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THE DISTRIBUTION OF EARNINGS PROFILES IN LONGITUDINAL DATA

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I. Introduction

The availability of longitudinal microdata on earnings and on other aspects of personal histories provides a new range of opportunities to improve our understanding of the interpersonal structure of earnings.

Recent research on the determinants of earnings, especially the human capital approach, stresses the whole life-cycle earnings stream as the basic unit of analysis rather than a single period observation. Indeed, by emphasizing individual accumulation of earning power, the analysis directly focuses on the longitudinal dimension, albeit one that is rather abstract, since all economy-wide trends and fluctuations in prices and productivities must be removed from it.

In the cross-section studies of Census and other data, earnings of different individuals are analyzed as if they were pieced together around a single synthetic earnings profile, typical for all groups or distinguishable for groups classified by school education. The profiles so obtained slope upward through most of the working age, decelerating after some initial interval, and levelling off at a later stage.[1]

In the human capital interpretation of the earnings profile, its level is proportional to (since it is a rental payment on) the accumulated stock

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[1]Declines are observed in annual earnings, but not in wage rates.

of market skills, its rate of growth is a positive function of current investment in such skills or earning powers, and the deceleration reflects the declining rate of investment over the life cycle. It is understood that the term "investment" covers a broad range of activities such as schooling, occupational choice, job training and learning, job and geographic mobility, job search and acquisition of information, work effort, and so forth.

This interpretation is summarized in the following model:[2]

$$\ln Y_t = \ln E_o + r_s \sum_{i=0}^{s-1} k_i + r_p \sum_{j=0}^{t-1} k_j + \ln (1-k_t) \tag{1}$$

where

Y_t = earnings at working age t

E_o = "original" earning capacity, or "endowment"

r_s = average rate of return to schooling

r_p = average rate of return to postschool investments

$k_t = \frac{C_t}{E_t}$, where C_t is the dollar investment expenditure and E_t is the earning capacity at working age t.

With simplifying assumptions $k_i = 1$ and $k_t = k_o - \beta t$, we have:

$$\ln Y_t = \ln E_o + r_s s + r_p k_o t - \frac{r_p \beta t^2}{2} + \ln (1-k_t) \tag{2}$$

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[2] For a more complete exposition of the model and of the econometric specification see Mincer (1974), or a summary in Mincer (1976).

and an approximate estimating equation is:

$$\ln Y_t = b_o + b_1 s + b_2 t + b_3 t^2 + u \qquad (3)$$

where:[3]

$$b_o = \ln E_o - k_o$$

$$b_1 = r_s$$

$$b_2 = r_p k_o + \beta$$

$$b_3 = -\frac{r_p \beta}{2}$$

Note that β may also be expressed as $\frac{k_o}{T}$, where T is the investment period.

When applied to a cross-section, equation (3) may be augmented by information on personal, background, or regional characteristics of the individuals. We shall have a look at these personal characteristics later on, but will direct our attention first to the application of equation (3) both in time series and in the cross-section.

In this equation there are only two schematic variables, years of schooling and years of work experience. Perhaps surprisingly, these two crude but readily available variables contain relatively sizable explanatory power. This has been shown in Census and other cross-section microdata which cover complete ranges of schooling and of working ages.[4]

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[3] This is a single term Taylor expansion of the term $\ln (1-k_t)$. The degree of approximation seemed to make little difference in our empirical applications.

[4] For references see the bibliography in Mincer (1976).

The coefficients of the variables in (3) represent rates of return and investment ratios, and the intercept ln E_o reflects endowment. These parameters obviously vary among individuals, but aside from schooling and working age no such variation is observable. Distributional analyses, therefore, miss a potentially important source of interpersonal variation in earnings.

We take advantage of our longitudinal data to explore individual variation in the parameters of individual earnings functions. (1) For this purpose we fit an earnings function to each of the individual histories in the sample. (2) We then try to ascertain the extent to which the estimated variation in individual parameters helps in explaining the cross-sectional variation in earnings. (3) We further inquire into the relation between the individual parameters and a vector of personal characteristics, as well as (4) into indirect (via variables and parameters) and direct effects of these characteristics on earnings.

The analysis was carried out on the Coleman-Rossi Life History data, a sample of males aged 30-39 in 1968 who were residing in households in the U.S. The data contains information on the starting and ending dates (month and calendar year), earnings and hours worked for every job the individual held from the time he first entered the labor force until the date of interview in January 1969. Thus we have a job history for the individual, and for every job we have at least two earnings points: initial and ending wages or salaries. Respondents also provided a lifetime family and educational history, as well as all the characteristics listed in our notes to Table 5 below.

The sample contains 1,589 men of whom 739 are black. Data requirements and omissions reduced our sample almost in half.[5] As the information was collected retrospectively, we caution ourselves and the readers that large memory errors may exist in such data.[6]

II. Longitudinal Earnings Profiles

We estimated individual earnings functions [using equation (3)] for each of the 884 men in the usable sample. The data for the dependent variable are logarithms of price-deflated monthly earnings. Table 1 presents the average intercepts and coefficients of equation (3) together with their standard errors for all men, each of the two race groups, and four education groups. In the individual regressions schooling is a constant, so the intercept is $(b_0 + b_1 s)$ of eq. (3). The coefficient of t (working age, or experience) which is b_2 in eq. (3), we call β_1 and it equals $(r_p k_0 + \beta + g)$, where g is the economy-wide rate of growth of productivity per worker, assumed fixed over the period and net of the contribution of human capital. The coefficient of t^2 is b_3 of eq. (3), which we call β_2.

