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THE EARNINGS OF SCIENTISTS, 1960-1970: EXPERIENCE, AGE AND VINTAGE EFFECTS*

by

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Introduction

In recent years we have seen the rise of a bold and fruitful approach which attempts to explain the development of individual earnings as if they result from a continuous choice process. A basic part of this approach of the on-the-job training hypothesis (See Becker [1964], Mincer [1962, 1974], Ben Porath [1967], Rosen [1972, 1973]) whereby individuals are facing, at each point in their life, a set of options which involves the trading of current earnings in exchange for higher future earning capacity. Given these options the individual chooses an optimal strategy which is then reflected in his observed earning profile.

An often noted obstacle to the empirical implementation of this idea is the lack of data on individual profiles. The empirical analysis was mostly confined to a single cross section, and the implicit assumption was that there are no systematic differences among individuals who entered the labor force at different points of time. Studies which dutifully lamented this situation, did not provide much lead into what could be the expected differences in alternative types of data. To spell out such differences clearly seemed premature in light of the absence of any such alternatives. However, with the growing availability of successive cross sections as well as individual follow-up data it is no longer possible to escape the issue. An important potential source of a systematic relation between single cross section, successive cross section, and longitudinal data is provided by vintage effects (See Welch [1973]). The purpose of this study is to present a simple but explicit model of on-the-job training which may enable us to separate and identify various types of vintage effects. An attempt is made to apply the model to the data on the earnings of American scientists in the period 1960-1970.

I. The Model

We shall present in this section a simple model of investment in human capital which can be solved analytically. The purpose is to obtain a formulation which is amenable to estimation and to comparative statics analysis.

Suppose that observed earnings are governed by the following equation

$$(1) \qquad Y = KG\left(\frac{\dot{K}}{K}\right)$$

where K is human capital $\frac{\dot{K}}{K}$ is its rate of change. The rate of change $\frac{\dot{K}}{K}$ is bounded between the maximal potential rate denoted by $a - \delta$ and a lower rate $-\delta$ which is the depreciation rate. (We do not allow negative gross investment.) Jobs are assumed to offer different "growth options" and $1-G\left(\frac{\dot{K}}{K}\right)$ measures the <u>proportion</u> of earning capacity which the individual has to give up in order to purchase a specified growth rate. It seems natural to assume $G(a - \delta) = 0$ and $G(-\delta) = 1$, that is, all earning capacity is sacrificed for the best growth prospect, and if nothing is sacrificed then human capital will deteriorate at the rate δ. It is clear that $G'(\ )$ should be negative in an equilibrium wage structure.

We ignore here the issue of leisure choice and assume that the objective of each individual is the maximization of the present value of lifetime earnings.

Let us define $g\left[\left(\frac{\dot{K}}{K} + \delta\right)\frac{1}{a}\right] = G\left(\frac{\dot{K}}{K}\right)$ The maximation problem can now be described as follows.

$$(2) \qquad \underset{\{x\}}{\text{Max}} \int_0^T e^{-r\tau} Kg(x)d\tau$$

$$\text{s.t} \quad \frac{\dot{K}}{K} = ax - \delta \qquad 0 \leqslant x \leqslant 1 \quad , K(0) = K_0$$

The auxiliary variable x can be interpreted as an index of the training content of the various job opportunities. The length of life is denoted by T, and r is the exogenously given rate of interest. Using the Hamiltonian function the above maximization can be transformed into the following maximization problem:

$$(3) \qquad \max_{0 \leq x \leq 1} \quad e^{-r\tau} K[g(x) + \psi\,(ax - \delta)]$$

$$\text{with } \dot{\psi} = r\psi - g(x) - \psi(ax - \delta) \qquad , \psi(T) = 0$$

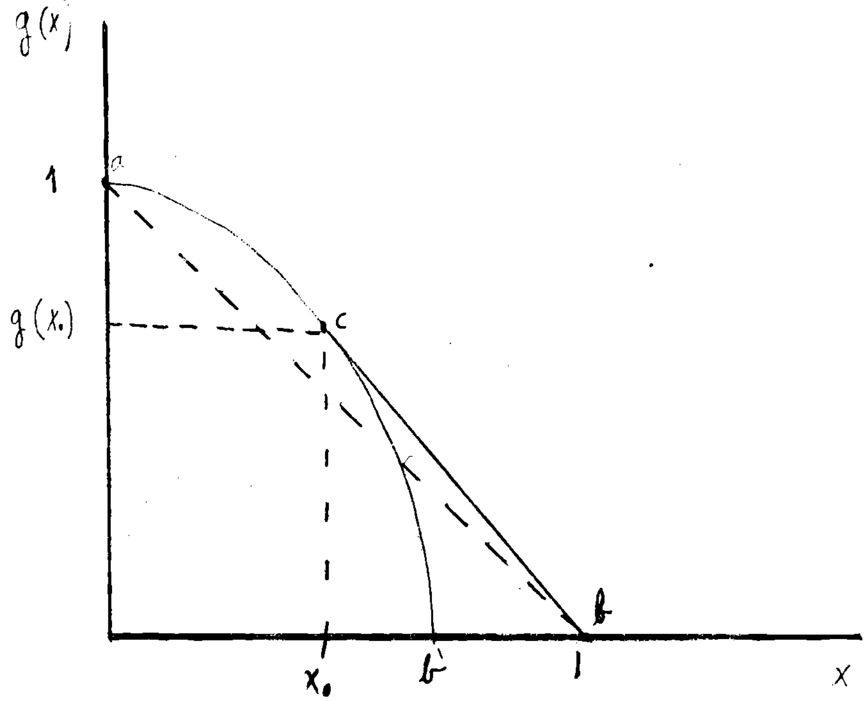
This maximization problem is easy to interpret. The returns from human capital, (in the form of "full" wages per unit of capital) depend on the amount of investment. The "full" wage consists of the observed current wages $Kg(x)$ and of the returns for investment $K\psi\,(ax - \delta)$. Were

$$(4) \qquad \psi(\tau) = \int_{\tau}^{T} e^{-r(\xi - \tau)}\,[g(x) + \psi(ax - \delta)]\,d\xi$$

denotes the average (and marginal) benefits of the investment activity. Note that at each point of time these benefits are equal to the present value of future optimal "full" rates of returns. The optimal path is such for any given shadow price, ψ, the individual chooses the level of investment which maximizes the full wage.

The optimal path of investment can be presented graphically as a movement along the investment frontier $g(x)$, which is associated with the changing shadow price for investment. We propose the following specification for the investment frontier (See figure 1).

Figure 1



The broken line ab describes the allocutions which the individual can achieve by dividing his time between "school" and work at the activity which maximizes current earnings. The line ab' describes the training options offered by the job market. Our basic assumption is that there is a range in which higher efficiency is achieved by pure on-the-job training than by <u>any</u> combination of schooling and work. This is reflected by the line ab' being above ab for some x. It is also reasonable to assume that high levels of training are more efficiently obtained at school so that ab is ab' for some x. The actual frontier is then given by the line acb where the point c is determined by

$$(5) \qquad -g'(x_0) = \frac{g(x_0)}{1-x_0}$$

As long as $a\psi > -g'(x_0)$ the individual will specialize in schooling ($x = 1$). If $a\psi = -g'(x_0)$ the individual will be indifferent among the various allocations of time between school and work at the job x_0. For $-g'(0) < a\psi < -g'(x_0)$ the individual will choose a tangency point in which $a\psi = -g'(x)$. Finally if $a\psi < -g'(0)$ there will be no investment and the job with maximal current earning will be chosen.

The above specification of the investment frontier is designed to capture, among other things, the discontinuity in the investment in human capital which seems to occur upon leaving school.

Since we are interested, in this paper, in a model which is solvable in a closed form we proceed by specifying a functional form for the investment frontier.

Suppose that the opportunity set for pure on-the-job training is given by:

$$\frac{Y}{K} = [1 - \frac{1}{\beta}(\frac{\dot{K}}{K} + \delta)]^{\alpha} \qquad a > \beta > 0 \qquad 0 < \alpha < 1 \qquad \alpha < \beta/a \tag{6}$$

The parameter β can be interpreted as the efficiency of producing human capital on the job. Higher values of β imply that for given growth rate a higher proportion of earning capacity is retained. The assumption that $\beta < a$ means that even if all earning capacity is given up then the rate of growth which is attained by pure on-the-job training will be less than that which can be achieved in school. In the same vein 'a' can be interpreted as the efficiency of producing human capital in school. Higher values of 'a' mean that upon giving up all earning capacity and choosing the schooling activity higher growth is attained. Finally, α is a parameter which governs the concavity of the opportunity set; we assume that $0 < \alpha < 1$. The condition $\alpha < \beta/a$ guarantees that for small levels of investment on-the-job training is more efficient.

Using the definition $x = \frac{1}{a}(\frac{\dot{K}}{K} + \delta)$ we obtain the following specification for $g(x)$.

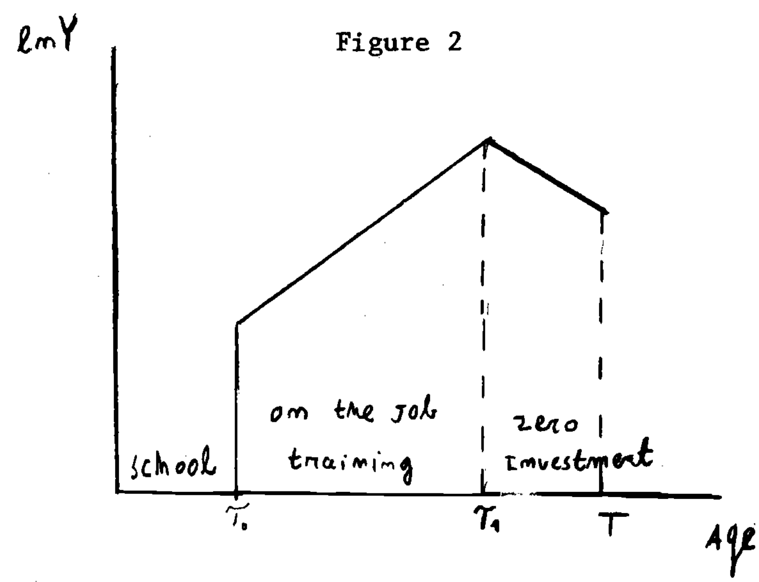
(7) $$g(x) = (1 - \frac{a}{\beta} x)^{\alpha} \qquad \text{for } x \leqslant x_0$$

$$(1 - \frac{a}{\beta} x_0)^{\alpha} - \alpha \frac{\alpha}{\beta} (1 - \frac{a}{\beta} x_0)^{\alpha-1}_{x} \qquad \text{for } 1 \geqslant x \geq x_0$$

where $x_0 = \frac{\frac{\beta}{a} - \alpha}{1-\alpha}$, $a > \beta$ and $\alpha < \frac{\beta}{a}$

This particular form leads to an extremely simple optimal pattern for the observed net earnings. The rate of growth of earnings is piece-wise constant. (See figure 2)

Figure 2



Productive life is thus divided into three phases: a schooling phase in which no earnings are observed, an investment period in which observed earnings are positive and grow at a constant rate, and a non-investment period in which earnings decline at a constant rate. The length of each phase, as well as the slope of the earnings and investment profiles in each phase can be related to the basic parameters which the individual faces.

These solutions are (see Appendix for derivations):

$$\tau_1 = T + \frac{1}{r+\delta} \ln\left(1 - (r+\delta)\frac{\alpha}{\beta}\right) \tag{8}$$

$$\tau_0 = \tau_1 - \frac{1-\alpha}{\beta-r-\delta} \ln\left[\frac{\beta(a-r-\delta)(1-\alpha)}{(\beta-\alpha(r+\delta))(a-\beta)}\right] \tag{9}$$

$$\frac{\dot{Y}}{Y} = \beta - \delta + \frac{\alpha}{1-\alpha}(\beta-r-\delta) \qquad \text{for } \tau_0 \leq \tau < \tau_1$$
$$= -\delta \qquad \text{for } \tau_1 \leq \tau \leq T \tag{10}$$

$$\frac{\dot{y}}{y} = \alpha \frac{\beta-r-\delta}{1-\alpha} + \beta y^{1/\alpha} \qquad \text{for } \tau_0 \leq \tau < \tau_1$$
$$= 0 \qquad \text{for } \tau_1 \leq \tau < T \tag{11}$$

where Y denotes observed earnings and $y = \frac{Y}{K} = g(x)$ is the proportion of earnings capacity spent at the "production" of earnings and 1-y is the proportion invested. Even though these activities are performed jointly on the job one may think of y as the "proportion of time" spent in producing goods, and 1-y as the proportion of time spent in producing new knowledge. (see Mincer [1974, p. 19])

The boundary conditions for this system are:

$$y(\tau_1) = 1, \qquad y(\tau_0) = g(x_0) = \left[\frac{\alpha}{1-\alpha}\left(\frac{a}{\beta} - 1\right)\right]^{\alpha} \tag{12}$$

$$Y(\tau_0) = K_0 e^{(a-\delta)\tau_0} y(\tau_0) \tag{13}$$

where $Y(\tau_0)$ can be interpreted as observed starting salaries and K is the exogenously given initial level of human capital.

