Volume Title: Schooling, Experience, and Earnings

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Volume Publisher: Columbia University Press

Volume ISBN: 0-870-14265-8

Volume URL: http://www.nber.org/books/minc74-1

Publication Date: 1974

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Chapter URL: http://www.nber.org/chapters/c1767

Chapter pages in book: (p. 83 - 96)

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The Human Capital Earnings Function

5.1 EMPIRICAL SPECIFICATION

The interpretation of age and experience profiles of earnings as consequences of investment behavior makes it possible to expand the schooling model to include post-school investments in an econometric analysis of the distribution of earnings.

The importance of the life-cycle distribution of post-school investments in creating earnings inequality is empirically quite obvious: As Charts 4.1–4.3 show, annual earnings nearly double after two to three decades of experience in each schooling group, a differential almost as great as that between the earnings of males with 8 and 16 years of schooling. It is, of course, known from previous work, not tied to human capital analysis, that the inclusion of age in addition to schooling in a multivariate regression analysis of earnings increases the explanatory power of the analysis. It is also known that since age interacts with schooling in affecting earnings (in dollars and in logs), a linear additive form of regression without interaction terms is not adequate. Now, we have not only obtained a behavioral interpretation of this interaction but also noticed that there is less of an interaction, if any, between experience and schooling than between age and schooling: experience profiles of log earnings are much more nearly parallel than age profiles. If so, in an earnings function in which earnings are logarithmic, years of work experience should be entered additively[1] and in arithmetical form. The experience term is, of course, not linear, but concave. For example (see formulation 5.2a, below) the earnings function might be parabolic in the experience term:

$$\ln E_t = \ln E_s + \beta_1 t - \beta_2 t^2,$$

where t is years of experience and E_s is earning capacity after completion of schooling. Since

$$\ln E_s = \ln E_0 + rs;$$

$$\ln E_t = \ln E_0 + rs + \beta_1 t - \beta_2 t^2.$$

If work experience is continuous and starts immediately after completion of schooling, then work experience is equal to current age minus age at completion of schooling; $t = (A - s - b)$, where A is current age and b is age at the beginning of schooling. Thus, the use of age alone instead of experience in the earnings function results in the omission of some variables, as can be seen if the expression for t, above, is substituted in the function:

$$\ln E_t = \ln E_0 + rs + \beta_1(A - s - b) + \beta_2(A - s - b)^2.$$

The quadratic term leaves out an age-schooling interaction variable (As). What is more, the partial omission of s leads to a change in its coefficient which can no longer be interpreted as a rate of return to schooling.[2]

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1. The possibility of interaction between experience and schooling is explored in the regression analysis in the next section.

2. The coefficient is biased downward. A simplified example is (cf. Griliches and Mason, 1972):

$$\ln Y = \alpha_0 + \alpha_1 s + \alpha_2 A.$$

Neglecting the quadratic term also in the alternative specification

$$\ln Y = \alpha + rs + \beta t,$$

and substituting $t = (A - s - b)$, yields

$$\ln Y = (\alpha - \beta b) + (r - \beta)s + \beta A.$$

Thus α_1 is an underestimate of r.

The proper form of the experience function depends on the form of the life-cycle investment function. The economic theory of optimizing behavior implies that investment in human capital declines over the life cycle, at least beyond an early stage. Apart from this, economic theory provides no guidance to the specific form of the investment function. Accordingly, a few simple specifications of investment profiles are introduced here. From these, earnings functions are derived which are applied, in the next section, to the individual data in an analysis of the entire cross section of male earnings in 1959.

Mathematical simplicity and statistical tractability call for a consideration of linear and log-linear experience functions (profiles) of net dollar investments (C_t) and "time-equivalent" investment ratios (k_t). Four simple specifications are considered:

$$C_t = C_0 - \frac{C_0}{T}t \tag{5.1}$$

$$C_t = C_0 e^{-\beta t} \tag{5.3}$$

$$k_t = k_0 - \frac{k_0}{T}t \tag{5.2}$$

$$k_t = k_0 e^{-\beta t} \tag{5.4}$$

C_0 and k_0 are the instalments of investment and investment ratios during the initial period of experience, $t = 0$. T is the total period of positive net investment;[3] e, the base of natural logs; and β, a parameter indicating the rate of decline of investment.