A similar set of regressions was performed using hourly wage rates rather than monthly earnings. The results were quite similar. We decided to continue our analysis with monthly earnings only, especially since we believe these to be more reliable than retrospective data on hours of work.[7]

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[5]The sample was restricted to 884 males who reported at least three earnings points, who never held multiple jobs, and who provided all the necessary basic information.

[6]We have the reassuring statement from James Coleman that a cross-check of the earnings and employment data with the Social Security file showed "rather good conformity."

[7]Evidently, the source of similarity is that very little variation over time was reported by individuals in their histories of hours of work.

The standard errors in Table 1 are actually upper limits since each individual regression utilized more than one degree of freedom.[8] At any rate this statistic indicates that, on average, the longitudinal earnings profiles has an upward slope. This is true also when the economy-wide rate of growth g is subtracted from the coefficient at t. The annual rate of productivity growth was estimated to be 2.5 percent. It was found as the average rate of growth of wages of men age 25-35 at fixed levels of education for the period 1956-66.[9] Thus, in Table 1 the coefficient of t which includes g, for all men, is .077; excluding g it is .052. The coefficient of t^2 is -.0014 and the small standard error indicates a significant deceleration of earnings over the observed working life.

Given these coefficients it is possible to analyze the rate of growth of earnings at any working age by including and excluding g. Since $\frac{d \ln Y_t}{dt} = \beta_1 - 2\,\beta_2 t$, we find that two-thirds of the growth of earnings with working age is accounted for by individual progress and one-third by economy-wide progress at the start of working life (when t = 1). The contribution to growth are reversed one and a half decades later (at t = 15), and they are about equal after a decade of work experience (at t = 10).

The important conclusion to be drawn from Table 1 is the concavity of the typical earnings profile revealed in these longitudinal data. This shape, heretofore observed only in cross-sections cannot, therefore, be viewed as an artifact of the cross-section. It characterizes both races in

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[8] The mean number of observations for each individual regression was 11.3. The standard deviation was 6.6

[9] Estimated from U.S. Census data. For details see Mincer (1974), p. 79.

TABLE 1
Longitudinal Earnings Functions - Summary Statistics[a]

Variable	All Men	s < 12	s = 12	13 ≤ s ≤ 15	s ≥ 16
			A. Pooled Sample		
Constant	5.442 (.597) [.020]	5.206 (.688) [.036]	5.540 (.448) [.030]	5.594 (.455) [.032]	5.833 (.358) [.037]
t	.077 (.137) [.005]	.083 (.142) [.007]	.068 (.143) [.010]	.076 (.130) [.009]	.075 (.112) [.012]
t^2	-.0014 (.010) [.0003]	-.0021 (.008) [.0004]	-.0015 (.011) [.0007]	-.0013 (.010) [.0007]	.0013 (.013) [.0013]
Number of Observations	884	373	220	198	93
			B. White Men		
Constant	5.518 (.574) [.027]	5.260 (.714) [.061]	5.565 (.466) [.043]	5.577 (.471) [.042]	5.836 (.353) [.042]
t	.079 (.135) [.006]	.079 (.124) [.011]	.062 (.158) [.015]	.091 (.134) [.012	.088 (.114) [.014]
t^2	-.0009 (.011) [.0005]	-.0015 (.007) [.0006]	-.0004 (.013) [.0012]	-.0018 (.011) [.0010]	.0010 (.014) [.0017]
Number of Observations	446	136	116	124	70

(continued on next page)

TABLE 1 (concluded)

Variable	All Men	s < 12	s = 12	13 ≤ s ≤ 15	s ≥ 16
			C. Black Men		
Constant	5.365	5.174	5.512	5.623	5.825
	(.611)	(.672)	(.430)	(.431)	(.378)
	[.029]	[.044]	[.042]	[.050]	[.079]
t	.074	.084	.076	.050	.036
	(.139)	(.152)	(.124)	(.120)	(.098)
	[.007]	[.010]	[.012]	[.014]	[.020]
t^2	-.0019	-.0024	-.0028	-.0003	.0023
	(.009)	(.009)	(.008)	(.010)	(.012)
	[.0004]	[.0006]	[.0008]	[.0012]	[.0025]
Number of Observations	438	237	104	74	23

[a]The statistics are: Mean, (Standard Deviation), [Standard Error].

the sample and all education groups, with an apparent exception of the highest education group. However, a significant degree of concavity is evidently not apparent until after a decade of work experience, and the most educated group in this sample does not have more than a decade of work experience. Given the relatively narrow age range in the sample, work experience is inversely related to years of schooling. Therefore, the less schooled the group the more clearly discernible is the shape of its earnings profile.[10]

There is, of course, a great deal of individual variation in the slopes and curvatures of this early segment (an average of 16 years) of the earnings profile. While the standard errors in Table 1 are small enough to lend significance to mean values, the standard deviations in the sample are larger than the means. This is perhaps not surprising since the individual profiles are fit to a few observed points only, so a great deal of instability can be expected. In addition, lack of reliability of the individual regression is attributable to a certain degree of arbitrariness in the timing of initial earnings: We defined initial as the first full time job after completion of schooling, but many persons worked before on a part- or full-time basis.

