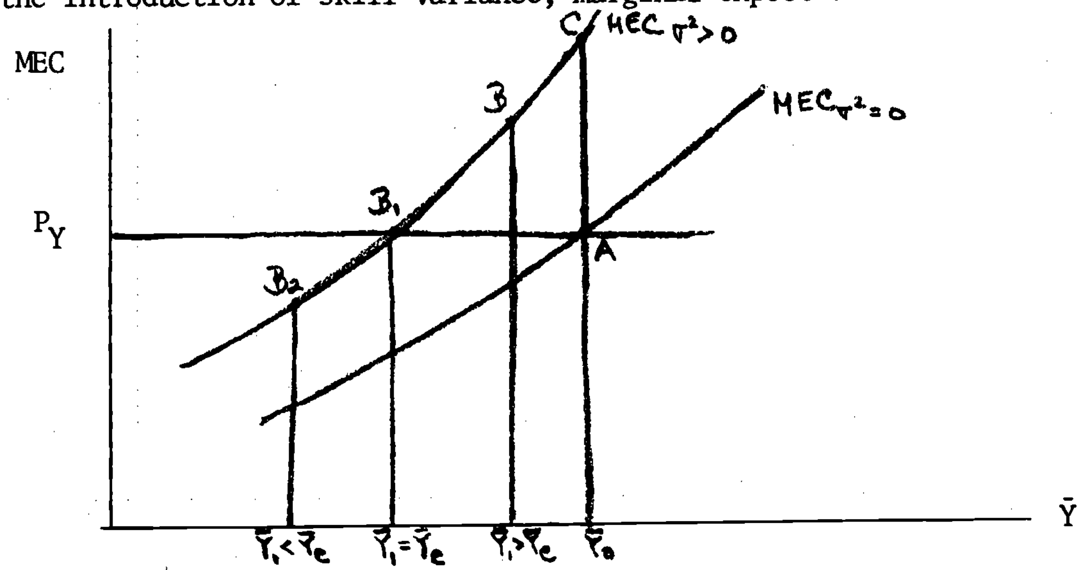
11 The notion that convexities of marginal curves are important for dispersion effects is not new. In fact, it forms the basis for the Rothschild and Stiglitz (1971) criticism of the mean-variance approach in expected utility analysis.

12 From (3)

$$\phi_{K\sigma^2} = \frac{1}{2} L F_{\bar{S}\bar{S}K}, \quad \text{and} \quad \phi_{L\sigma^2} = \frac{1}{2} (F_{\bar{S}\bar{S}} + \bar{S}F_{\bar{S}\bar{S}\bar{S}}).$$

13 As examples, for the quadratic production function all third partials vanish and the sign of the substitution effect must be negative; less of the uncertain factor is utilized. However, for a Cobb-Douglas production function, $\phi_{L\sigma^2} > 0$ and $\phi_{K\sigma^2} < 0$ so that the substitution effect works in favor of the labor input.

14 For the competitive firm scale effects are depicted in the accompanying figure. Labelled points correspond to those in Figure 1 of the text. Given product price, P_Y, output is $\bar{Y}_0$ prior to the introduction of uncertainty. With the introduction of skill variance, marginal expected cost rises.



There are three possibilities for the net scale effect. If the initial impact of uncertainty is to reduce expected output to $\bar{Y}_1 = \bar{Y}_e$, the net scale effect is zero; the direct production effect is a movement from B_1 to C and the induced effect from C back to B_1. If expected output initially falls only to $\bar{Y}_1 > \bar{Y}_e$ (B, as in Figure 1) the direct production effect is outweighed by the induced effect and the net scale effect is negative; output falls further from $\bar{Y}_1$ to $\bar{Y}_e$. Likewise, B_2 illustrates a positive net scale effect.

[15]By our previous analysis, $\bar{L}$, the no-screening optimal labor input, is not invariant to the use of the information. The perceived potential gain from screening is, therefore, larger than that depicted in equation (17).