As seen from the above set of equations there are some restrictions on the parameters which are implicit in a life time earnings profile which includes all three phases. The basic condition is:

$$a > r+\delta \qquad \text{which implies} \qquad \beta > (r+\delta)\alpha \tag{14}$$

The two conditions in 14 are required if investment is ever to be profitable. Specifically, if $\beta < (r+\delta)\alpha$ then the zero investment period will exhaust the whole working life. If $a < r+\delta$ then a period of specialization is not optimal. This can be verified by noting that in this case $\frac{\dot{y}}{y}$ evaluated at τ_0 is negative and stays negative thereafter, so that $y(\tau_1) = 1$ cannot be satisfied. The interpretation of these two conditions is quite transparent; for positive investment to exist, it is necessary that the returns from investment exceed the costs associated with the postponement of earnings.

As suggested by Becker [1964, pp. 14-15] and Ben-Porath [1967], one may explain the general shape of the earning profile as if it reflects investment decisions. In particular the positive slope during the on the job investment period reflects positive <u>and</u> decreasing investment on the job.[1/] The concavity of the log earnings profile depends, however, on the specific trade-off function g(x). The specific form (7) which we adopted has the property that $\frac{\dot{y}}{y}$ increases with age as y increases. The degree of convexity in y (concavity in investment time) is just sufficient to offset the reduction in $\frac{\dot{K}}{K}$ as investment decreases.

The comparative statics of the model are also extremely simple. Consider first a change in the interest rate. One of the specific aspects of the theory of investment in human capital as applied to the development of earnings is that an increase in the interest rate will tend to reduce the <u>slope</u> of the log earnings profile. This is directly evident from equation (10). It can be seen from equation (8) that the length of the no investment period, $T - \tau_1$, will increase; that is, the peak in earnings will be attained at an earlier age. Since $y(\tau_0)$ and $y(\tau_1)$ are both independent of r and since $\dot{y}$ is decreasing with r for every y, the individual will stay a longer period in the region of on-the-job investment. It follows that τ_0 must decrease, i.e., the individual will invest less in schooling. These changes are summarized in fig. 3.

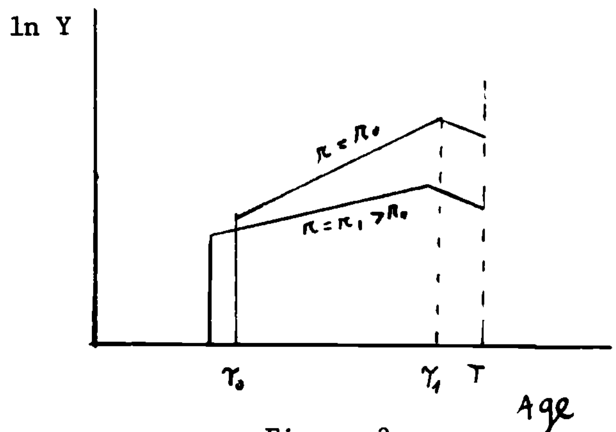


Figure 3.

Consider, next, the issue of differences in ability. Differences in the initial stock of human capital K_0 will induce parallel shifts in logarithmic earnings function without any further effect on the length of the various investment period. An alternative specification is to associate increase in ability with an increase in the efficiency of "producing" human capital as represented by the parameters a and β . If a person is a better student at school (higher a) the effect will be higher y_0 while $\frac{\dot{Y}}{Y}$ and τ_1 remain the same. It is easy to show that τ_0 must go up.[2] In other words, there will be a longer period in school with a lower investment on the job once out of school. The log earnings profile will shift in a parallel fashion with the peak remaining unchanged. (See figure 4a.)

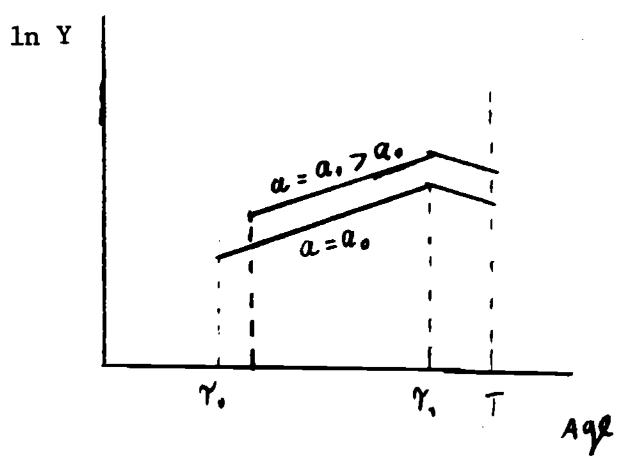


Figure 4a.

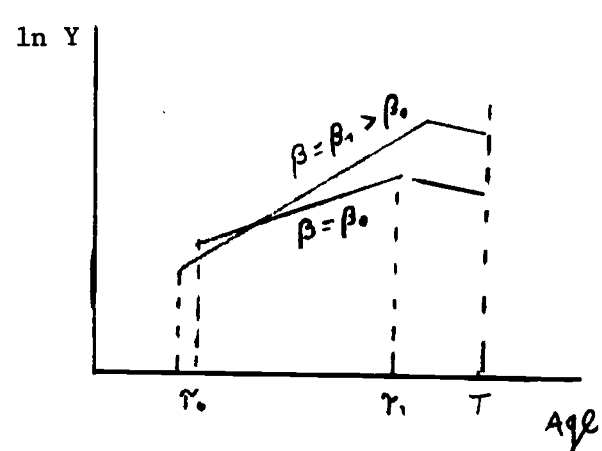


Figure 4b.

If a person is a better on-the-job student (higher β) $\frac{\dot{Y}}{Y}$ will increase while y_0 will decrease. The effect on τ_1 is positive and on τ_0 negative[3/]. In other words this individual will invest less in schooling and more in on the job training. The log earnings profile will have a higher slope, and will peak at a later age. (See figure 4b.)

The most realistic case seems to be that in which <u>both</u> a and β increase. As seen, the effect on the length of the schooling period is in this case ambiguous. An interesting special case is that in which the optimal level of schooling, τ_0 remains the same. The implication of higher ability will be a higher log earnings profile with a higher slope and a later peak. Another special case is that in which a and β grow at the same rate so that y_0, the initial investment in on the job training, remains the same. In this case higher ability will lead to more schooling, and the log earnings profile will have a higher slope and a later peak.

An important empirical phenomenon is the existence of considerable variation in the <u>age</u> in which a given level of schooling is obtained. Possible reasons for a postponement in the completion of schooling are:

1. Imperfection of the capital market.
2. Exogenous events such as military service.
3. Differences in preferences towards leisure.
4. Uncertainty with respect to one's own abilities and preferences.

Each of these causes for delay may have different implications for the shape of the log earnings profile after the completion of school.

Individuals with limited access to the capital market may take longer to obtain a given level of schooling. If they continue to face a higher rate of interest after completing school their log earnings profile will be flatter with an earlier peak. The question rises, however, why would individuals who face different rates of interest choose the same level of schooling. One possible reason is that schooling is only partially divisible. So that a whole distribution of desired optimal levels of schooling collapses into three single levels, i.e., B.A., M.A., and Ph.D.

If differences in the access to the capital market is the prime cause for the variation in the age at which degree is obtained, we are likely to find a negative interaction between the duration of the postponement and the slope of the log earnings function during the post school period.

The effect of an exogenous time "tax" such as military service is to shorten the horizon. If an individual who has performed military service, whom we may call a late starter (see Johnson and Stafford [1974]), is restricted to leave the labor force at the same age as the "early" starter he will simply reduce his period of specialization. His log earnings profile will be lower with the age of peak and entry remaining the same. This, of course, is a quite unrealistic result which follows from the assumption that the age of retirement is exogenous. A perhaps more realistic assumption is that for brief postponements the length of the working period is constant (See Mincer [1974, p.10-11]).

The effect of leisure preferences is more complex and was discussed elsewhere. (See Blinder and Weiss [1975]). Suffice it to say that individuals with a high rate of time preference may decide to choose an increasing profile of hours of work with a possible "retirement" period before school. Such individuals will later show a relatively steep earnings function. The result is a possible <u>positive</u> interaction between the slope of the earnings profile and the age of entry into the labor force.

The role of schools in providing information to the individual and to the market (via certification) is well known. Depending upon their specific characteristics and their tastes towards risk, individuals with a given amount of formal schooling may have different investments in search. At the present level of analysis the expected effects on the slope of the earning profile can only be incorporated within the residual as part of our ignorance.

Age Effects

As we have seen a basic property of the simple model is that the change in log earning is constant during the investment period. For the purpose of empirical estimation one would prefer a formulation in which the concavity of the log earning function would be determined by, rather than imposed on, the data. Non-linearities can be introduced in many ways with varying degrees of complexity. We will suggest some possibilities and then choose the one which turns out to be mathematically the simplest.

Our special form for g(x) has the property that the growth of log earnings is independent of x. It is easy to choose any number of alternative specifications for g(x) which would lead to a smoothly concave log earnings profile.[4/] Since on purely economic considerations there seems to be no justification to prefer one or the other, and since the specification which we have chosen is clearly of the simplest possible form we would give it up only as a last resort.

An implicit simplifying assumption which we used in the construction of the simple model is that the rate of transformation between $\frac{Y}{Y}$ and $\frac{\dot{K}}{K}$ depends only on the choice of occupation, and is independent of K. This neutrality assumption means that the "productivity" of the individual in "producing" rates of growth depends only on the proportion of his current earnings which he is willing to give up. An obvious generalization therefore is to allow the amount of accumulated human capital to affect this trade-off. Again it is easy to produce such generalizations which would lead to a smoothly concave log earnings function. Clearly, the necessary assumption is that past accumulation reduces the capacity for further growth. Without the explicit introduction of job specific components of human capital it is not clear whether such an assumption is in fact plausible, and again it can be incorporated only at the price of a considerable increase in complexity.

A perhaps more plausible extension is to introduce explicit age effects. We have already included in the model depreciation as a function of past accumulation of human capital. We shall assume that the capacity to produce new human capital via learning in school or on-the-job training is decreases with age. Consider a model in which $a(\tau) = a_0 e^{-\gamma\tau}$ and $\beta(\tau) = \beta_0 e^{-\gamma\tau}$. That is, the ability to learn in school and on the job depreciates with age, τ, at the same constant rate, γ. In this case (see appendix) the rate of change in earnings during the investment period is given by:

$$(15)\quad \frac{\dot{Y}}{Y} = \frac{\beta(\tau)}{1-\alpha} + \frac{\alpha}{1-\alpha}(r + \delta - \gamma) - \delta \qquad \text{for} \quad \tau_1 > \tau \geqslant \tau_0$$

and

$$(16)\quad \ln Y(\tau_0) = \ln K_s + \int_{\tau_s}^{\tau_0} (a(\tau) - \delta)\,d\tau + \ln \left[\frac{\alpha}{1-\alpha}\left(\frac{a(0)}{\beta(0)} - 1\right)\right] \alpha$$

where τ_s is the age at which the schooling period begins. (We are now allowing for individual differences in τ_s ; previously it was assumed zero for all individuals.)