It is convenient, at this point, to treat the investment and earnings functions as continuous functions of time. The "gross" dollar earnings function is:

$$E_t = E_s + r_t \int_{j=0}^{t} C_j dj, \tag{a}$$

where E_s denotes earnings obtainable after s years of schooling with no further investments, and r_t is the rate of return to post-school investment, which is assumed to be equal in all periods t.

The logarithmic version is:

$$\ln E_t = \ln E_s + r_t \int_{j=0}^{t} k_j dj. \tag{b}$$

3. T need not be specified a priori. It is implicit in the statistically estimated parameters.

By substitution of specifications (5.1) and (5.3) into the arithmetical earnings function (a), and (5.2) and (5.4) into the logarithmic function (b), the earnings functions are transformed from functions containing investment variables (C_t or k_t) that cannot be observed into functions of years of experience,[4] which can be observed and can therefore be used in empirical analysis. Since observed earnings are more akin to "net" earnings (Y_t) than to "gross" earnings, E_t must first be transformed into Y_t by letting $Y_t = E_t - C_t$, and $\ln Y_t = \ln E_t + \ln (1 - k_t)$.

I now derive the empirically observable earnings functions corresponding to the four specifications of investment profiles:

1. The assumption of a linear decline in dollar net investments yields the gross earnings function:

$$E_t = E_s + rC_0 t - \frac{rC_0}{2T} t^2; \tag{5.1a}$$

and the net earnings function:

$$Y_t = (E_s - C_0) + C_0 \left(r + \frac{1}{T}\right) t - \frac{rC_0}{2T} t^2. \tag{5.1b}$$

Here both the dollar earnings profiles are parabolic in years of experience (t). Note also that the time derivative of E_t and Y_t, that is, the dollar increment of earnings, is a linearly declining function of time.

2. If the investment ratio is assumed to decline linearly, the gross log-earnings function becomes parabolic:

$$\ln E_t = \ln E_s + rk_0 t - \frac{rk_0}{2T} t^2; \tag{5.2a}$$

and the net earnings function becomes:

$$\ln Y_t = \ln E_s + rk_0 t - \frac{rk_0}{2T} t^2 + \ln (1 - k_t). \tag{5.2b}$$

In this case, the logarithmic increment in earnings is only approximately a linear declining function of time.

4. Years of experience were directly observed in the AEA study of economists' earnings. Direct information is, unfortunately, not available in the Census data. In the current study, therefore, the "observable" is only an imperfect estimate. Its construction was shown in columns 1 and 3 of Table 3.1.

3. If dollar investments decline exponentially with increased experience, then the earnings functions are:

$$E_t = E_s + \frac{rC_0}{\beta} - \frac{rC_0}{\beta} e^{-\beta t} \tag{5.3a}$$

and

$$Y_t = E_s + \frac{rC_0}{\beta} - \frac{(r+\beta)C_0}{\beta} e^{-\beta t}. \tag{5.3b}$$

Here, both dollar earnings and dollar increments of earnings are exponential in t. The logarithm of the increment is linear, since

$$\frac{dY_t}{dt} = (r+\beta)C_0 e^{-\beta t}. \tag{5.3c}$$

In discrete form:

$$Y_{t+1} - Y_t = \frac{(r+\beta)C_0}{\beta} e^{-\beta t}(1 - e^{-\beta}).$$

Let $e^{-\beta} = \gamma$ and $E_s + (rC_0/\beta) = E_p$ (peak earnings). Then

$$Y_{t+1} - Y_t = (1-\gamma)(E_p - Y_t)$$

and

$$Y_{t+1} = (1-\gamma)E_p + \gamma Y_t. \tag{5.3d}$$

According to (5.3d), dollar earnings follow a first-order linear autoregression.