While Table 1 depicts the typical longitudinal earnings profile, Table 2 takes account of the individual variation around the average profile. It measures the importance of that variation in inducing a corresponding variation in earnings of individuals in the cross section.

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[10] Weiss and Lillard (1976) find a concave longitudinal profile among Ph.D's in science. Their sample (NSF) covers one decade in a wide spectrum of ages.

TABLE 2

Current Earnings Functions[a]

Variable	(1) Coeff.	(1) t	(2) Coeff.	(2) t	(3) Coeff.	(3) t	(4) Coeff.	(4) t
				A. Pooled Sample				
Constant	5.8378		5.4784		5.8635		5.4967	
s	.0504	(10.02)	.0524	(13.78)	.0502	(11.83)	.0526	(17.47)
t	-.0141	(-.82)			-.0153	(-1.04)		
t^2	.0006	(1.11)			.0005	(1.15)		
$\beta_1 \cdot t$			.3516	(17.27)			.3201	(19.79)
$\beta_2 \cdot t^2$			.4067	(17.40)			.3954	(21.35)
v					.4333	(18.84)	.4361	(22.88)
RACE	-.2181	(-8.10)	-.1487	(-6.32)	-.2014	(-8.86)	-.1363	(-7.31)
R^2	.220		.419		.445		.636	
				B. White Men				
Constant	5.6491		5.3931		5.6051		5.4347	
s	.0660	(7.93)	.0557	(9.44)	.0664	(9.43)	.0540	(11.72)
t	-.0219	(-.83)			-.0200	(-.89)		
t^2	.0011	(1.27)			.0010	(1.46)		
$\beta_1 \cdot t$			.4149	(13.79)			.3837	(16.30)
$\beta_2 \cdot t^2$			.4890	(14.02)			.4815	(17.70)
v					.4790	(13.23)	.4817	(16.89)
R^2	.141		.400		.385		.635	

(continued on next page)

TABLE 2 (concluded)

Variable	Coeff. (1)	t	Coeff. (2)	t	Coeff. (3)	t	Coeff. (4)	t
				C. Black Men				
Constant	5.6995		5.4394		5.8419		5.4522	
s	.0368	(6.31)	.0464	(9.69)	.0364	(7.59)	.0480	(12.66)
t	.0009	(.04)			-.0089	(-.48)		
t^2	-.00003	(-.04)			.00004	(.07)		
$\beta_1 \cdot t$			.2707	(10.04)			.2410	(11.25)
$\beta_2 \cdot t^2$			.3804	(10.06)			.2959	(12.18)
v					.3944	(14.31)	.3894	(16.10)
R^2	.105		.276		.393		.547	

[a]Notation used:

β_1 = Linear coefficient from longitudinal function

β_2 = Quadratic coefficient from longitudinal function

v = Earnings capacity measure

Specifically, we observe the effect on R^2 of introducing the individual longitudinal parameters β_{1i} and β_{2i} into the earnings function (3) applied to the cross-section. In column (1) of each panel we show the usual cross-section regression for the 1968 survey data. It includes the variables schooling (s) and years of work experience (t and t^2). The parameters are some sort of average of individual parameters. In this sample these are rather unstable and the signs appear perverse, compared to previous studies based on much larger samples.[11] At any rate the replacement of variables t_i and t_i^2 by estimated $(\beta_1 t)_i$ and $(\beta_2 t^2)_i$ in column 2, more than doubles the explanatory power of the cross-section regression.[12]

This is not to say that we have managed to explain more, but simply that if the information underlying the slope and curvature parameters of individual earnings functions were available to analysts, an additional 20-25 percent of the relative variance of (monthly or weekly) earnings could be explained. The information in these parameters pertains to the unobserved individual variation in volumes of postschool investments and in their efficiencies.

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[11]The coefficients of t and t^2 acquire the proper signs in our own sample when experience is defined as total number of months ever worked (rather than time elapsed since the start of a full-time job after completion of schooling), and when earnings (in logs) are averaged over several years.

[12]We postpone the discussion of variable v in columns 3 and 4 of Table 2.

III. Estimating Individual Investment Parameters

With very few degrees of freedom and less than a complete life-cycle available, the individual longitudinal earnings regressions are far from being reliable. But even if they were reliable, it is not, in general, possible to solve the estimated coefficients for the component investment parameters which are of interest: These are: the vectors of postschool investments indexed by k_{oi} (the initial investment ratio), the (average) rates of return to postschool investment (r_i), and individual "endowments" or "initial earning capacities," $\ln E_{oi}$.

It is tempting, nevertheless, to use the concept of an "overtaking stage" in the life-cycle of postschool investment for a procedure which is somewhat better than guesswork.