Using our assumptions on $a(\tau)$ and $\beta(\tau)$ we can solve for $Y(\tau)$. This results in the non-linear equation:

$$(17)\quad \ln Y(\tau) = \ln K_s + \int_{\tau_s}^{\tau_0} (a_0 e^{-\gamma\tau} - \delta)d\tau + \alpha\ln\left[\frac{\alpha}{1-\alpha}\left(\frac{a_0}{\beta_0} - 1\right)\right]$$

$$+ \int_{\tau_0}^{\tau} \left[\frac{\beta_0}{1-\alpha} e^{-\gamma\tau} - \frac{\alpha}{1-\alpha}\left(r + \frac{\delta}{\alpha} - \gamma\right)\right]d\tau \qquad \text{for } \tau_0 \leqslant \tau \leqslant \tau_1$$

To facilitate the estimation we can use a second degree Taylor approximation around $\gamma = 0$, to obtain:

$$(17')\quad \ln Y(\tau) \simeq c_o + c_1(\tau_0 - \tau_s) + c_2(\tau_0^2 - \tau_s^2) + c_3(\tau - \tau_0)$$

$$+ c_4(\tau^2 - \tau_0^2) + c_5\tau_s \qquad \text{for } \tau_0 \leqslant \tau \leqslant \tau_1$$

where

$$c_0 = \ln K_0 + \alpha\ln\left[\frac{\alpha}{1-\alpha}\left(\frac{a_0}{\beta_0} - 1\right)\right]$$

$$c_1 = a_0 - \delta \qquad > 0$$

$$c_2 = -\frac{\gamma}{2}a_0 < 0$$

$$c_3 = \frac{\alpha}{1-\alpha}\left[r + \delta - \gamma - \frac{\delta}{\alpha} + \frac{\beta_0}{\alpha}\right] > 0$$

$$c_4 = -\frac{\gamma}{2}\frac{\beta_0}{1-\alpha} < 0$$

$$c_5 = \frac{\ln K_s - \ln K_0}{\tau_s} \geq 0$$

An important implication of the assumed age dependence is that "late starters" will tend to have a flatter experience-log earning profile during their post school years. The slope of their age-log earning profile is the same as that of early starters but its level is lower.

Vintage and Time Effects

So far we assumed a perfectly static economy. Time as such did not appear in the analysis. There are, however, changes in supply and demand, and changes in technology which affect the wage level and its structure by age (or experience). We now turn to examine these effects.

In the analysis of a static economy we could define human capital, without ambiguity in terms of potential earnings. If, however, prices and technology change, the same amount of knowledge will "buy" different amounts of goods depending upon the date of its application. Let us therefore define $K(\tau,t)$ as the maximum amount of earnings that an individual who is of age τ, at time t, could obtain at some fixed prespecified date. Let $R(t)$ be the rental rate of human capital at time t. We can then write the individual's earning capacity at time t as $R(t)K(\tau,t)$ while $K(\tau, t)$ is controlled by the individual via his investment policy, $R(t)$ is exogenous to him and is determined by the conditions of supply and demand.[5/]

It may be useful to sketch briefly the determination of the rental rate of human capital in the context of a simple aggregate general equilibrium model. Consider an economy with a fixed population and a uniform age distribution.

At each point of time the amount of "working human capital" in the economy is given by $\bar{K}(t) = \int_0^T y(\tau,t)K(\tau,t)d\tau$ where $y(\tau,t)$ is the proportion of "time" which individual of age τ spends in the production of goods at time t. Each individual also produces his own new human capital according to the production function $y(\tau,t) = G\left[\frac{dK}{d\tau}\frac{1}{K}\right]$. This investment process can be carried out either at work or at school in which case $y(\tau,t) = 0$. Let there be a single composite good z which can be accumulated or consumed. The production function of z is $Z(P,\bar{K})$ where P is the amount of accumulated physical capital.

A potential source of growth in this model with fixed population is the improvement in the labor force through learning by doing. In the simplest case, each generation can be viewed as starting with a higher initial level of human capital, thus embodying the knowledge accumulated by past generations.[6/] Let $\mu = t-\tau$ be the individual's vintage, we may write $K(\tau,t) = K(\mu,\tau)$ and assume that $K(\mu,0)$ is an increasing function of μ. We have seen that for given interest and rental rates an increase in the initial level of human capital will not change the investment pattern of the individual. Later vintages will have uniformly higher levels of human capital throughout their life. If $K(\mu,0)$ grows at a constant rate, so will the aggregate of all age groups. The model then becomes identical to one in which population grows at a constant exogenous rate. If the production function is homogenous of degree 1 and if savings are, say, a constant proportion of output then the economy will have the usual steady state properties; the interest rate and the rental rate will in fact remain constant, so that expectations are fully realized.

It is clear that past knowledge is not transmitted in such a costless one shot fashion. In fact, schools and firms serve as a vehicle for the intergenerational transfer of knowledge. The embodiment of past knowledge requires the investment of time on the part of the individual and is therefore spread over a considerable part of his life. As the general knowledge accumulates, recent vintages benefit more from the investment of their time in school. It seems plausible that they also become more "efficient" in terms of their learning on the job.

Put differently, the rate of transmission depends jointly on the stock of existing knowledge as well as the amount of time (and other resources) that each individual spends learning, and on the amount of resources which are spent teaching him.

It is obvious that such a trend of increasing learning efficiency is not neutral with respect to its effect on the shape of the investment plan. Other things being equal, new vintages will tend to invest more in human capital. They will spend more time in school and their earning profiles will be steeper. It is, however, not clear whether other things can in fact remain constant. For instance, if a larger initial segment of life is spent investing in human capital the demand for borrowing by the young vintages will increase, old vintages will be induced to provide the necessary transfer only at increasingly higher interest rates. The increase in the interest rate will, of course, provide a check to the tendency for increased investment. Also the proportion of physical capital and human capital used in production will decrease and the rental for human capital will thus decline.[7/] Since there is a limit to the amount of productive capacity which can be transmitted in a given period of time, and also to the amount which can be stored in a given individual, the process which we described is likely to stop at some stationary state.

For the purpose of empirical implementation it is important to distinguish between two alternative specifications of the increase in individual learning efficiency. We may assume that the parameters a and β depend simply on the chronological time of investment. Thus, independently of the date of entry into the labor force all investors at t have equal learning efficiency. Under such circumstances there will be a motivation to postpone the investment in human capital. It is possible, for instance, that individuals will decide to enter or re-enter school at later stages of their life. An alternative view which is perhaps more plausible is that at each point of time the general advance in knowledge affects individuals differentially depending upon how recently their human capital was acquired. The reason is that new knowledge is often different from past knowledge, that is, a different technique, a different theory, and occasionally a different language is used to present it. Therefore, recent vintages will find the general advance of knowledge to be more complementary to their human capital, and will be relatively more efficiency in producing new human capital than older vintages at any given point in time. An extreme version of this view, one that allows us to retain the simple structure of the individual maximization problem, is that each successive vintage is endowed with a superior production function (i.e. higher a and β as well as higher K_0) for new knowledge which remains fixed throughout its life.

In a changing economy, expectations play a crucial role. Rather than assuming perfect foresight we may assume that the individual can correctly predict trends, so that his expectations are realized only in some average sense over his lifetime. The development of earning over the life cycle will thus contain a systematic part which is determined by the initial expectations and a transitory part which depends on current realizations.

The maximization problem facing an individual of vintage μ can be described as follows. The individual is endowed with an initial stock K_μ and learning parameters a_μ and β_μ. He forms expectations on the time path for the interest rate $r_\mu + \tau$ and for the rental rate on human capital $R(\mu+\tau)$. The solution of this maximization problem is almost identical to the one given by equations (7) and (10) (see Appendix) and the development of the systematic part of earnings can be written as:

$$(18)\quad \frac{dY}{d\tau}\frac{1}{Y} = [\beta_\mu + \hat{g}_{\mu+\tau} - \delta - \alpha r_{\mu+\tau}]\frac{1}{1-\alpha} \qquad \text{for } \tau_0^\mu \le \tau < \tau_1^\mu$$

$$= -\delta \qquad \text{for } \tau_1^\mu \le \tau \le T$$

where $\hat{g}_{\mu+\tau}$ is the expected rate of change in R at time $\mu+\tau$. The initial value of earning is given by:

$$(19)\quad \ln Y(\tau_0) = \ln K_\mu + a_\mu \tau_0^\mu + \alpha \ln[\frac{\alpha}{1-\alpha}(\frac{a_\mu}{\beta_\mu} - 1)] + \ln R(\mu+\tau).$$

If g and r are expected to remain constant then each vintage will have a lifetime profile for log earnings which is piecewise linear. However, different vintages will have different profiles. In Figure 5 we draw the profiles of two individuals of successive vintages but with the same level of schooling.

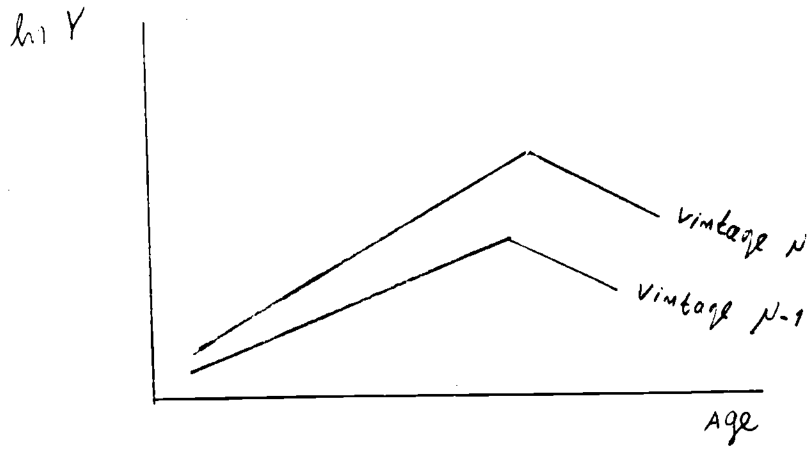


Figure 5

It is seen that under our assumptions later vintages show a higher slope of the log earnings profile. This is a reflection of the vintage effect on the productivity of learning on the job. The difference in the level of the two profiles reflects the increase in the productivity of learning in school (and possibly the increase in K). The observed difference in level probably underestimates these effects since the newer generation is likely to choose a higher level of initial investment on the job.

It should be pointed out that vintage or cohort effects may arise in a number of additional ways. Some are specific exogenous factors such as a war, for instance; others may reflect trends other than the general advance in knowledge. Specifically, we would expect the average ability (or productivity) of scientists who obtained their degrees during World War II to be lower than that of vintages of more normal times. More to the point, if there is in fact a trend of decreasing school admission standards, and if there is a high correlation in the population between the two types of learning abilities a and β, then such a trend would mitigate (or possibly offset) the effects of the advance in knowledge on the level and slope of the earning profiles.

II. Empirical Implementation

1. General Considerations

Having described the simple model of on-the-job training in some detail we are now ready to present some testable implications and to suggest the methods by which they can be tested.

There are two broad types of implications which follow from the model. One relates to individual earnings profiles. The other relates to the earnings profiles of a group of individuals who differ in some systematic fashion.

Consider first individual profiles. Our basic interest here is in the relationships between the exogenous parameters which the individual faces and his various schooling and training decisions. An inherent difficulty, however, is that most of the exogenous variables are either in principle or in practice unobservable. We are thus reduced to testing hypotheses on the relationships between various observed aspects of individual behavior. Within our simple model these hypotheses assume the form of predicted relations between the level of degree, the quality of schooling, the age at which the highest degree was obtained, its vintage, and the slope of the log earning profile during the on-the-job investment period. Similarly we may examine the effects of sex and type of employer on the slope of the log earning profiles. Finally we may analyze the effect of some current rather than initial conditions on the slope. Thus one may consider the effect of age or experience on the slope of the log earning profile. (This amounts to specifying the appropriate non-linear log earning profile.)

Most frequently obtainable are data on the earnings of a set of individuals at a single point in time. We may fit an earnings function to such cross sectional data, but since individuals of different experience in this kind of sample must come from different vintages, the resulting function will not be the earnings function of some representative individual. However, given some specific assumptions on the individual profiles and on the manner in which vintages differ, we can predict the form of the cross section relation. Furthermore, we can predict the relationship between the slopes of the earnings profiles in successive cross sections. More generally, the existence of vintage effects introduces systematic interrelationships between observed cohort and cross section data. Given an appropriate specification they can be identified from pooled cross section time series data.

2. Definition of Variables and Functional Forms

The purpose of this section is to describe a specification of individual earnings profiles and vintage effects which can be used to extract information on the slope of individual earnings profiles and cross section profiles from pooled cross section data. For the purpose of exposition I shall discuss first the case of linear individual log earnings profiles and introduce non-linear age effects at a later stage.

Let us assume that the individual expects the interest rate and the rate of change in the rental on human capital to remain fixed. The systematic part of the earnings profile is then obtained by integrating equation (18). The observed earnings of a particular individual are:

$$(20)\quad \ln Y(\tau,\tau_0,t) = \hat{g}t + \ln k_\mu + (a_\mu-\delta)(\tau_0-\tau_s) + \alpha\ln\left[\frac{\alpha}{\alpha}\left(\frac{a_\mu}{\beta_\mu} - 1\right)\right] + \frac{\beta_\mu}{1-\alpha}(\tau-\tau_0) + \frac{1}{1-\alpha}\left|\alpha(r-\hat{g}) + \delta\right|(\tau - \tau_0) + d_t \quad . \text{ For } \tau_0^\mu \leqslant \tau \leqslant \tau_1$$

where d_t denotes a cyclical unexpected deviation from trend.