[16]The exact relationship between the group parameters in order to have a preference for the more educated is that

$$\sigma_C^2 - \sigma_H^2 < -\left(\frac{\bar{S}\phi_{\bar{S}} - \phi_R}{\phi_R}\right)(\mu_C - \mu_H)$$

Note that since $\phi_R < 0$ and $\phi_{\bar{S}} > 0$, $-\left(\frac{\bar{S}\phi_{\bar{S}} - \phi_R}{\phi_R}\right)$ must be positive and greater than unity. In some sense, mean differences dominate. Preference for the more schooled at equal wages will be exhibited when the above inequality holds at $L_C = L_H$.

[17]Actually, the necessary and sufficient condition is

$$\phi_{\bar{S}\bar{S}} < \frac{\bar{S}\phi_{\bar{S}}}{\phi_R} F_{\bar{S}\bar{S}\bar{S}} .$$

Since $\phi_R < 0$, the statement in the text is only valid if $F_{\bar{S}\bar{S}\bar{S}} > 0$. If $F_{\bar{S}\bar{S}\bar{S}} < 0$, $\phi_{\bar{S}\bar{S}} < 0$ is sufficient but not necessary for convexity.

[18]This is again an understatement of the gain since $\bar{L}$ will, in turn, be altered. See Fn. 11.

[19]Under the strict preference assumption $\frac{d\bar{Y}}{dL_C}\Big|_{\bar{L}}$ must be positive for all $L_C \leq \bar{L}$. If strict preference is not assumed it will be positive to the point where the optimal L_C/L_H ratio is realized and negative thereafter. Note also that the size of the return is also related to the level of marginal skill product ($\phi_{\bar{S}}$) and the output cost of uncertainty (ϕ_R).

[20]It can further be demonstrated that, assuming convexity, the revenue increment declines as preferred workers are added, i.e., $\frac{d^2\bar{Y}}{dL^2_C} < 0$.

[21]Actually, they may both rise relative to the certainty case if the introduction of uncertainty increases the overall demand for labor relative to capital.

[22]Output responses are again ignored.

[23]There is a third component not discussed here which concerns the firm's uncertainty about the true value of average skill levels. Assuming that firms have a subjective notion as to the level of average skill one can derive similar expressions for factor demand as those in the text. See Wolpin (1974).

[24]The preceeding analysis has several obvious extensions. First, non-zero cost devices (to the firm) can be treated and optimal patterns of screening techniques can be traced. The intensity with which firms interview or test prospective employees will depend on the level of the marginal expected revenue function (equation 18) and its rate of decline in conjunction with the marginal expected cost of identifying more productive types. Second, since aggregate skill is simply the product of average skill and the number of workers one can just as easily apply the model to uncertainty about hours of work associated with different subpopulations. Thus, even if women, for example, on average can be expected to work the same number of hours per year, the fact that , as a group, there is more variability in their labor supply will lead to a reduction in the demand for their services relative to men.

[25]No mechanism has been discussed so far which would motivate the more "able" individuals to obtain schooling and, thus, make it a viable screen if there are no productivity augmenting effects. In fact, the less productive, if they perceive the same benefits, would have the same schooling incentive. One way in which to generate a positive correlation between ability and schooling is to assume that schools are themselves capable of sorting out the less productive. In essence, the less able face lower schooling success probabilities and, thus, have higher expected schooling acquisition costs. This is, in essence, Spence's major assumption.

[26]This assumes that μ, the population mean, is unchanged for otherwise aggregate skill would be altered, changing the magnitude of $F_{\bar{S}\bar{S}}$.

[27]Throughout this analysis factor employment was fixed. The social benefit to screening will also include a component which allows firms to alter their factor proportions in response to the information.

[28]This is the case treated by Arrow (1973) and Spence (1974).

[29]See Gintis (1971) and Griliches and Mason (1973).