The "overtaking stage" is the working age $\hat{t}$ at which observed earnings $Y_{\hat{t}}$ reach equality with initial postschool capacity earnings E_s. Note that initial earnings $Y_o \doteq E_s - C_o$, or $\ln Y_o \doteq \ln E_s + \ln (1-k_o)$, so that $\ln Y_o < \ln E_s$. Later on $\ln Y_t = \ln E_s + r \sum_{j=0}^{t-1} k_j + \ln (1-k_t)$. At some stage the growing positive second term on the right begins to outweigh the declining (in absolute value) negative third term. This happens at about $\frac{1}{r}$ years of experience.[13] The ratio of $Y_{\hat{t}}$ to Y_o does, therefore, provide estimates of k_o. The overtaking stage differs among persons as does r_i, but we do not know the latter either. A guess about the average r_i, which judging from past studies, is probably not too far away from 10 percent, may serve the purpose.

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[13] The proof is on p. 17, Mincer (1974).

Alternatively, we may locate an average overtaking period $\hat{t}$ by studying the correlation between schooling and earnings across all persons in the sample for sequential years of experience. Presumably the highest simple correlation is between schooling and earning capacity E_s, that is earnings unaffected by subsequent investments. A common overtaking stage would produce, therefore, a clear maximum correlation at $\hat{t}$. This need not happen in practice, if the central tendencies in r_i or in the rate of decline of investments (β_i) are not well defined. In that case, the "overtaking stage" may be quite diffuse. When "random shocks" and data errors are superimposed on such data, a monotonically declining pattern of correlations may be observed in them.

In cross-section Census data the correlation has been found to decline clearly and strongly only after a decade of experience.

In our sample the correlation does, indeed, increase from an initial .40 to .47 at 10-13 years of experience, and declines continuously thereafter. This pattern is due mainly to the correlations in the sample of white men which rise from .39 to .50, while a very weak but persistent decline is observed in the sample of black men. We use the tenth year of experience as the common "overtaking" period. We then estimate k_{oi} as the percent differential between initial earnings (Y_o) and earnings one decade later ($Y_{10} \approx E_s$), after deflation for the 2.5 percent annual rate of the productivity trend. The means and standard errors of k_o by race and schooling group are shown in Table 3.

According to Table 3 the average "initial investment ratios" are about one-third of the initial earning capacity and they increase with schooling

TABLE 3
Summary Statistics of k_o and r^*

Variable	All Men	s < 12	s = 12	13 ≤ s ≤ 15	s ≥ 16
			A. Pooled Sample		
k_{oi}	.294	.312	.240	.286	.370
	(.553)	(.661)	(.454)	(.484)	(.398)
	[.019]	[.034]	[.031]	[.034]	[.041]
r_i	.070	.055	.073	.077	.105
	(.080)	(.083)	(.068)	(.078)	(.080)
	[.003]	[.004]	[.005]	[.006]	[.008]
			B. White Men		
k_{oi}	.350	.350	.290	.340	.444
	(.528)	(.640)	(.443)	(.524)	(.399)
	[.025]	[.055]	[.041]	[.047]	[.048]
r_i	.075	.058	.074	.077	.110
	(.079)	(.084)	(.067)	(.081)	(.073)
	[.004]	[.007]	[.006]	[.007]	[.009]
			C. Black Men		
k_{oi}	.250	.291	.168	.207	.162
	(.574)	(.674)	(.460)	(.397)	(.325)
	[.027]	[.044]	[.045]	[.046]	[.068]
r_i	.064	.054	.073	.078	.090
	(.080)	(.083)	(.070)	(.075)	(.097)
	[.004]	[.005]	[.007]	[.009]	[.020]

*The statistics are: Mean, (Standard Deviation), [Standard Error].

starting with S = 12. The dispersion in k_{oi} across individuals is large and appears to be inversely related to education: Recall errors may be larger at lower levels of education, since work experience of persons with lesser schooling starts early and requires, therefore, a longer memory span.

The black sample shows smaller average k_o in each schooling class, and the white-black differences appear to increase with schooling level. The implication that relative black-white differences in earnings grow over the life-cycle are confirmed in our data: Where the initial earnings differ by 5-8 percent in the various schooling groups, the percent differential increases several fold by the time 15 years of experience have elapsed.

The k_{oi} estimates enable us to attempt the estimation of the rates of return r_i. This successive step compounds the preceding errors and inaccuracies, but hoping that some fraction of the estimate is "true" we follow our curiosity. We use every individual longitudinal earnings function for this purpose.[14]

Note that equation (3) can be written as:[15]

$$[\ln Y_t - \ln Y_o] - [\frac{k_o}{T} + g]\ t = r\ [k_o\ (1 - \frac{t}{2T})\ t\ ] \qquad (4)$$

Using estimates k_{oi}, g, and trying several values[16] of T, we obtain

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[14]In principle, the idea can serve as a start of an iteration procedure. We do not go beyond the first step.

[15]To obtain equation (4) it is necessary to assume that $\beta = k_o/T$, where T is the length of the working life cycle.

[16]T = 40 appeared to fit best.

individual r_i's by estimating (4) using the earnings data given by each individual's earnings profile. These estimates are shown in Table 3.