4. Finally, if the investment ratio declines exponentially, then the earnings functions are:

$$\ln E_t = \ln E_s + \frac{rk_0}{\beta} - \frac{rk_0}{\beta} e^{-\beta t} \tag{5.4a}$$

and

$$\ln Y_t = \ln E_s + \frac{rk_0}{\beta} - \frac{rk_0}{\beta} e^{-\beta t} + \ln(1 - k_0 e^{-\beta t}). \tag{5.4b}$$

The gross earnings function (5.4a) is the familiar modified Gompertz curve. The percentage increments $d(\ln E_t)/dt$ are exponential, while $d(\ln Y_t)/dt$ are approximately so.

Here also:

$$\ln E_{t+1} - \ln E_t = (1-\gamma)(\ln E_p - \ln E_t) \tag{5.4c}$$

and

$$\ln E_{t+1} = (1-\gamma)\ln E_p + \gamma \ln E_t. \tag{5.4d}$$

The Gompertz earnings function (5.4c) is equivalent to a Koyck adjustment equation in logs (5.4c) and follows a log-linear first-order autoregression (5.4d). The net earnings function (5.4b) is approximately Gompertz, and has the corresponding approximate properties.

For regression analysis, the logarithmic forms (5.2b) and (5.4b) are preferable, because the schooling investment data used in this study are in years. This requires the use of $\ln E_s (= \ln E_0 + r_s s)$ rather than E_s in the earnings function. Also, as was noted above, the logarithmic form minimizes the need for interaction terms, permitting an application of the same estimating equation to the whole cross section.

The parameter estimates in the earnings function can also be interpreted in terms of gross rather than net investment, if a fixed depreciation rate δ is assumed. As was shown in Part I, equation (1.21), the general earnings function in those terms is:

$$\ln E_t = \ln E_0 + (r-\delta)s + r\int_{j=0}^{t} (k_j^* - \delta j)dj,$$

where k^* is the gross investment ratio. For example, the parabolic earnings function becomes:

$$\ln E_t = \ln E_0 + (r-\delta)s + (rk_0^* - \delta)t - \frac{rk_0^*}{2T^*}t^2, \tag{5.2e}$$

where T^* is the gross investment period; and the corresponding Gompertz function is:

$$\ln E_t = \ln E_0 + (r-\delta)s - \delta t + r\frac{k_0^*}{\beta}(1-e^{-\beta t}). \tag{5.4e}$$

Some empirical analyses of earnings relate dollar earnings to years of schooling. This is a misspecification from the point of view of the human capital model. In the NSF study, described in the preceding chapter, it was reported that logarithms of earnings yielded stronger statistical fits than dollar earnings when related to years of schooling and experience.[5]

Another form of earnings function, which is not derived from a human capital model, was used in a recent study by Thurow (1970). He used the log of schooling, instead of years of schooling, in the regression with earnings in logs:

$$\ln Y_t = a + b \ln s + c \ln t.$$

Goodness of fit cannot be compared because the function was fitted by Thurow to averages of groups, not to microdata. However, Heckman and Polachek fitted it at the microlevel and found the fit inferior to specification (5.2b), above. Apparently, also, the rate of return to schooling is underestimated in the Thurow equation, and the returns to experience are substantially overstated.[6]

5.2 REGRESSION ANALYSIS OF INDIVIDUAL EARNINGS

We are now ready to apply the human capital earnings function to the cross-sectional distribution of individual earnings. The specification of that function relates the distribution of logs of earnings to the distribution of cumulated ratios of investment to gross earnings. If the post-school investment profile can be summarized by a pair of parameters, k_0 and β, as in equation (5.4), then the earnings function will involve the variables s and t and the parameters r_s, r_t, k_0, and β, where r_s and r_t are rates of return to schooling and to post-school investments, k_0 is the initial post-school investment ratio, and β is its rate of decline:

$$\ln Y_{i,t} = \ln E_{0i} + r_{si}s_i + f(t/k_{0i}, \beta_i, r_{ti}) + \epsilon_i. \tag{5.5}$$