For the purpose of empirical application the simples possible assumption for the vintage effects is that they are linear in time. We thus assume

$$(21) \quad \beta_\mu = \beta_0 + \beta_1\mu$$
$$a_\mu = a_0 + a_1\mu$$
$$\ln K_\mu = k_0 + k_1\mu$$

We shall identify μ as the year at which the individual obtained his highest degree. Thus the following identity holds for every individual.

$$(22) \quad \mu = t-[(\tau-\tau_0) + \varepsilon]$$

where t is the time at which income is observed, $\tau - \tau_0$ is post school experience, and ε is a possible "break" in the accumulation of human capital. Let us also denote $s = \tau_0 - \tau_s$ as the schooling period, then equation (20) can be rewritten as

$$(23) \quad \ln Y(t, \tau-\tau_0, s) = k_0 + \ln y_0^\mu + (a_0 + a_1 t - \delta)s + (\hat{g} + k_1)t + d_t$$
$$+ \frac{1}{1-\alpha}[\beta_0+\beta_1 t-\alpha(r-\hat{g})-\delta- (1-\alpha)(a_1 s + k_1)](\tau-\tau_0)- \frac{\beta_1}{1-\alpha}(\tau-\tau_0)^2$$
$$- \varepsilon(\frac{1}{1-\alpha}(\tau-\tau) + k_1+a_1 s)$$

If all individuals are observed at the <u>same</u> point of time, if the unobserved initial investment y_0^μ is ignored, and if we further assume uninterrupted accumulation of experience $(\varepsilon = 0)$,
then equation (23) is identical in form with that which was used extensively by Mincer [1974] and his students. Notice, however, that within our simple framework it is purely a cross section phenomenon and a <u>different</u> form, possibly linear in the logs should be fitted to longitudinal data. Notice the special form in which the cross section function depends upon time. Under the vintage

hypothesis both the constant and the coefficient of experience should be higher in a later cross section. Note also that the coefficient of the linear term is an underestimate of the experience effect (of the latest vintage in the cross section under study), since it captures, in part, the vintage effects on schooling and on initial level of human capital.

In fields with fast rates of advance (i.e., high a_1 and β_1 ,) where vintage effects are relatively important, the constant and the coefficient of experience^2 will be relatively high (in absolute value). The effect on the coefficient of experience is ambiguous and may be different depending upon which cross section we consider. If vintage effects operate only at the school level, and are relatively weak in their effect on the efficiency of learning on the job then the coefficient of experience will tend to be smaller in fields with fast advance, while the coefficient of exp^2 will be unaffected.

For the purpose of empirical estimation from pooled cross sections for a group with fixed level of schooling it will be convenient to rewrite equation (20) in the following form:

$$\text{(24)} \quad \ln Y = c + (a_0 - \delta)s + (\hat{g} + k_1 + a_1 s)t + d_t + \frac{1}{1-\alpha}[\beta o - \alpha(r - \hat{g}) - \delta - (1-\alpha)(k_1 + a_1 s)](\tau - \tau_0)$$
$$+ \frac{\beta_1}{1-\alpha}(\tau - \tau_0)\mu \qquad - \varepsilon(k_1 + a_1 s)$$

The slope of the longitudinal (cohort) profile for the reference vintage (i.e. with $\mu = 0$) is obtained by adding the coefficient of time (eliminating d_t through averaging) to the coefficient of experience in equation (24). The slope of the cross sections profile is obtained by adding t times the coefficient of the interaction between year of highest degree and experience to the coefficient of experience in equation (24).

It is obvious that the basic parameters of the model, that is a_0, a_1, β_0, β_1, δ, r, $\hat{g}$ cannot be identified from equation (24). There is a hope of identification only if one incorporates simultaneously all the aspects of the individual profile, including the age at which the profile peak, the slope of the earning profile during the zero investment interval and the length of the schooling period. Since we have information on individuals only during 10 years of their life, and since our data on the length of the schooling period is very limited (we only have the level of degree) there is little hope in identifying the basic parameters from the present data. It should be pointed out that even if all the information on individual profiles is available, there are still two parameters which must be determined a-priori. The most natural candidates are perhaps the interest rate and the exogenous growth rate.From an estimation point of view, it seems most convenient to predetermine α in which case the remaining parameters are linear functions of the regression coefficients so that one can derive unbiased (but not most efficient) estimates for them.

A basic difficulty towards which we shall now address ourselves is the separation of vintage effects from non-linearities in individual profiles. The approach taken by Mincer in the analysis of cross section data was to assume that individuals of different vintages have the same profile and that for each individual the log earning profile is quadratic in experience. It is clear that neither of the two alternative interpretations can be rejected on a basis of a single cross section. However, if one has data on a sequence of cross sections over a sufficiently long period of time the two effects may be sorted out separately. Unfortunately our data covers a relatively short period of ten years so that the multicollinearity between experience and year of highest degree is still considerable. We have therefore chosen to represent the non-linearity of the profile by using age rather than experience as the factor which causes the reduction in slope of the earning profile. Due to the considerable variation in the age at which the highest degree was obtained, the multicollinearity of age and year of highest degree is smaller, and one can better separate vintage effect from non-linearities in individual profiles. Introducing age effects we may rewrite equation (17') as

$$(25)\qquad \ln Y = c_0^{\mu} + gt + c_1^{\mu}s - c_2^{\mu}s^2 + \tau_0(c_5^{\mu} + c_2^{\mu}s) + c_3^{\mu}(\tau-\tau_0) + c_4^{\mu}\,[2\tau-(\tau-\tau_0)]\,(\tau-\tau_0)$$

Where t is the year of observation, s is the length of schooling period, τ_0 age at highest degree, $\tau-\tau_0$ is post degree experience, and τ is age. The coefficients c_0^{μ}, c_1^{μ}, $c_2^{\mu}\ldots c_5^{\mu}$ are defined on page 14; the superscript μ indicates that they are linear functions of μ (i.e. year of highest degree).

If one assumes away vintage effects then the implied cross section relation is again very close to the form which was adopted by Mincer. It can be rewritten in an unrestricted form using the identity:

$$(26)\qquad (2\tau-(\tau-\tau_0))(\tau-\tau_0) = 2\tau_0(\tau-\tau_0) + (\tau-\tau_0)^2 + \varepsilon(\tau-\tau_0)$$

and allowing the coefficients for the three terms on the L.H.S. of (26) to differ. In this generalization age at highest degree, breaks in experience, and their interactions with experience appear as explanatory variables, in addition to standard experience and experience^2 terms. However, if one admits vintage effects as well as non-linear individual profiles the cross section relation becomes more complicated and is essentially of a cubic rather than quadratic form in experience.

In trying to isolate the effects of age, experience, and vintage we shall attempt to control for other factors which may affect the slope or the level of the log earning function. We shall now briefly describe these variables.

Predegree experience. Many individuals have some professional work experience prior to obtaining their degrees. It is reasonable to assume that given their postdegree experience the accumulation of predegree experience will increase their earnings. Furthermore we may assume that those who worked a longer period before obtaining a given degree had less access to the capital market and faced a higher rate of interest. It is therefore expected that the interaction between predegree experience and postdegree experience will be negative.

Quality of school and level of degree. We obtained data on the ranking of the schools which the various scientists attended. One may expect those who attended schools which are ranked in the top ten to possess a higher learning-on-the-job coefficient. This is possibly true for two reasons; the top ten schools may select the students with a better native ability, and they also provide more knowledge which can then be utilized in on-the-job training. Furthermore, individuals who studied in the top ten, typically more expensive, schools are likely to have better access to the capital market. We would therefore expect a higher slope for the earnings profiles of those who obtained their degree from high quality schools. For very similar reasons we shall expect positive interaction between the level of degree and the slope during the investment period.

Sex. In a world in which human capital is at least partially specific, women may be required to pay more in order to obtain general training. The reason is that the expected duration of their employment within a given firm is probably shorter. Depending upon the precise parameterization of this effect it is possible (but not necessary) that as a result the female scientist will have a lower slope of the earnings profile.

Type of employer. Observed earnings profiles as a function of experience tend to differ both in slope and in level across type of employer (i.e. government, private industry, and educational institutions). Most probably these differences are due to factors which our simple model does not explicitly account for. Among them are differences in the nature of the contract, and thus the sharing of risks, and differences in nonmonetary returns. For these reasons it seems desirable to control for the type of employment. There is, however, an opposing view, if there is considerable mobility across types of employment, one may view it at least in part as a manifestation of the on-the-job training process. In this case one would prefer not to adjust for the type of current employer in analyzing the slope of the earnings profile.

I have estimated equation (25) with and without control for the type of employer. The effect on the earnings profiles in most fields is negligible. It appears that despite the fair amount of mobility across types of employer the correlation of type of employer and age (or experience) is small.[8/] To avoid duplication we present results only for the case with control for type of employer.

Broken careers. Most Ph.D.s follow a straight career and their postschool experience is therefore identical with the difference between their age and the age at which they obtained their degrees. Occasionally there will be a break; a woman scientist may drop out for awhile, military service may intervene, etc. Within our simplified framework these breaks are viewed as exogenous. Their main effect is to increase the gap between age and experience and vintage and experience. To partially control for the effects of such interruptions we add the difference between years since degree and postdegree experience as an explanatory variable.[9/]

In order to complete the specification we must consider the error terms which one would add to equations (20), (24), and (25). We may distinguish three different components of the error term: Pure chance elements which are independent across observations, persistent unobserved level effects, and persistent unobserved slope effects. The persistent elements can be eliminated to some extent if we have data on the same individuals over a period of time. In the present study we use samples of different individuals at different points of time and such control is impossible. Among the unobserved level effects we have the initial level of human capital K_0 and the initial investment in on-the-job training y_0. Under the present model K_0 is unrelated to the investment pattern of the individual and its omission causes no bias. On the other hand, if we assume that more recent vintages start their working life investing a larger proportion of their earnings capacity, the omission of y_0 will cause an overestimate of the experience effect and an underestimate of the growth effect. Among the unobserved slope effects are individual differences in learning abilities and in access to the capital market. When uncontrolled, these effects will cause heteroscedasticity in the errors and thus misspecification of the variance of the estimated coefficients.

III. Estimation and Empirical Results

Our source of data is the National Register of Technical and Scientific Personnel. We produced three random samples of 10,000 scientists each from the National Registers of 1960, 1966, and 1970. The regression results which we report below are estimated from the pool of these three samples.

Our working hypothesis is that vintage effects as well as other market conditions are likely to be different in different scientific fields; we therefore divided the sample into seven separate fields: Agriculture, Biology, Chemistry, Earth Sciences, Mathematics, Physics, and Psychology. Since level of schooling interacts with many of the explanatory variables it was considered preferable to control for the level of degree by further subdividing each sample into B.A., M.A., and Ph.D. holders. For the sake of brevity we report on the effects of changes in the level of degree only for the aggregate of all fields. Results for the separate fields will be presented only for scientists with a Ph.D. degree.

In each subsample we shall estimate equation (25) in two forms: restricted and unrestricted.[10/] The dependent variable is the log of basic earnings. (Observations with zero basic earnings were eliminated.) Scientists who were employed in academic institutions could report their annual basic income on a 9 to 10, or an 11 to 12 month basis. We use a dummy variable to distinguish these cases.[11/] The data also contained information on gross earnings, which include consulting fees, honoraria, and the like. Though conceptually superior, this measure of income was not used by most researchers using the N.S.F. data. A probable reason is the problem of measurement errors which may arise when the reporting scientist estimates his gross earnings. To allow comparability to other studies we present here earnings functions only in terms of basic earnings.

When data on both experience (i.e. years of professional work experience) and years since highest degree are available we break total experience into predegree and postdegree experience along the lines suggested by Johnson and Stafford [1974].[12/] In the fairly large number of cases (up to 15 percent in 1970) in which experience is not reported we set postdegree experience equal to years since degree and preschool experience at the mean of the corresponding group with complete information on both experience and years since degree.

Strictly speaking equation (25) is applicable only during the investment on-the-job period. However, the length of the investment period is not observed. On the arbitrary assumption that everyone below 50 is still investing, we may truncate the sample at that age. However, by reducing the age (and experience) range one loses considerable variation in the explanatory variables and the result is a reduction in the precision of the estimates. Due to the small sample size in some of the separate fields we present the effects of the truncation only for the aggregate of all scientists. In order to separate investment in on-the-job training from investment in schooling we eliminated all students from the sample; scientists who were not fully employed were also eliminated.