The "rate of return" coefficients increase with schooling level in both race groups. They are only slightly lower among black than among white men. Hence, the main reason for the flatter profiles of blacks is the lesser volume of job-related investments as measured by k_o.[17]

The remaining parameter which the assumed overtaking point allows us to extract from the data is ln E_{oi}, the "endowment" or "earning capacity" which exists apart from measured investments. In contrast to the parameters k_{oi} and r_i which affect <u>shapes</u> of earnings profiles, the endowment component is a shift factor which creates differences in <u>levels</u> of individual earnings profiles in addition to those created by differences in individual accumulations of investments. The cross-section distribution of earnings should therefore contain the endowment capacity E_{oi} as a persistent factor at various stages of experience. It can be estimated very roughly as the residual from the cross-section regression of earnings on schooling at the overtaking stage. The estimate is rough, because it assumes the same rate of return to schooling for all individuals and the same period of overtaking (i.e. the same rate of return to post school investments). Of course, differential rates of return to schooling, all the unmeasured components of investment, such as quality of schooling, aspects of work experience, efficiencies of various sorts,

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[17] To the extent that these are firm-specific, they are jointly determined by employers and workers. The greater job turnover and shorter job tenure of blacks is consistent with this interpretation.

not to speak of errors and of transitory factors, all of these are impounded in the residual v. For all these reasons the residual variance overstates the variance of endowments. We estimate the residual v_i from the overtaking regression:[18]

$$\ln Y_{10} = \overline{\ln E}_o + r_s \cdot S_i + v_i \tag{5}$$

The residual variance of earnings at overtaking is large (74 percent for whites and 89 percent for blacks). For reasons discussed above, of which measurement error is not the least important, the residual variance $\sigma^2(v_i)$ overtakes the variance of endowments $\sigma^2(\ln E_{oi})$ perhaps significantly. In columns 3 and 4 of Table 2 we show the effects of v_i in the current (survey) cross-section of earnings.

Despite large errors in v_i as an estimate of $\ln E_{oi}$ indicated partly by the attenuated coefficient of v_i (it is much less than 1) the transplanted residual is a strong "explanatory" factor in current earnings. Whether fixed (column 3) or variable (column 4) experience coefficients are used, the introduction of v_i "explains" an additional 20-30 percent of the cross-section inequality in earnings.

An interesting conclusion based on Table 2 (column 4) is that the understanding and measurement of factors underlying individual postschool-investments and their efficiency would contribute nearly as much as the understanding of the factors impounded in the residual category.

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[18] We also included calendar year of entry into the labor force in the equation in order to standardize for productivity growth in the economy.

The fact shown in Table 4 that this conclusion does not survive the attempt to decompose the experience coefficients into parameters k_{oi} and r_i does not mean that it is wrong. The decomposition compounds the errors in k_{oi} and r_i, reducing their explanatory power in the cross-section earnings function, while v_i is unaffected. It is nevertheless of some interest to proceed with a step-wise introduction of the r_i, k_{oi}, and v_i parameters into the cross-section. If not entirely attenuated by error, at least their qualitative conformity to the human capital model can be observed.

The steps are shown in Table 4. In column 1 we have the standard function

$$1. \quad \ln Y_t = (\ln E_o - k_o) + r_s s + (rk_o + \beta)t - \frac{r\beta}{2} t^2$$

In column 2 we allow r_i in the coefficients of t to vary:

$$2. \quad \ln Y_t = (\ln E_o - k_o) + r_s s + k_o (r_i t) + \beta t - \frac{\beta}{2} (r_i t^2)$$

Note that the experience coefficients acquire "correct" signs after r_i has been included and that the coefficient of $(r_i t^2)$ is not far from half the size of the coefficient of t (in absolute value). Some increase in R^2 is also observed. In column 3 we allow k_o in the coefficient of t to vary:

$$3. \quad \ln Y_t = (\ln E_o - k_o) + r_s s + r (k_{oi} t) + \beta t - \frac{r\beta}{2} t^2$$

The signs of t and t^2 remain perverse (or non-significant) but $k_{oi} t$ is positive and strong. Indeed the effect of k_{oi} on R^2 appears stronger than that of r_i.

TABLE 4
Set of Current Earnings Functions

Variable	Coeff. (1)	t	Coeff. (2)	t	Coeff. (3)	t	Coeff. (4)	t	Coeff. (5)	t
					A. Pooled Sample					
Constant	5.8378		5.5597		5.7947		5.6084		5.7996	
s	.0504	(10.02)	.0482	(9.67)	.0530	(10.67)	.0537	(10.92)	.0522	(13.78)
k_{oi}							.0929	(3.17)	-.4253	(-13.75)
t	-.0141	(-.82)	.0119	(2.98)	-.0158	(-.92)	.0042	(1.23)	-.0054	(-2.01)
t^2	.0006	(1.11)			.0006	(1.12)				
v									.6926	(24.51)
$r_i t$			.2030	(4.41)						
$r_i t^2$			-.0093	(-3.72)			-.0002	(-.29)	.0006	(1.32)
$k_{oi} t$					.0061	(5.52)				
$r_i k_{oi} t$							.0389	(2.43)	.2227	(15.41)
RACE	-.2181	(-8.10)	-.2189	(-8.23)	-.2039	(-7.67)	-.1952	(-7.42)	-.2010	(-9.92)
R^2	.220		.242		.246		.267		.565	