5. Multiple R^2 was .55 for log earnings compared to .41 for dollar values (Tolles et al., p. 65). The goodness of fit could not be directly compared. However, statistical tests devised by Box and Cox (1964) confirm the superiority of the logarithmic dependent variable in the earnings regressions based on the Census 1/1,000 sample, reported in the next section. See Heckman and Polachek (1972).

6. Since $r_s = \partial \ln Y/\partial s$, and $b = \partial \ln Y/\partial \ln s$, $r_s = b/\bar{s} = .72/11 = .06$ in the 9-to-12-year schooling group. This is half the size of my estimates. At the same time $r_p k = \partial \ln Y/\partial t = Ct = .65$ over the 6-to-15-year experience range. Since k cumulated over this range is not likely to exceed 2—it is less than 2 in the first decade of experience according to Table 4.1, above—the implicit estimate of r_p, the rate of return to post-school experience, is very high.

If information were available on all variables and parameters for each individual i, the equation would represent a complete accounting (short of the random factor ϵ_i) of the human capital characteristics entering into the formation of earnings.

Of course, the availability of such information is not even conceivable. A more modest research objective is to abstract from individual variation in initial earning capacity ($\ln E_{0i}$) and in rates of return on investments, and consider only the effects of the *volume* of investment on earnings. Average parameters $\ln E_0$, r_s, and r_t would then appear in the statistically estimated coefficients of equation (5.6):

$$\ln Y_{i,t} = \ln E_0 + r_s s_i + f(t/k_{0i}, \beta_i, r_t) + u_i. \qquad (5.6)$$

Individual variation in r_{si}, r_{ti}, and $\ln E_{0i}$ would be impounded in u_i.

Unfortunately, while information on schooling attainment s_i is available for each individual, this is not true for post-school investment. Differences in quantities of post-school investment among individuals are given by differences in k_{0i} and β_i in addition to differences in years of experience. It is therefore necessary to suppress the index i inside the experience function f, and use as the earnings function:

$$\ln Y_{i,t} = \ln E_0 + r_s s_i + f(t/k_0, \beta, r_t) + v_i. \qquad (5.7)$$

The data selected from the 1/1,000 sample which were usable for the regression analysis were 31,093 observations of annual earnings in 1959 of white, nonfarm, nonstudent men up to age 65. Parabolic and Gompertz functions [equations (5.2b) and (5.4b) of the preceding section] were fitted to this set, as well as to a somewhat smaller set (28,678 observations) consisting of earnings in each of 40 years after completion of schooling. Here, the oldest age was 55 for men with 8 years of schooling and 64 for those with 16 years of schooling. The variance of log earnings in the (40 years of) experience set was 0.668, compared to 0.694 in the age (under 65) set.

The parabolic and Gompertz estimating equations were specified to a quadratic approximation in a Taylor expansion. Formulated in terms of net investments the parabolic earnings function,

$$\ln Y_t = \ln E_0 + r_s s_i + r_t k_0 t - \frac{r_t k_0}{2T} t^2 + \ln\left(1 - k_0 + \frac{k_0}{T} t\right), \qquad (5.2b)$$

is estimated by

$$\ln Y_t = a + b_1 s + b_2 t + b_3 t^2 + v, \tag{P}$$

where

$$a = \ln E_0 - k_0\left(1 + \frac{k_0}{2}\right); \qquad b_2 = r_t k_0 + \frac{k_0}{T}(1 + k_0);$$

$$b_1 = r_s; \qquad b_3 = -\left[\frac{r_t k_0}{2T} + \frac{(k_0)^2}{2T^2}\right].$$