In Table 1 we present the mean and the standard deviations of the main explanatory variables which are used in the regression analysis. There is a surprising amount of variation in some of these means across fields. The proportion employed by private industry varies from about 6 percent in agriculture to 50 percent in chemistry. The proportion of female scientists varies from 2 percent in physics to 12 percent in psychology. The proportion of scientists owning degrees from schools which are ranked in the top ten varies from 6 percent in agriculture to 39 percent in earth sciences.

Table 1. Sample means and standard deviations of selected variables.

Variable \ Sub-Sample	Scientists with Ph.D. Degree									Scientists with:	
	Agri-Culture	Biology	Chem-istry	Earth Sciences	Mathe-matics	Physics	Psych-ology	All fields	All fields-age less than 50	B.A., all fields	M.A., all fields
Female	.012	.072	.044	.024	.051	.024	.124	.058	.049	.054	.095
School ranked in top 10	.060	.253	.192	.388	.268	.288	.189	.232	.215	.052	.109
Private industry	.057	.113	.500	.190	.147	.301	.134	.260	.269	.635	.429
Educational institution	.713	.623	.366	.563	.765	.521	.523	.513	.528	.038	.211
Government	.220	.252	.125	.241	.081	.170	.286	.193	.188	.288	.244
Year of highest degree-1958	-4.2 (9.8)	-5.3 (10.5)	-5.1 (10.4)	-3.6 (10.8)	-1.8 (10.4)	-2.6 (9.9)	-1.8 (8.9)	-4.0 (10.2)	-.4 (7.0)	-7.2 (10.4)	-3.4 (9.9)
Age at highest degree - 22	10.4 (5.9)	7.7 (4.9)	6.8 (4.0)	9.1 (4.8)	7.8 (5.1)	7.2 (4.3)	10.5 (5.9)	8.0 (5.0)	7.5 (4.1)	2.4 (3.6)	6.3 (5.4)
Age - 22	21.7 (9.4)	20.5 (9.7)	19.2 (9.9)	20.7 (9.7)	17.9 (9.9)	17.6 (9.3)	19.9 (9.3)	19.5 (9.7)	15.5 (6.1)	16.7 (10.0)	17.3 (9.8)
Predegree experience	5.1 (5.8)	2.6 (3.9)	2.3 (3.6)	4.0 (4.1)	3.8 (4.8)	2.9 (4.2)	4.3 (4.8)	3.1 (4.3)	2.7 (3.5)	.6 (2.1)	2.9 (4.2)
Postdegree experience	11.2 (8.6)	12.2 (9.5)	12.2 (9.6)	11.3 (9.6)	9.6 (8.9)	9.9 (8.9)	9.3 (7.6)	11.2 (9.2)	7.8 (5.7)	13.1 (9.6)	10.4 (8.8)
Years since degree-post exp	.1 (.6)	.6 (1.7)	.3 (1.2)	.2 (1.3)	.3 (1.5)	.2 (.9)	.2 (1.0)	.3 (1.3)	.2 (.9)	1.2 (2.4)	.6 (1.9)
Sample size	332	2403	2795	547	750	1304	1369	9500	7505	6213	5288

The variation in type of employer across levels of schooling is also very large. Associated with increased schooling is a decrease in the proportion of scientists who are employed in private industry and an increase in the proportion employed in academic institutions.[13/] There is also some reduction in the proportion of female scientists. The amount of predegree experience tends to increase with the level of schooling. It appears that a considerable portion of the professional experience is accumulated through work during the schooling period.

Breaking the sample by age appears to have little effect on the variables which are not directly age related. In particular, the distribution by type of employer is invariant. It is interesting to note, however, that the proportion of female scientists in the over 50 group is somewhat higher, indicating a late reentry of female scientists.

There is a considerable variation in the age at degree within field. The standard deviation for age at Ph.D. is about five years, which is about half the standard deviation in the chronological year at which the degree was obtained. As one would perhaps expect, the variation in age of highest degree tends to decrease with the level of schooling. There is also considerable variation within fields (and across fields) in predegree experience and in the difference between years since degree and postschool experience (i.e. "break").[14/]

The estimates of the coefficients of equation (25) for the restricted case are presented in Table 2. The method of estimation is ordinary least squares. We intend to use the estimates from the pooled regression in order to answer two basic questions:

1. Which are the observed determinants of the starting salaries of scientists?
2. Which are the observed determinants of the growth in the earnings of scientists?

Table 2. Earnings functions of scientists in government, private industry, and educational institutions Restricted form.

Sample \ Explanatory variable	Constant	9 month salary indicator	1970 sample	1966 sample	Age at Ph.D.	Pre-degree experience	Post-degree experience	Break
Ph.D.s, all fields								
All ages	4.057 (294.6)	-.121 (-13.9)	.503 (50.4)	.292 (30.6)	.0100 (9.2)	.0116 (8.9)	.0639 (50.0)	.0368 (17.1)
Less than 50 years of age	3.992 (241.0)	-.118 (-12.7)	.499 (43.9)	.290 (27.4)	.0141 (9.9)	.0114 (6.9)	.0784 (30.9)	.0530 (15.2)
Ph.D.s, each field								
Agriculture	4.155 (90.2)	-.141 (-2.4)	.466 (14.8)	.242 (8.1)	.0051 (1.2)	.0155 (3.2)	.0550 (10.8)	.0776 (4.2)
Biology	3.931 (128.5)	-.151 (-7.3)	.528 (25.0)	.306 (15.0)	.0173 (7.0)	.0107 (3.5)	.0751 (26.8)	.0604 (15.1)
Chemistry	3.996 (150.1)	-.079 (-4.2)	.478 (23.8)	.290 (14.7)	.0081 (3.6)	.0039 (1.4)	.0616 (27.0)	.0264 (6.6)
Earth sciences	4.103 (72.0)	-.162 (-5.5)	.515 (14.1)	.284 (8.3)	.0041 (1.0)	.0233 (5.0)	.0532 (10.1)	.0004 (.0)
Mathematics	4.107 (107.4)	-.090 (-4.2)	.545 (21.6)	.307 (12.5)	.0061 (1.9)	.0078 (2.2)	.0541 (14.6)	.0170 (2.9)
Physics	4.139 (113.3)	-.130 (-6.3)	.449 (17.2)	.274 (11.1)	.0068 (2.1)	.0140 (4.1)	.0637 (18.8)	.0163 (2.2)
Psychology	4.154 (123.8)	-.124 (-5.8)	.497 (20.1)	.276 (11.6)	.0093 (4.3)	.0077 (2.7)	.0564 (16.6)	.0318 (4.3)
B.A.s, all fields	3.627 (81.3)	-.149 (-2.4)	.294 (6.4)	.414 (8.5)	.0172 (9.3)	.0097 (3.1)	.0714 (26.5)	.0252 (13.7
M.A.s, all fields	3.847 (155.5)	-.107 (-5.2)	.515 (23.8)	.319 (14.0)	.113 (7.5)	.130 (6.6)	.0527 (24.4)	.0177 (7.6)

Continued

Table 2 (continued). Earnings functions of Ph.D.'s in government, private industry, and educational institutions. Restricted form.

Sample \ Explanatory variable	Year of Ph.D. × post experience	Pre × post experience	(2 age − post) × post	Female	School ranked in top 10	Female × post experience	Top 10 × post experience	Private industry
Ph.D.s, all fields								
All ages	.00039 (9.9)	−.00027 (−2.9)	−.00073 (−18.0)	−.125 (−5.6)	.012 (0.9)	−.0059 (−3.8)	.0015 (1.7)	.393 (26.0)
Less than 50 years of age	.00044 (5.8)	−.00018 (−0.9)	−.00108 (−12.5)	−.092 (−3.5)	.020 (1.2)	−.0145 (−4.5)	−.0002 (−.1)	.411 (24.6)
Ph.D.s, each field								
Agriculture	.00022 (1.3)	.00018 (.5)	−.00071 (−4.4)	−.213 (−.7)	−.086 (−1.0)	.0618 (.8)	.0037 (.8)	.114 (1.0)
Biology	.00030 (3.5)	−.00037 (−1.8)	−.00093 (−10.8)	−.126 (−3.0)	.005 (.2)	−.0070 (−2.4)	−.0002 (−.1)	.322 (7.2)
Chemistry	.00047 (6.7)	.00026 (1.5)	−.00064 (−8.7)	−.144 (−3.1)	.006 (.2)	−.0041 (−1.3)	.0012 (.7)	.458 (18.5)
Earth sciences	.00049 (3.4)	−.00083 (−2.5)	−.00041 (−2.5)	−.331 (−2.6)	.018 (.5)	−.0017 (−.2)	.0000 (.0)	.353 (5.7)
Mathematics	.00044 (3.5)	−.00027 (−1.0)	−.00053 (−4.1)	−.063 (−1.2)	−.006 (−.2)	−.0182 (−4.6)	.0045 (2.2)	.424 (8.0)
Physics	.00057 (5.2)	−.00056 (−2.2)	−.00064 (−5.4)	−.206 (−1.8)	−.004 (−.1)	.0037 (.4)	.0045 (2.0)	.413 (11.2)
Psychology	.00022 (2.2)	−.00014 (−.5)	−.00072 (−7.4)	−.095 (−2.3)	.016 (.4)	−.0025 (−.8)	.0028 (1.1)	.367 (7.0)
B.A.s, all fields	.00005 (.7)	.00011 (.3)	−.00093 (−14.9)	.007 (.1)	.114 (1.0)	−.0149 (−2.8)	−.0087 (−1.5)	.426 (9.6)
M.A.s, all fields	.00022 (3.4)	−.00001 (−.0)	−.00073 (−11.3)	−.116 (−3.0)	−.008 (−.2)	−.0026 (−.9)	.0026 (1.0)	.354 (13.8)

(continued)

Table 2 (concluded). Earnings functions of Ph.D.'s in government, private industry, and educational institutions. Restricted form.

Explanatory variable / Sample	Government	Private industry × exp.	Gov. × experience	Private industry in 1970	Private industry in 1966	Government in 1970	Government in 1966	Standard error	R^2
Ph.D.s, all fields									
All ages	.067 (4.1)	-.0060 (-7.1)	.0023 (2.6)	-.109 (-7.0)	-.097 (-6.3)	.001 (.1)	-.027 (-1.5)	.256	.634
Less than 50 years of age	.097 (5.5)	-.0109 (-8.1)	-.0013 (-.8)	-.084 (-5.1)	-.086 (-5.2)	-.014 (-.7)	-.0335 (-1.8)	.244	.643
Ph.D.s, each field									
Agriculture	-.081 (-1.7)	-.0001 (.0)	.004 (1.5)	-.045 (-.4)	.007 (.1)	.150 (2.6)	.066 (1.1)	.174	.758
Biology	-.025 (-.7)	-.0024 (-1.0)	.0038 (2.1)	-.102 (-2.1)	-.122 (-2.7)	.004 (.1)	-.016 (-.4)	.285	.632
Chemistry	.287 (2.5)	-.0074 (-5.9)	.0001 (.1)	-.104 (-4.3)	-.102 (-4.1)	-.032 (-.9)	-.036 (-1.0)	.241	.664
Earth science	.064 (.9)	.0053 (1.5)	.0008 (.2)	-.116 (-1.8)	-.226 (-3.7)	.087 (1.4)	.007 (.1)	.216	.737
Mathematics	.281 (4.1)	-.0040 (-1.1)	-.0053 (-1.4)	-.102 (-.1)	-.131 (-2.2)	-.102 (-1.4)	-.037 (-.5)	.205	.757
Physics	.232 (5.4)	-.0020 (-.9)	-.0009 (-.3)	-.134 (-3.7)	-.100 (-2.6)	.006 (.1)	-.062 (-1.4)	.232	.675
Psychology	-.019 (-.5)	.0023 (.7)	.0046 (1.9)	-.047 (-.9)	-.016 (-.3)	.049 (1.3)	-.0054 (-.1)	.238	.660
B.A.s, all fields	.167 (3.6)	-.0134 (-5.9)	-.0114 (-4.8)	.114 (2.4)	-.239 (-4.8)	.229 (4.7)	-.123 (-2.4)	.292	.576
M.A.s, all fields	.128 (4.6)	.0018 (1.3)	.0027 (1.8)	-.055 (-2.2)	-.111 (-4.1)	.008 (.3)	-.064 (-2.1)	.287	.585

One of the most important factors which determine the level of starting salaries is the year at which the scientist entered into the labor force. The coefficients of the sample years in Table 2 provide estimates of these effects. As was previously explained, these coefficients reflect exogenous changes in the rental price of human capital which are common to all scientists in the sample as well as the specific gains due to increase in the efficiency of learning in school. These last effects are embodied differentially into scientists of different vintages.