(continued on next page)

TABLE 4 (continued)

Variable	Coeff. (1)	t	Coeff. (2)	t	Coeff. (3)	t	Coeff. (4)	t	Coeff. (5)	t
					B. White Men					
Constant	5.6491		5.3025		5.6866		5.3933		5.4749	
s	.0660	(7.93)	.0605	(7.30)	.0658	(8.03)	.0647	(7.97)	.0689	(11.46)
k_{oi}							.0663	(1.45)	-.5425	(-11.68)
t	-.0219	(-.83)	.0175	(2.72)	-.0304	(-1.17)	.0082	(1.45)	.0012	(.30)
t^2	.0011	(1.27)			.0013	(1.53)				
v									.8080	(19.09)
$r_i t$			.2452	(3.41)						
$r_i t^2$			-.0109	(-2.75)			.0003	(.31)	.0025	(3.31)
$k_{oi} t$					.0071	(3.78)				
$r_i k_{oi} t$							.0674	(2.84)	.2593	(12.83)
R^2	.141		.171		.168		.197		561	

(continued on next page)

TABLE 4 (concluded)

Variable	Coeff. (1)	t	Coeff. (2)	t	Coeff. (3)	t	Coeff. (4)	t	Coeff. (5)	t
					C. Black Men					
Constant	5.6995		5.5868		5.6260		5.6317		5.8892	
s	.0368	(6.31)	.0365	(6.31)	.0409	(7.03)	.0419	(7.24)	.0376	(8.35)
k_{oi}							.1376	(3.74)	-.3125	(-7.99)
t	.0009	(.04)	.0056	(1.15)	.0035	(.16)	.00001	(.00)	-.0121	(-3.74)
t^2	-.00003	(-.04)			-.0002	(-.23)				
v									.5996	(16.85)
$r_i t$			.1423	(2.51)						
$r_i t^2$			-.0069	(-2.26)			-.0008	(-1.20)	-.0010	(-1.97)
$k_{oi} t$					.0051	(3.98)				
$r_i k_{oi} t$							-.0063	(-.30)	.1703	(8.76)
R^2	.105		.120		.137		.159		.493	

When both k_{oi} and r_i are introduced in column 4 including k_{oi} in the intercept, the explanatory power increases further, but the sign of k_{oi} (in the intercept) is positive instead of negative: The equation is:

$$4. \quad \ln Y_t = \ln E_o - k_{oi} + r_s s + (r_i k_{oi} t) + \beta t - \frac{\beta}{2} (r_i t^2)$$

Finally, v_i is added into the equation in column 5, so that:

$$5. \quad \ln Y_t = \overline{\ln E}_o - k_{oi} + r_s s + (r_i k_{oi} t) + \beta t - \frac{\beta}{2} (r_i t^2) + v_i$$

We then find that k_{oi} becomes negative and strong, and the other signs are mostly correct (in the sense of the model) as well.[19]

Errors in the decomposed investment coefficients k_{oi} and r_i weaken their measured effects on earnings (compare Table 4 with Table 2). At the same time these errors cause an inflation of v_i, since v_i contains unmeasured components of k_{oi}, r_i, and s_i apart from true endowment. Consequently the contribution of v_i to R^2 is over 30 percent in Table 4, when it was over 20 percent in Table 2, while the experience coefficients appear to contribute less than 10 percent in Table 4, but were adding about 20 percent to R^2 in Table 2.

As already remarked, the patterns of observed sizes and signs of the investment parameters are not inconsistent with the human capital interpretation. The coefficients of t and $r_i t^2$ (in column 2) are consistent

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[19]In the white sample the size of the coefficient k_o is -.5, of v_i is +.8 and of $(r_i k_{oi} t)$ is .26. Under certain zero correlation assumptions the deviation of these coefficients from unity represents a measure of the importance of error in the data or concepts.

with a linear investment decline described by coefficients β and $-\frac{\beta}{2}$ respectively. More basic is the strong negative effect of k_{oi} in step 5, an observation for which, short of econometric sins, it would be difficult to find alternative explanations.

IV. Individual Parameters, Personal Characteristics, and Earnings

The potential explanatory power of the usually unmeasured individual variation in endowment, in postschool investments, and in investment efficiencies (or abilities) was demonstrated in Tables 2 and 4. The Coleman-Rossi survey provides a great deal of information on personal and behavioral characteristics of respondents which may affect earnings indirectly by influencing the magnitudes of endowments, investments, and efficiency, or directly, that is net of these variables and parameters.

As a first step in exploring this matter we relate the individual parameters k_{oi}, r_i, v_i, and s_i to a vector of personal characteristics described in Table 5. One subset of these variables represents information on human capital investments; such as: education, work experience before completion of schooling, training on the job, and job mobility. A second set represents background characteristics: parental education, number of siblings, and whether or not both parents were present in the household at the age of 14.

Other variables such as age and marital status do not necessarily fit into these categories. One important variable which straddles the human capital and the background characteristics is "verbal ability" measured by a score on a test administered at the interview.