The Gompertz earnings function,

$$\ln Y_t = \ln E_0 + \frac{r_t k_0}{\beta} + r_s s - \frac{r k_0}{\beta} e^{-\beta t} + \ln(1 - k_0 e^{-\beta t}), \tag{5.4b}$$

is estimated by:

$$\ln Y_t = a + b_1 s + b_2 x_t + b_3 x_t^2 + v, \tag{G}$$

where

$$x_t = e^{-\beta t}; \qquad b_2 = -\frac{r_t k_0}{\beta} - k_0;$$

$$a = \ln E_0 + \frac{r_t k_0}{\beta}; \qquad b_3 = -\frac{k_0^2}{2}.$$

$$b_1 = r_s;$$

When earnings are expressed as a function of gross investment, k_0^* replaces k_0, T^* replaces T, and $-\delta$ is an additional term in the coefficients b_1 and b_2.

Table 5.1 contains the estimated parabolic (P) and Gompertz (G) regression equations and multiple coefficients of determination of the earnings distribution for forty years of experience.[7]

All the estimated coefficients shown in Table 5.1 are highly significant in a sampling sense: the coefficients are many times larger than their standard errors. This is due to the very large sample size, though size alone is not a sufficient condition for statistical significance.

The coefficient of determination R^2 is of special interest as an

7. The regression results of the under-65 age distribution are not presented. The regression coefficients in the age cross section were very close to those in the experience cross section, but the multiple coefficients of determination were .02–.03 points lower in the age set in both the parabolic and Gompertz formulations.

TABLE 5.1

REGRESSIONS OF INDIVIDUAL EARNINGS ON SCHOOLING (s), EXPERIENCE (x), AND WEEKS WORKED (W)

(1959 annual earnings of white, nonfarm men)

	Equation Forms	R^2
S(1)	$\ln Y = 7.58 + .070s$	.067
	(43.8)	
P(1)	$\ln Y = 6.20 + .107s + .081t - .0012t^2$	.285
	(72.3) (75.5) (−55.8)	
P(2)	$\ln Y = 4.87 + .255s - .0029s^2 - .0043ts + .148t - .0018t^2$	.309
	(23.4) (−7.1) (−31.8) (63.7) (−66.2)	
P(3)	$\ln Y = f(D_s) + .068t - .0009t^2 + 1.207 \ln W$	.525
	(13.1) (10.5) (119.7)	
G(1a)	$\ln Y = 7.43 + .110s - 1.651x_{at}$	.313
	(77.6) (−102.3)	
G(1b)	$\ln Y = 7.52 + .113s - 1.521x_{bt}$	.307
	(74.3) (−101.4)	
G(2a)	$\ln Y = 7.43 + .108s - 1.172x_{at} - .324x_{at}^2 + 1.183 \ln W$	.546
	(65.4) (−16.8) (−10.2) (105.4)	
G(2b)	$\ln Y = 7.50 + .111s - 1.291x_{bt} - .162x_{bt}^2 + 1.174 \ln W$	.551
	(65.0) (−3.5) (−16.0) (107.3)	
G(3)	$\ln Y = f(D_{s,x}) + 1.142 \ln W$	.557
	(108.1)	
G(4)	$\ln Y = 7.53 + .109s - 1.192x_{bt} - .146x_{bt}^2 - .012t + 1.155 \ln W$	.556
	(−2.4)	

NOTE: Figures in parentheses are t ratios. R^2 = coefficient of determination; S = linear form; P = parabolic form; G = Gompertz form; $D_{s,x}$ = dummies for schooling and experience; $x_{at} = e^{-.15t}$, $x_{bt} = e^{-.10t}$; W = weeks worked during 1959.

estimate of the fraction of earnings inequality that is associated with the distribution of human capital investments. The regression coefficients are not the primary concern in this study. They do, however, represent an important check on the consistency of the interpretation of the regression equations as human capital earnings functions.