As seen, nominal starting salaries grew at an average rate of 5 percent per year for scientists with Ph.D.s who are employed in academic institutions. The increase in government is similar but in private industry it was only 4 percent. We thus note a narrowing of the wage differential between academic institutions and private industry from about 40 percent in 1960 to about 30 percent in 1970. The nominal rate of increase was fairly uniform over the period, but due to the acceleration in the inflation rate (the consumer price index increased by 1.53 percent per annum during 1960-1966, by 4.48 percent during 1966-1970, and by 2.71 percent during the period as a whole) there is a marked reduction in real growth in the late sixties. The period is thus characterized by changing demand and possibly supply conditions. The reduction in real growth is most pronounced in physics where real starting salaries actually declined during the period 1966-1970 (see Freeman [1975]. It is interesting to note that in most fields the reduction is less pronounced in private industry.

Comparing across levels of schooling we note that scientists who are employed in private industry enjoyed a similar rate of growth in starting salaries (4 percent) whether they have a B.A. or a Ph.D. degree; scientists with an M.A. degree fared a little better. Disaggregating by field we were unable to discern a consistent pattern of higher rate of increase in starting salaries for higher levels of schooling as one would expect under the vintage hypothesis.

On the other hand there is a distinct tendency for the year of highest degree experience interaction to increase with the level of degree. It appears that there is a "catching up" phenomenon whereby the increase in the vintage effect by level of schooling is observed only after some years of experience.

Two other major sources of differences in starting salaries are associated with the choice of level of schooling and type of employer. As we have already indicated, the effects of these factors tend to interact with the year of entry into the labor force, either due to systematic vintage effects or as a reflection of changing market conditions and imperfect substitution in the short run among various types of human capital. Choosing 1970 as a reference year, we see that a scientist with a Ph.D. can increase his starting salary by 28 percent if he chooses to work in private industry. A scientist who plans to work in private industry and who acquires a Ph.D. (at age 26) will have a starting salary which is 42 percent higher than that of a B.A. (at age 22). The corresponding difference for an M.A. degree (at 23 versus a B.A. at 22) is 21 percent.

Differences in starting salaries across fields appear to be relatively less important. Using again 1970 for comparison, we see that scientists with Ph.D.s (age 26) who are employed in academic institutions could expect the highest starting salary in psychology. The lowest starting salary would be in chemistry, with a difference of 18 percent. The range of the differences across field remained the same, but the structure varied during the period. In 1960 psychology again had the highest starting salary, while biology had the lowest. The difference in this case is about the same, 19 percent. As seen, there is considerable variation in the <u>growth</u> of starting salaries during the period. The lowest growth is observed in physics and agriculture, while in mathematics and biology we note a relatively high rate of growth.

We finally note the role of some other variables which affect starting salaries. Both predegree experience and age at highest degree appear to have a similar positive effect on starting salary. A one year postponement of acquiring the Ph.D. degree will increase starting salary not only by the general growth and vintage effect but also by an additional 1 percent. If the scientist also accumulates some predegree work experience the additional effect will be 2 percent. These effects can be attributed to some positive accumulation of knowledge while holding the level of degree constant, but they are considerably smaller than the effects of learning from experience after the acquisition of a degree. It is also seen that female M.A. and Ph.D. scientists can expect a starting salary which is about 12 percent less than that of males.[15/] Obtaining a degree from a school which is ranked among the top ten does not have a significant or systematic effect on the level of starting salaries.

One of the main lessons which is to be learned from the human capital approach to the analysis of earning is that the focusing on starting salaries to the exclusion of later effects of individual choices may lead to highly misleading conclusions. Generally we would expect some trade-off between current and future earnings, and it is therefore important to examine also the effects of the various explanatory variables on the slope of the earnings profile after the entry into the labor force.

For the purpose of describing the various effects on the growth of earnings we will choose as a reference group scientists with Ph.D.s in academic employment (all fields) who received their degrees in 1958. We will further restrict ourselves to the case where no breaks in the accumulation of experience occur so that the scientists' age and experience increase simultaneously with the passage of time.[16/] Then, apart from specific (cyclical) year effects, the expected growth in earnings of the reference group is governed by the equation:

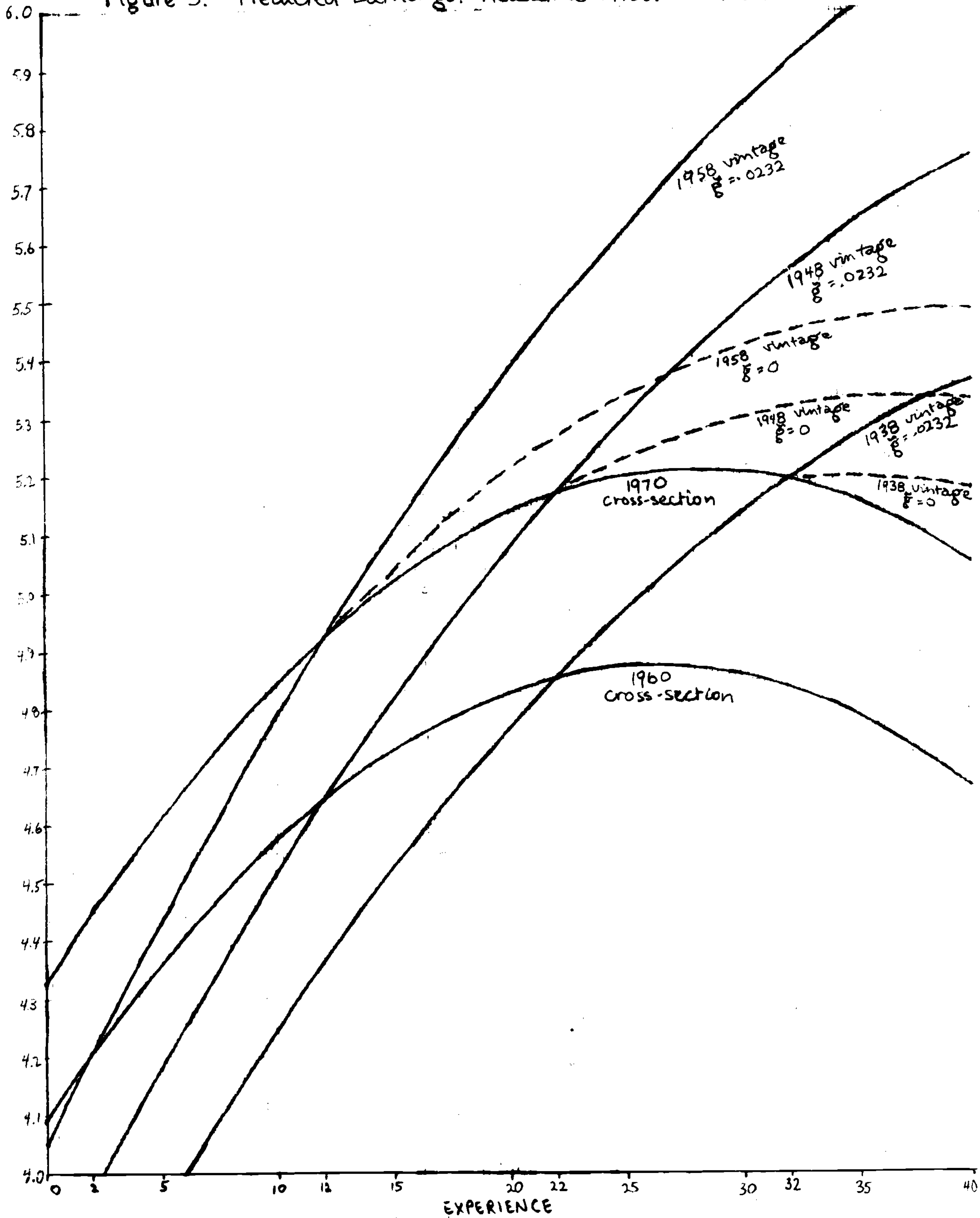
$$(27) \quad \frac{d \ln Y}{dt} = .023 + .0639 - .00146 \text{ (Age-22)}.$$

The first constant on the R.H.S. of equation (27) is an estimate of the real growth in starting salaries.[17/] It can be viewed as an upper bound on the exogenous change in the rental price of human capital. Similarly the second constant, which is the coefficient of postdegree experience in Table 2, can be viewed as a lower bound for the initial effects of experience on the growth of earnings (see equation 24). The sum of the two coefficients provide an exact estimate of the combined effects of experience and growth.

As seen, the 1958 vintage enjoyed very substantial increases in real earnings during the sixties. The predicted rate varied from 7.8 percent in 1960 (assuming that the Ph.D. degree was obtained at age 26) to 6.4 percent in 1970. This reduction in the rate of increase in the rate of growth reflects the effects of aging and the concavity of individual earnings profiles. The actual reduction in the rate of growth was probably higher due to the changes in demand during the decade.

The striking aspect of equation (27) is that even under the conservative assumption that scientists will not enjoy any real increase in the rental price of their human capital, we still would not predict a peaking of the individual profile of the 1958 or later vintages during their working lifetimes. These results are in contrast to the observed downturn in cross section profiles. In Figure 5 we draw some selected cross section profiles and individual (cohort) profiles which are predicted by our pooled regression with various assumptions on the real growth rate. Specifically, the solid vintage profiles present the assumption that growth will follow the trend of the sixties. The broken vintage profiles present the assumption that from 1970 onwards exogenous growth will stop. Starting with 1970 and thereafter we thus put the growth in starting salaries $\tilde{g}$ to zero to obtain a lower bound for the experience

Figure 5. Predicted Earnings. Academic PhDs. All fields.



effect. As seen, the cross section profiles tend to peak after 26 or 27 years of experience, and they are considerably flatter than the profiles of any given vintage. The difference reflects vintage effects both in school and on the job. The latter effect is captured by the positive interaction between year of highest degree and postdegree experience (see Table 2). This interaction is the cause of the two related tendencies of later vintages to have steeper profiles, and of later cross sections to be steeper and to peak later.

Some scientists in the sample report their years of professional experience to be less than the number of years which passed since they obtained their highest degree. We may interpret the difference as a temporary break in the accumulation of experience due to, say childbirth by a woman scientist. Allowing the break to vary while holding age at highest degree and experience constant, we obtain:

$$(28) \quad \frac{d \ln Y}{dt} = .023 + .025 - .00146 \times \text{postdegree experience.}$$

As seen, unless experience is quite high, a scientist who suffers a break in the accumulation of experience will reenter the labor force at a higher wage. Of course, the gain in earning power is less than that of an otherwise identical scientist who did not drop from the labor force,[18/] but the size of the gain which is at least 2.5 percent per year still seems surprisingly high. It seems likely that at least some of the scientists who reported professional work experience to be less than their years since highest degree did not withdraw completely from the labor force. Instead, they may have been in some other occupation and accumulated experience which though not perfectly transferable is nevertheless useful in their main occupation.

Estimation of the age and experience effects from the younger (less than 50) group of scientists (see Table 2) retains the qualitative pattern of the coefficients, but some of the age related effects are affected. In particular, the concavity of the age log earnings profile tends to increase. It appears that there is considerable variation in the age at which investment in human capital stops. Such a variation leads to a flattening of the observed average earnings profile at older ages. Alternatively, the differences may reflect some omitted variables which are age related, such as hours of work, for instance.

In order to compare the slope of the earnings profile in the different fields, we may evaluate equation (27) at some common age level. The expected rates of growth for scientists of the reference vintage (1958) at age 42 (which is the mean age for the Ph.D.'s sample) are:

.0195 + .0266 in agriculture,

.0257 + .0388 in biology,

.0207 + .0360 in chemistry,

.0244 + .0367 in earth sciences,

.0273 + .0328 in mathematics,

.0178 + .0381 in physics,

.0226 + .0276 in psychology.

Again, the first number in each pair provides an estimate of the upper bound for the growth in the rental price of human capital and the second as an estimate of the lower bound of the effects of experience at that age. As seen, the effects of experience tend to be large in biology, physics, and chemistry and relatively low in agriculture and psychology. These last two fields provide a sharp example for the trade-off between future and current earnings in that high starting salaries are associated with low experience effects. It appears that fields differ in the trade-off which they offer between current and future earnings. In fields with considerable amounts of joint research where highly experienced scientists and new entrants can combine their research effort there is more opportunity for young scientists to invest in on-the-job training. This is reflected in relatively large numbers of young scientists who report research as their primary work activity in fields like chemistry, physics, and biology.[19] Such fields are likely to have a larger coefficient of experience.