The regressions in Table 5 tell a striking story: At least in the white sample, schooling levels are easily and powerfully "explained" by the four family background variables by pre-graduation work experience, and by verbal ability (R^2 = .50 in the white sample, and .28 in the black sample). These variables have the expected effects: Father's and mother's education, previous experience, and verbal ability affect son's education positively; number of siblings and broken home negatively. Of course, the verbal ability may be an effect of schooling rather than a background variable.[20] Verbal ability is probably a mix of both: Without it R^2 falls to .28 and the coefficients of the background variables become attenuated. At any rate a range for R^2 from .28 to .50 represents very strong explanatory power.

In contrast, the k_o, r, and v parameters are barely affected by a dozen or so variables, even though some of them are statistically significant. We also regressed the longitudinal coefficients β_1 and β_2 (first shown in Tables 1 and 2) on the same battery of variables, again with little success. In the white sample R^2 was .04 and .08, respectively. The black sample, however, shows R^2 of .12 and .14 respectively. This finding is due mainly to the "training" (apprenticeship or other formal job training) variable which was not significant in the separated components k_{oi} and r_i.

One might argue that the reasons k_i, r_i and v_i, are not really explainable is because of the overwhelming amount of error attached to them.

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[20] The regression of verbal ability on schooling and family background yields an r^2 = .43, on schooling alone R^2 = .31.

TABLE 5
Determinants Regressions[a]

Variable	Dependent = k_{oi} Coeff.	t	Dependent = r_i Coeff.	t	Dependent = v_i Coeff.	t	Dependent = s Coeff.	t
				A. Pooled Sample				
Constant	.1359		-.1974		-.3125		7.1909	
s	-.0083	(-.75)	.0018	(1.36)				
PREV	.0159	(1.03)	-.0001	(-.07)	.0088	(.81)	.1683	(3.72)
AGE1	-.0242	(-1.86)	-.0025	(-1.58)	-.0132	(-2.10)		
CALEN	.0091	(1.12)	.0049	(5.02)				
MARITAL	.1258	(1.85)	.0061	(.75)	.1076	(2.19)		
ABILITY	.0192	(1.53)	.0031	(2.04)	.0298	(3.49)	.6014	(14.63)
NJOBS	.0006	(.09)	.0001	(.16)	.0118	(2.54)		
TRAIN	.0281	(.99)	-.0014	(-.41)	.0034	(3.73)		
CURRENT	.0026	(.51)	.0021	(3.41)	.0131	(.16)		
SIBLINGS	.0161	(2.30)	.0008	(.98)	.0093	(1.86)	-.1333	(-5.22)
FATHER	.0108	(1.44)	-.0006	(-.71)	.0031	(.57)	.0722	(2.62)
MOTHER	-.0108	(-1.27)	.0006	(.63)	.0109	(1.77)	.1369	(4.42)
BROKEN	.1398	(2.77)	.0026	(.43)	.0771	(2.11)	-.7191	(-3.87)
RACE	-.1548	(-3.21)	-.0031	(-.54)	.0117	(.33)	-.1347	(-.77)
R^2	.042		.076		.053		.403	

(continued on next page)

TABLE 5 (continued)

Variable	Dependent = k_{oi} Coeff.	t	Dependent = r_i Coeff.	t	Dependent = v_i Coeff.	t	Dependent = s Coeff.	t
				B. White Men				
Constant	-.4609		-.1422		-.3468		7.0073	
s	.0270	(1.60)	.0045	(2.16)				
PREV	.0418	(1.92)	.0002	(.08)	.0365	(2.23)	.3167	(5.92)
AGE1	-.0503	(-2.96)	-.0043	(-2.01)	-.0159	(-1.76)		
CALEN	.0178	(1.62)	.0039	(2.89)				
MARITAL	.2293	(2.18)	.0093	(.71)	.0984	(1.23)		
ABILITY	.0290	(1.59)	.0048	(2.11)	.0345	(2.77)	.7041	(13.86)
NJOBS	.0037	(.46)	.0001	(.13)	.0066	(1.08)		
TRAIN	.0271	(.84)	-.0036	(-.89)	.0102	(.41)		
CURRENT	.0052	(.80)	.0017	(2.06)	.0139	(2.91)		
SIBLINGS	.0228	(2.05)	.0003	(.23)	.0170	(2.04)	-.1552	(-4.21)
FATHER	.0122	(1.28)	-.0004	(-.30)	.0038	(.53)	.0981	(3.09)
MOTHER	-.0119	(-1.07)	-.0004	(-.28)	.0139	(1.64)	.0511	(1.36)
BROKEN	.0928	(1.26)	-.0123	(-1.33)	.1159	(2.06)	-.1724	(-.69)
R^2	.055		.087		.087		.498	

(continued on next page)

TABLE 5 (concluded)