5.3 MAJOR FINDINGS OF THE REGRESSION ANALYSIS

1. Equations (P1), (G1), and (G2) specify the same shape of logarithmic experience functions for each individual, permitting only dif-

ferences in levels. They also specify the same rate of return to schooling for all. Despite these strong restrictions, the two variables s and t alone explain about 30 per cent—28.5 per cent in (P), 32 per cent in (G)—of aggregate earnings inequality.

2. Relaxation of these restrictions is achieved in a parametric fashion in (P2): Here the s^2 term is added to allow for systematically different rates of return to schooling at different levels of schooling. The results are statistically significant and already familiar: the coefficient at s^2 is negative, indicating a lower rate of return to schooling at higher levels of schooling.

A similar nonparametric relaxation is obtained in (G3) by use of dummy variables. These yield separate intercepts for each schooling level. They are not shown in the table, as their features are the same as those already seen in (P2).

3. The partial coefficient of schooling is an estimate of the average rate of return to schooling. The marginal rates are approximated in nonlinear formulations, such as (P2), which permit the estimation of different rates at different levels of schooling. In (P2), the marginal rates:

$$r_s = \frac{d \ln Y}{ds} = .255 - .0058s - .0043t,$$

when estimated at $t = 8$ (roughly at overtaking), are 17.4 per cent at 8 years of schooling, 15.1 per cent at 12 years, and 12.8 per cent at 16 years.

The negative coefficient of the interaction term (st) describes the apparent convergence of experience profiles. Both the nonlinearity of s and the interaction st become insignificant when weeks worked is included in the regressions, such as (P2) and (G2). The same behavior of s^2 was observed in the overtaking set (cf. Table 3.3); and the parallelism of weekly earnings (no interaction st), in Chart 4.4.

4. The experience variable $x_t = e^{-\beta t}$ in the Gompertz equations was iterated for β, the rate of decline of time-equivalent investments, between 0.30 and 0.05 in 0.05 intervals. The highest R^2 and most plausible coefficient values were found in the 0.10–0.15 range. While R^2 changes little in a wider interval, the partial regression coefficients are sensitive to the specification of β. The coefficient at the quadratic term is particularly unstable when different values of β are tried.

At any rate, k_0 and r_t can be calculated from the b_2 and b_3 coefficients of the Gompertz equations, since $b_3 = -k_0^2/2$, and $b_2 = -k_0[(r_t/\beta) + 1]$. When $\beta = 0.15$ in (G2a), $k_0 = 0.81$, and $r_t = 6.7$ per cent, while for $\beta = 0.10$ in (G2b), $k_0 = 0.56$, and $r_t = 13.1$ per cent.

The post-school investment parameters cannot be identified in the parabolic equations unless values of T, the period of positive net investment, can be specified. Since T corresponds to the number of years of experience until earnings reach a plateau, $T = 20$ is used for annual earnings (P1) and $T = 30$ for weekly earnings (P3). In (P1) $k_0 = 0.58$ and $r_t = 6.3$ per cent, while in (P3), $k_0 = 0.42$ and $r_t = 11.9$ per cent.

In order to interpret the parameters of the earnings function in terms of gross investment and depreciation the Gompertz function is expanded to include a linear term in experience (equation 5.4g). This is shown in (G4). The coefficient of the linear term is an estimate of the depreciation rate δ (= 1.2 per cent). The estimate of initial gross investments k_0^* is 0.54, and the rate of return to post-school investment is estimated to be 12.1 per cent.

The high values of k_0 and low values of r_p in (Gb) make the assumed rate of decline of investment, $\beta = 15$ per cent, somewhat less plausible than the alternative assumption of $\beta = 10$ per cent in (Ga).[8]

The parabolic gross investment formulation precludes the identification of the parameters: two need to be assumed to identify the remaining three.

5. Adding variation in weeks worked by (ln W) to the equation raises the explanatory power of the regressions to 52.5 per cent in the parabolic, and to 55.7 per cent in the Gompertz, equations. In both cases the coefficient at ln W is significantly larger than unity, suggesting a positive correlation between weeks worked and weekly earnings within schooling and experience levels.