Comparing across levels of schooling for scientists of the 1958 reference vintage who are employed in private industry, the expected rates of growth at age 42 are:

.0123 + .0287 for Ph.D.s,

.0189 + .0252 for M.A.s,

.0137 + .0207 for B.A.s.

As seen, for a given age level there is a distinct tendency for the slope of the age earnings profile to decrease with the level of schooling. Again, these coefficients are underestimates of the effects of the accumulation of experience; taking into account the difference in the vintage effects by level of schooling, the discrepancy in slope is in fact larger. These differences are consistent with the view that scientists with a higher level of education invest more in on-the-job training. This may be a result of either better access to the capital market or higher learning ability.

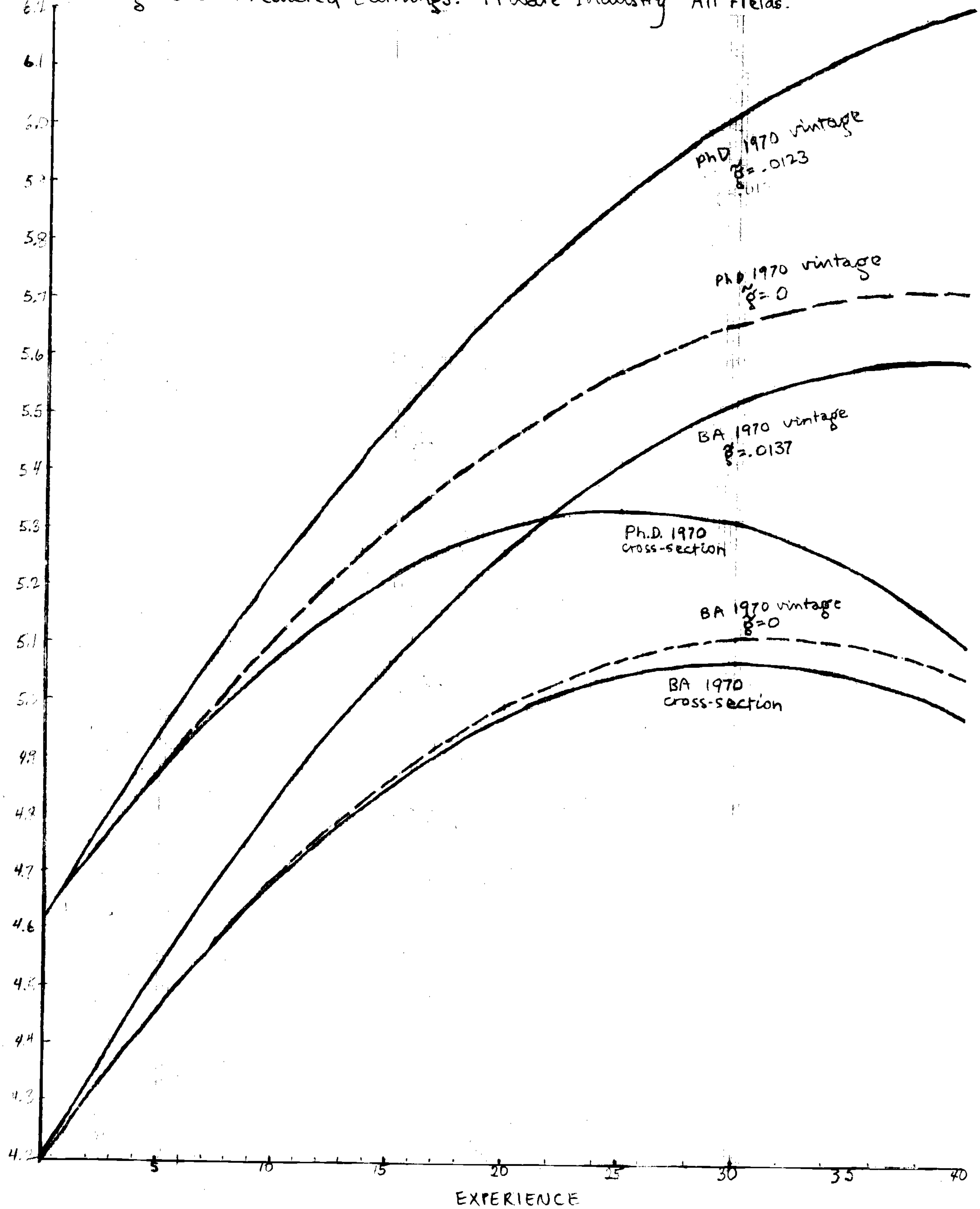
As we have pointed out, there appears to exist a positive interaction between year of highest degree and experience in their effect on earnings. This tendency, however, is not uniform across fields or level of schooling. The interaction effects tend to be relatively strong in physics and weak in agriculture and psychology. They also tend to decrease with the level of that schooling. The interaction is virtually absent among B.A.s. It appears that among scientists with B.A. degrees the advances in knowledge are spread relatively uniformly across various levels of experience. The reason is probably that their schooling and experience tend to be more general and less oriented toward new techniques.

In Figure 6 we plot the 1970 cross section profiles for scientists with Ph.D. and B.A. degrees in private industry. We also draw the predicted earnings of the 1970 vintages of Ph.D.s and B.A.'s, again under the two alternative assumptions on real growth in earnings: (1) Real earnings will continue to grow as during the sixties; (2) growth will stop. In the second case the broken lines in the diagram describe the lower bound of growth in earnings. As seen, due to the stronger vintage effects for Ph.D.s their cross section profile tends to be somewhat flatter and to peak earlier. At the same time the vintage profile of the Ph.D. scientist tends to be steeper. It is clear from the diagrams that a rate of return for schooling which is calculated from the comparison of two cross sections will tend to underestimate the true differential in lifetime earnings.

Given the rather strong implications of the assumption that vintage effects exist in on-the-job investment, it is important to test the robustness of our estimate of the years of highest degree-experience interaction. As I have already indicated, in a short period of observation such as 10 years, it is difficult to separate the effects which are due to differences in experience from the effects which are due to the chronological year at which the highest degree was obtained. For that reason a restriction was used which amounted to stating that given the age of the scientist, changes in the age of highest degree as such (or in break) have no effect on the expected slope of his earnings profile. If there is an associated change in the year of highest degree, all the effect on the slope is ascribed to it. It is, of course, possible that this is a faulty specification, and it would be useful to examine at least one alternative specification, especially since this alternative is frequently used by other researchers.

I have therefore estimated equation (25) also in its unrestricted form. For the sake of brevity I will not present the full results here, but merely

Figure 6. Predicted Earnings. Private Industry All Fields.



indicate the main findings. In all subsamples there are strong age effects which are reflected in significant negative interactions for age at highest degree and "break" with experience. (Recall that the square of postdegree experience is also included.) With respect to the identification of the vintage effects we encounter a considerable degree of multicollinearity. In most fields the result is an insignificant effect for either postdegree experience^2 or the interaction of year of highest degree with experience. This interaction tends to be somewhat smaller than that of the restricted equation in those fields (chemistry and physics) in which the effects can be separated. Associated with these changes is a slight increase in the coefficients of the sample year. The unrestricted model thus predicts that the effects of growth are more uniformly distributed across levels of experience, indicating smaller vintage effects. The direction of the interaction between year of highest degree and experience tends to remain positive. In terms of Figure 5 the unrestricted version produces identical cross section predictions, but the cohort predictions tend to be flatter than in the restricted case.

A somewhat different test of robustness arises from the question whether the apparent positive interaction between experience and year of highest degree reflects conditions which are specific to the decade 1960-1970. In particular, one may think that in a period of reduction in demand such as occurred in physics, scientists of different experience levels are affected differently. Probably the hardest hit will be new entrants and we shall thus find an increase in the experience earnings differentials which we misinterpret as a change in the slope of individual profiles. A rudimentary test of this possibility can be performed by estimating the earnings function separately for the periods 1960-1966 and 1966-1970, since the two periods had rather different demand conditions. Performing this test I found that the interaction of year of highest degree with experience is positive also within each subperiod; in fact, it tends to be stronger in the period 1960-1966.

It seems clear that further study is required in order to identify the size and the sign of the experience-year of highest degree interaction. Our attempts for such an identification are inescapably restricted by the short length of the period. Hopefully we shall be able to obtain sharper estimates with the use of longitudinal data.[20/]

We shall conclude with a brief discussion of the effects of sex and quality of school on the slope of the earnings profile. Despite the relatively small number of women in the sample we are able to identify a significant reduction in the slope of the earnings profile for females. Similar results were reported by Johnson and Stafford [1974]. It is interesting to note, however, that the reduction persists even when one controls for breaks in the accumulation of experience.

Surprising is the fact that being ranked among the top ten schools appears to have little effect on the earnings profiles. The only fields in which we find the expected positive interaction between quality and experience to be significant are physics and mathematics. This is a troubling finding since if quality effects are weak, why should we expect vintage effect to be important?

A possible explanation is that there is a learning and selection process whereby employers are initially paying more to the holders of Ph.D.s from prestigious universities, since without any additional information they are presumed to be more productive. However, as experience accumulates employers learn to separate the wheat from the chaff in both groups and the wage differences among those actually employed in the two groups are reduced. For that reason one may overestimate the expected slope of the scientists from low quality schools and underestimate that of scientists from top ranked schools. A similar argument, by the way, may lead us to underestimate the vintage effects.

Conclusions

An attempt was made in this study to explain earnings differentials among American scientists within the confines of a rather narrowly specified model. We thus related differences in the level and the rate of growth in earnings to differences in occupation, type of employer, age, experience, and schooling level. Our basic presumption was that such observed relations can be interpreted to some extent as reflecting individual differences in investment behavior.

The basic principle that individuals can at some cost increase their future earnings and that consequently observed earnings differentials and changes in them contain a voluntary and potentially predictable element is probably widely accepted. There may be a considerable difference of opinion, however, as to the specification of the degree of competitiveness of the labor market, the importance of borrowing constraints, the quality of information which is available to employer and employees, and the relative importance of nonmonetary considerations. As the reader probably observed, we assumed that decisions are made under conditions which, though convenient to the researcher, are not necessarily the best first approximation to "reality." We thus assumed that the individual earning capacity, though not directly observable to the researcher, is known to employer and employee, that markets are sufficiently competitive to make general training a feasible alternative, that individuals can borrow freely on account of their future earnings, and that the effects of uncertainty and nonmonetary differentials are negligible. The problem, of course, is how to incorporate such elements in a sufficiently precise fashion so as to generate testable hypotheses.

It should be recognized that in the present context the choice of specification is extremely difficult since we do not observe the investment process directly. We only observe its outcomes in the form of earnings. The promotion of unobservables such as human capital, permanent income, or ability to a central theoretical role put a heavy burden on the empirical researcher. A partial solution is to use data on the same individuals observed over a period of time to estimate the model in a differential form (e.g. equation 15). I am currently working on such an estimation, using the earnings of the same scientists during the period 1960-1970.

Appendix

The purpose of this appendix is to derive equations 8 to 11, 15 and 18 in the text. We shall reverse the order of the exposition and start with the more general case in which age and time effects are included.

The problem can be written as:

$$\text{(A1)} \quad \max_{0\le x\le 1} \mathcal{H} = D(\mu+\tau)R(\mu+\tau)K\left[\, g(x) + \psi(a_\mu(\tau)\, x - \delta)\,\right]$$

where,

$$\text{(A2)} \quad g(x) = \left[\, 1 - \frac{a_\mu(\tau)}{\beta_\mu(\tau)}\, x \,\right]^\alpha \qquad \text{for } 0 \le x \le x_0$$

$$= \left[\, 1 - \frac{a_\mu(\tau)}{\beta_\mu(\tau)}\, x_0 \right]^\alpha - \frac{\alpha a_\mu(\tau)}{\beta_\mu(\tau)}\left[\, 1 - \frac{a_\mu(\tau)}{\beta_\mu(\tau)}\,\right]^{\alpha-1} x \qquad \text{for } x_0 \le x \le 1$$

The assumption that the functions $a_\mu(\tau)$ and $\beta_\mu(\tau)$ are proportional to each other guarantees that $g(x)$ is independent of τ.

We denote by $D(\mu+\tau)$ the market discount factor for future earnings so that $\frac{\dot{D}}{D} = -r_{\mu+\tau}$. Similarly we denote $\frac{\dot{R}}{R} = \hat{g}_{\mu+\tau}$.