[30]See Layard and Psacharopoulos (1974) for a fuller treatment of this point. Note, however, that this test concerns the use of schooling as an informational device, information that would be imparted regardless of schooling's underlying role.

[31]Taubman and Wales (1973) have no theoretical justification for this definition of screening. It is indeed possible that the informational content of schooling is such that there is little, if any, occupational misallocation even with occupational restrictions.

[32]The data set utilized is the same as the one used by this author, the NBER-Thorndike sample, so that its discussion will be deferred until later.

[33]Layard and Psacharopoulos make basically the same argument. However, they fail to note that the problem is strongly reflected in TW's results.

[34]P. Taubman and T. Wales. "Education, Ability and Screening." Journal of Political Economy (81). p.46.

[35]Initial job, which may have occurred prior to WW II, is also reported.

[36]For this table, individuals were categorized on the basis of their last reported job. Thus, an individual who, in 1969, was self-employed was entered as such regardless of his previous status, i.e., all of the experience points corresponding to the individual were assigned to the self-employed class. Clearly, it would have been more accurate to make the assignment on the basis of all jobs between the first and last but, since many individuals did not report intermediate jobs, this method would have severely restricted the sample size, particularly within the self-employed class. However, regressions were also estimated for individuals reporting the same employment status on both the first and last job alone. The results are qualitatively unaltered as seen by a comparison of Table 2 in the text to Table 6 in Appendix B.

[37]The ability measure is a composite of the seventeen tests and was constructed by Al Beaton of the Educational Testing Service to approximate an IQ type measure.

[38]Letting $Y_1 = X_1 \beta_1 + u_1$ and $Y_2 = X_2 \beta_2 + u_2$ refer to the separate regressions for the two worker classes, the pooled regression is of the form

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = X\beta + u$$

This construction facilitates hypothesis testing between samples since, for example, simple t-tests require knowledge only of the variance-covariance coefficient matrix.

[39]We are assuming that customer screening by education is not so strong as to create a large incentive for the self-employed to acquire the signal. However, we also perform the analysis deleting professionals (doctors, lawyers, etc.), those for whom customer screening might be most relevant.

[40]The null hypothesis of coefficient equality is rejected as the associated t-values are 2.4 and 3.4 for the respective equations.

[41]The corresponding figures for those within the same worker class on the first and fifth jobs are 15.6 and 15.2 respectively. See Table 2 of Appendix B.

[42]The results when employment status (private vs self-employed) is also matched are reported in Table 7, Appendix B. The corresponding schooling levels are found in Table 4, Appendix B.

[43]The t-values for the tests of coefficient equality are 1.0 and 0.6 in equations 1 and 2 respectively.

[44]The quality variable is a Gourman rating. See J. Gourman, The Gourman Report, The continuing Education Institute, 1967.

[45]In fact, if schooling did not augment productivities then why would anyone choosing an occupation in which performance is easily measured incur the cost of schooling.

[46]This conclusion is not independent of the learning process. All that is being said is that the more educated may earn more relative to the less educated than is warranted by true productivity differences and that over time relative wages will begin to reflect this initial bias. The incorporation of learning into a human capital production framework is clearly relevant to the shape of earnings profiles. Firm learning may in fact be endogenous and may also interact with individual decisions about human capital accumulation.

[47]There are several qualifications to this statement. If schools themselves sort individuals by establishing entry barriers, but are rigidly and correctly applied, the less able among the self-employed can not err by choosing more than their optimal schooling level. Thus, the only way to obtain our results would be for the more productive to obtain less schooling than their privately employed counterpart. However, for this to occur the decision as to whether one is to be self-employed or not must be made prior to the termination of schooling. If it is not, then there is no reason for the self-employed to act differently than salaried workers. Moreover, even if individuals have some notion that they will be self-employed, they can hedge against uncertainty by obtaining more schooling than they otherwise would so as to be able to signal employers about their capabilities if necessary.

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