Even without W, adding an (imperfect) experience term in the human capital earnings function raises its explanatory power from 7 per cent in the schooling regression to over 30 per cent in the Gompertz function while the bias in the estimated rate of return to schooling is largely eliminated. How well the regression coefficients of the ex-

8. All the estimates of k_0 seem rather high. The overstatement may be due to some confounding of investment with maturation effects, or with higher rates of return to post-school investment than to schooling.

perience variables estimate the post-school investment parameters is difficult to tell.

Firmer estimates will require more evidence. The rates of return to schooling are somewhat lower than they were in the overtaking set (Table 3.3). Possibly, these rates decline with experience in the cross section, as older cohorts have older vintages of schooling. The R^2 measures do not seem to be very sensitive to alternative specifications, and the R^2 are of major interest here.

While the expansion of the schooling model to a function which includes post-school experience greatly increases the power of the human capital analysis of earnings, our regressions still understate that power. Because there is no direct information on individual post-school investments, these were assumed to be the same for all persons within a schooling group. In effect, estimates were made of the contribution of individual investments in schooling measured in years, and of *average* post-school investments in each schooling group to total earnings inequality. This contribution amounts to about one-third of total inequality in annual earnings. The remainder contains effects of individual differences in post-school investments, in quality of schooling, in time supplied to the market or spent in unemployment, in individual rates of return, and in "transitory" factors. Because the first two are components of the volume of human capital investment, the regressions understate the potential explanatory power of the distribution of human capital investments.

How much larger would R^2 be if information were available on post-school investments for each individual? This question can be answered in an indirect fashion. Assume that the desired equation (5.6) which includes individual information on post-school investments is homoscedastic. Then $\sigma^2(u_i)$ is the same for all sets of values of the independent variables in equation (5.6):

$$\ln Y = \ln E_0 + rs_i + f_i(t) + u_i,$$

where $f_i(t)$ is the contribution of post-school investments to earnings. To estimate $\sigma^2(u_i)$, hence $\hat{R}^2 = 1 - [\sigma^2(u_i)/\sigma^2(\ln Y)]$, it is sufficient to estimate the residual variance in one instance only. This has already been done in the case where $f_i(t) = 0$, i.e., in the overtaking set. The residual variance in the regression of log earnings on schooling in that set serves, therefore, as an estimate of the residual variance in the unobservable regression form (5.6). Based on the regressions in the overtaking set, previously shown in Table 3.3, $\sigma^2(u) = 0.333$. Hence $\hat{R}^2 = 1 - (0.333/0.668) = 0.50$.

In a similar fashion, the residual variance from the multiple regression of log earnings on schooling and log weeks worked in the overtaking set can be compared to the aggregate variance of log earnings net of the contribution of log weeks. The resulting[9] $\hat{R}^2 = 1 - (0.20/0.53) = 0.62$.

If most of the variation in weeks worked were considered transitory, the 62 per cent figure would be an estimate of the contribution of human capital investment to a longer-run earnings inequality. If all of it were permanent and related to human capital investments, then $\hat{R}^2 = 1 - (0.200/0.668) \doteq 0.70$.

In analyzing the regressions in the overtaking set I suggested that quality of schooling might account for at least 0.06 of the residual variance. If so, the indirect estimates $\hat{R}^2$ of the explanatory power of the distribution of human capital for the inequality of earnings increases to 0.55, 0.69, and 0.78, respectively.

It appears that, whatever the fraction of transitory variation in weeks worked, schooling and post-school investment accounted for close to two-thirds of the inequality of earnings of adult, white, urban men in the United States in 1959.

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9. The residual variance in equation (2) in the top panel of Table 3.3 is 0.204; $0.53 = \sigma^2(\ln Y) - (1.142)^2\sigma^2(\ln W)$, where 1.142 is the coefficient in (G4) in Table 4.4.