The necessary conditions for optimums are:

$$\text{(A3)} \quad g'(x) + a_\mu(\tau)\psi \ge 0 \text{ if } x_0 \le x \le 1$$

$$g'(x) + a_\mu(\tau)\psi \le 0 \text{ if } x = 0$$

$$g'(x) + a_\mu(\tau)\psi = 0 \text{ if } 0 < x < x_0$$

and

$$\text{(A4)} \quad \dot{\psi} = [r_{\mu+\tau} + \delta - \hat{g}_{\mu+\tau}]\,\psi - \psi a(\tau)x - g(x), \qquad \psi(T) = 0.$$

In the case of an interior solution we can take the derivative of the first order condition with respect to age to obtain a differential equation for x.

$$\text{(A5)} \quad \dot{x} = \frac{g'(x)}{g''(x)}\left[r_{\mu+\tau} + \delta - \hat{g}_{\mu+\tau} - \gamma_\tau \right] - \left[\frac{-g(x) + xg'(x)}{g''(x)} \right] a(\tau)$$

where $\gamma_\tau = -\frac{\dot{a}}{a}$ is the rate of decay in learning ability. The rate of increase in observed earning is given by

$$\text{(A6)} \quad \frac{\dot{Y}}{Y} = \hat{g}_{\mu+\tau} + \frac{\dot{K}}{K} + \frac{g'(x)}{g(x)}\,\dot{x} = \hat{g}_{\mu+\tau} + a(\tau)\,x - \delta + \frac{g'(x)}{g(x)}\,\dot{x}$$

and substituting for $\dot{x}$ we obtain

$$\text{(A7)} \quad \frac{\dot{Y}}{Y} = \hat{g}_{\mu+\tau} + a_\mu(\tau)x - \delta + \frac{g'(x)}{g(x)}\frac{g'(x)}{g''(x)}\left[r_{\mu+\tau} + \delta - \hat{g}_{\mu+\tau} - \gamma_\tau \right]$$

$$- \frac{g'(x)}{g(x)}\frac{g'(x)}{g''(x)}\left[\frac{-g(x) + xg'(x)}{g'(x)} \right] a_\mu(\tau)\,.$$

Under the special functional form (A2):

$$\text{(A8)} \quad \frac{[g'(x)]^2}{g(x)g''(x)} = \frac{\alpha}{\alpha-1} \quad \text{and} \quad \frac{-g(x) + xg'(x)}{g'(x)} = \frac{\beta_\mu(\tau)}{\alpha a_\mu(\tau)} + \frac{x(\alpha-1)}{\alpha}\,;$$

hence

$$\text{(A9)}\quad \frac{\dot{Y}}{Y} = \hat{g}_{\mu+\tau} - \delta + \frac{\alpha}{1-\alpha}\left[r_{\mu+\tau} + \delta - \hat{g}_{\mu+\tau} - \gamma_{\tau} \right] + \frac{\beta_{\mu}(\tau)}{1-\alpha}$$

Equation 10 is a special case with $\hat{g} = \gamma = 0$ and β and r are constant. Equation 15 is a special case with $\hat{g} = 0$ and γ and r are constant. Equation 18 is a special case in which $\gamma = 0$ and β is independent of age.

Let us now turn to the static case assuming no age effects and determine the <u>length</u> of each of the phases in the individual investment program. During the last phase of zero investment we have:

$$\text{A10}\quad \dot{\psi} = (r+\delta)\psi - 1 \qquad \text{and} \qquad \psi(\tau) = \frac{1}{r+\delta}\left[1 - e^{-(r+\delta)(T-\tau)} \right]$$

the age of the peak in earnings is determined by the condition:

$$\text{A11}\quad \psi(\tau_1) = \frac{-g'(0)}{a} = \frac{1}{r+\delta}\left(1 - e^{-(r+\delta)(T-\tau_1)}\right)$$

or

$$\text{A12.}\quad T-\tau_1 = \frac{-1}{r+\delta}\ln\left(1 - (r+\delta)\frac{\alpha}{\beta}\right)$$

To determine the length of the investment on the job phase, we have to solve equation 11 and use the boundary conditions in equation 12.

Define $q = y^{1/\alpha} = 1 - \frac{a}{\beta}x$, then equation 11 in the text can be rewritten as:

$$\text{(A13)} \quad \dot{q} = Aq + Bq^2 \text{ where } A = \frac{\beta-r-\delta}{1-\alpha} \text{ and } B = \frac{\beta}{\alpha};$$

with the solution:

$$\text{(A14)} \quad \tau-\tau_0 = \frac{1}{A}\left[\ln\frac{q}{A+Bq} - \ln\frac{q_0}{A+Bq_0}\right];$$

using the boundary conditions we obtain:

$$\text{(A15)} \quad \tau_1-\tau_0 = \frac{-1}{A}\left[\ln(A+B) + \ln\left(\frac{q_0}{A+Bq_0}\right)\right].$$

The schooling (or specialization period) is then found as a residual using the identity:

$$\text{(A16)} \quad \tau_0 = T - (T-\tau_1) - (\tau_1-\tau_0).$$

Equation A14 can be also used to derive an explicit solution for the investment profile. This solution assumes the form:

$$\text{(A17)} \quad y^{1/\alpha} = \frac{Ae^{A(\tau-\tau_0)}}{C - Be^{A(\tau-\tau_0)}} \text{ where } C = \frac{A+Bq_0}{q_0}.$$

Footnotes

1. It is possible that there exist an automatic process of learning from experience which is to some extent independent of individual decisions (that is, g(x) approaches 1 at a positive $\frac{\dot{K}}{K} + \delta$). In such a context the theory only explains differences in the slope of the earnings profiles in terms of differential investment. It is clearly not necessary to assume positive investment for the purpose of explaining a positive slope of the earnings profile.

2. Using equation (7) in the text we obtain

$$\frac{\partial \tau_0}{\partial a} = -\frac{1-\alpha}{\beta-r-\delta}\left[\frac{1}{(a-r-\delta)} - \frac{1}{(a-\beta)}\right] = -\frac{1-\alpha}{\beta-r-\delta}\left[\frac{r+\delta-\beta}{(a-r-\delta)(a-\beta)}\right] > 0.$$

3. It is now useful to use the notation of the appendix and to rewrite equation (9) as:

$$\tau_0 = T - \frac{1}{A}\ln\left[\frac{A+Bq_0}{(A+B)q_0}\right] + \frac{1}{r+\delta}\ln\left(1 - \frac{r+\delta}{B}\right)$$

where $A = \frac{\beta-r-\delta}{1-\alpha}$, $B = \beta/\alpha$, $q_0 = \frac{\alpha}{1-\alpha}\left(\frac{a}{\beta} - 1\right)$.

Note that $A + Bq_0 = \frac{a-r-\delta}{1-\alpha}$ is independent of β. We thus have:

$$\frac{\partial \tau_0}{\partial \beta} = \frac{1}{A^2}\ln\left(\frac{A+Bq_0}{(A+B)q_0}\right) + \frac{1}{A}\left(\frac{1}{A+B}\left(\frac{dA}{d\beta} + \frac{dB}{d\beta}\right) + \frac{1}{q_0}\frac{dq_0}{d\beta} + \frac{1}{B^2-(r+\delta)B}\frac{dB}{d\beta}\right.$$

After some manipulations we arrive at:

$$\frac{\partial \tau_0}{\partial \beta} = \frac{1}{A^2(1-\alpha)}\left[\ln\left(\frac{A+Bq_0}{(A+B)q_0}\right) - \frac{A}{Bq_0}(1-q_0)\right].$$

Due to the concavity of the log function,

$$\ln\left(\frac{A+Bq_0}{(A+B)q_0}\right) < \frac{A+Bq_0}{A+B} - 1 = \frac{A(1-q_0)}{(A+B)q_0}.$$

It follows that:

$$\frac{\partial \tau_0}{\partial \beta} < \frac{1}{A^2(1-\alpha)} \left[\frac{A(1-q_0)}{(A+B)q_0} - \frac{A}{Bq_0}(1-q_0)\right] < 0.$$

4. The relation between the form of $g(x)$ and the concavity of the log earning profile during the investment period is given by:

$$\ddot{z} = [\dot{x}]^2 F(x)$$

where $z = \ln Y$ and

$$F(x) = 2\frac{g''}{g} - \frac{g'''g'}{g''g} - [\frac{g'}{g}]^2 .$$

When $g(x) = (1 - \frac{a}{\beta}x)^\alpha$, then $F(x) = 0$ for all x.

For any function $g(x)$ such that $g > 0$, $g' < 0$, $g'' < 0$, a sufficient condition for $F(x) < 0$ and thus $\ddot{z} < 0$ is that $g''' \geq 0$.

For a detailed discussion of the case in which $g''' = 0$, see Rosen [1975]. Needless to say, under our specification $g''' < 0$.

5. An implicit assumption in this formulation is that individuals with different levels of skills are <u>perfect</u> substitutes in production. There is thus a single rental rate.

6. If the state of knowledge is a function of past investment of all generations, then this process implies a discrepancy between the private and social returns for investment in human capital (see Arrow [1962] and Levhari [1966]). Thus even if one may express doubts as to the importance of educational externalities within a generation, they are probably important within an intergenerational context.

7. For the sake of simplicity we ignored in the analysis the direct costs of the training process. If all costs are the opportunity costs of the individual (e.g. a new worker in the firm observes the others work without affecting their productivity), then changes in the rental rate of

human capital will not affect investment decisions. In the more realistic with direct costs the reduction in the rental rate will also put a check on the tendency for increased investment. The probable increases in the marginal cost of teaching will provide a further check.

8. The simple correlation between experience and being in private industry is .032 for Ph.D.s in all fields. The correlation between government employment and experience is .007.

9. Strictly speaking we can determine the effects of such breaks in career only if their timing is known. Consequently, equation (25) and the associated unrestricted form should only be viewed as an approximation. More specifically, let there be a break ε at time τ_1; then equation (17') should have the form

$$(17') \qquad \ln Y(\tau) \cong \ln Y(\tau_0) + \frac{1}{1-\alpha}\left[\beta_0 - \alpha\left(r + \frac{\delta}{\alpha} - \gamma\right)\right](\tau-\tau_0-\varepsilon) + \frac{\beta_0}{1-\alpha}\left[2\tau - (\tau-\tau_0-\varepsilon)\right](\tau-\tau_0-\varepsilon) + \frac{\tau_0}{1-\alpha}\,2\varepsilon(\tau_0-\tau_1).$$

The last term is not included in our specification. The error is likely to be larger (in absolute value) the later is the break.

10. Strictly speaking, we estimate a simplified version of equation (25), in which all higher than second order interactions are omitted. For instance, we omit the age by year of highest degree by experience interaction.

11. The indicator is missing for 1960, and we imputed for it the appropriate means from the 1966 and 1970 data.

12. Predegree experience is defined to be experience minus years since degree if the difference is positive. It is defined to be zero otherwise. It should be pointed out that in the cases in which the difference is positive but there is a break in career after the acquisition of the degree, then we in fact obtain true predegree experience minus break rather than predegree

experience alone. We cannot discover the existence of such breaks from the data. The only case in which a break is revealed is when reported experience is less than years since degree.

13. This is a phenomenon which requires explanation. There are clearly demand considerations which require that a teacher in academic institutions be at least as trained (or as selected) as the students which he produces. There are, however, some supply considerations as well. The more educated are more willing to forego the monetary advantage of private industry for the non-monetary advantage of educational institutions (see Weiss [1974]).

14. Partially this is a reflection of errors in reporting experience. My initial processing of the longitudinal data reveals conflicting reports of experience at different years by the same individual.

15. It would be interesting to interact this effect with time. But given the small number of women in the sample our treatment of the male-female differential is somewhat casual. For a detailed analysis, see Johnson and Stafford [1974b].

16. With respect to the remaining controls we assume that preexperience is zero, sex is male, and degree is from a school not ranked in the top ten.

17. We use as an estimate the coefficient for the 1970 sample divided by 10. A more efficient estimate, one which would incorporate the information on the rate of change between 60 and 66, would be to impose a restriction that the rate of growth is constant and reestimate equation (26). The marginal effect of such a procedure turned out to be negligible.

18. In agriculture and biology the estimate for the coefficient of break is suspiciously high. It indicates a very slight or negative advantage to a continuous accumulation of experience in these fields.

19. The proportions of scientists with less than 10 years of experience, who in 1970 reported their primary work activity as research are (by field):

Agriculture	.262
Biology	.485
Chemistry	.494
Earth sciences	.235
Mathematics	.244
Physics	.581
Psychology	.290.

20. In physics we have initial estimates which are derived from pooling six cross sections in which each of the physicists is observed six times. The results for the restricted form are extremely close to the results reported here. For the unrestricted form we obtain a considerably higher estimate for the year of highest degree-experience interaction. The lower stability of the unrestricted form reflects the multicollinearity problem.

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