Variable	Dependent = k_{oi} Coeff.	t	Dependent = r_i Coeff.	t	Dependent = v_i Coeff.	t	Dependent = s Coeff.	t
				C. Black Men				
Constant	.6880		-.2697		-.1738		7.3623	
s	-.0350	(-2.36)	-.0002	(-.12)				
PREV	-.0172	(-.77)	-.0003	(-.10)	-.0158	(-1.06)	.0033	(.04)
AGE1	-.0023	(-.11)	-.0007	(-.31)	-.0167	(-1.81)		
CALEN	-.0014	(-.12)	.0060	(4.23)				
MARITAL	.0628	(.70)	.0073	(.69)	.1016	(1.61)		
ABILITY	.0031	(.18)	.0010	(.47)	.0269	(2.26)	.4863	(7.65)
NJOBS	-.0074	(-.72)	.0001	(.09)	.0165	(2.32)		
TRAIN	.0391	(.72)	.0011	(.18)	.0042	(.11)		
CURRENT	-.0031	(-.40)	.0024	(2.70)	.0123	(2.36)		
SIBLINGS	.0114	(1.24)	.0012	(1.15)	.0057	(.89)	-.1291	(-3.68)
FATHER	.0022	(.18)	-.0015	(-1.07)	.0039	(.46)	.0348	(.76)
MOTHER	-.0099	(-.76)	.0014	(.96)	.0076	(.84)	.2198	(4.48)
BROKEN	.1718	(2.43)	.0139	(1.68)	.0470	(.95)	-1.0891	(-4.05)
R^2	.061		.093		.057		.277	

NOTES TO TABLE 5

[a]Key:

PREV	=	years of experience prior to entry into the labor force
AGE1	=	age of entry into the labor force
CALEN	=	calendar year of entry into the labor force
MARITAL	=	1 if married currently; 0 otherwise
ABILITY	=	score on a verbal comprehension test given at the time of the interview
NJOBS	=	number of jobs held since entry into the labor force
TRAIN	=	years of formal post-school training obtained
CURRENT	=	duration of current job
SIBLINGS	=	number of siblings in the family
FATHER	=	father's education
MOTHER	=	mother's education
BROKEN	=	1 if respondent lived in a broken family at age 14; 0 otherwise
RACE	=	1 if black; 0 otherwise

If this were true, but personal characteristics that we used in Table 5 are nonetheless relevant to earnings even if only indirectly (and certainly if directly), they should show up as significant when entered in the earnings regression.

This we do in three steps shown in Table 6: First we add to schooling (s) and experience (t, t^2) the subset of personal characteristics which represent additional information on postschool human capital, including "verbal ability" and marital status among them. The results are shown in column 2. The second subset, of family background variables, is then added and shown in column 3. Finally, the estimated parameter k_i, r_i, and v_i are included in column 4.

Generally, the results are negative. The personal characteristics on the whole do not substitute for parameters k_{oi}, r_i, and v_i, nor do they have net direct effects on earnings when these parameters are included. Actually, the first subset of personal characteristics especially verbal ability, marital status, and job mobility (or tenure) do supplement the experience parameters-- R^2 does increase from the first to the second column of Table 6. However, there is no increase in R^2 due to family background variables at any stage, while k_{oi}, r_i, v_i and education remain very strong (column 4), as they are without the vector of personal characteristics (Table 4). Indeed, comparing the last column of Table 4 with the last column of Table 6 we see that the explanatory power of the earnings equation is raised barely at all (from $R^2 = .57$ to $R^2 = .58$) when all the additional variables shown in Table 6 augment the last regression in Table 4. Of these additional variables only "ability," current job tenure, and marital status were

TABLE 6
Personal Characteristics in Current Earnings Function

Variable	Coeff. (1)	t	Coeff. (2)	t	Coeff. (3)	t	Coeff. (4)	t
				A. Pooled Sample				
Constant	5.8378		5.4607		5.3275		5.5229	
s	.0504	(10.02)	.0291	(4.70)	.0271	(4.24)	.0385	(7.87)
t	-.0141	(-.82)	-.0033	(-.17)	-.0005	(-.03)	-.0032	(-.89)
t^2	.0006	(1.11)	.0002	(.32)	.0001	(.23)		
RACE	-.2181	(-8.10)	-.1556	(-5.68)	-.1500	(-5.39)	-.1677	(-7.78)
PREV			-.0014	(-.15)	-.0002	(-.02)	-.0048	(-.70)
AGE1			.0043	(1.77)	.0041	(.53)	.0068	(1.17)
MARITAL			.1070	(2.73)	.1124	(2.88)	.0764	(2.54)
ABILITY			.0489	(6.84)	.0472	(6.54)	.0255	(4.53)
NJOBS			.0073	(2.00)	.0080	(2.17)	.0009	(.31)
TRAIN			.0093	(.57)	.0091	(.56)	.0012	(.09)
CURRENT			.0105	(3.61)	.0108	(3.73)	.0027	(1.18)
SIBLINGS					.0040	(.98)	-.0001	(-.03)
FATHER					.0050	(1.15)	.0019	(.57)
MOTHER					.0083	(1.76)	.0030	(.78)
BROKEN					-.0157	(-.54)	-.0018	(-.52)
k_{oi}							-.4032	(-12.95)
$r_i t^2$							.0004	(.84)
$r_i k_{oi} t$							.2154	(14.93)
v							.6559	(22.73)
R^2	.220		.283		.290		.584	

(continued on next page)

TABLE 6 (continued)

Variable	Coeff. (1)	t	Coeff. (2)	t	Coeff. (3)	t	Coeff. (4)	t
				B. White Men				
CONSTANT	5.6491		5.3074		5.1165		5.1197	
s	.0660	(7.93)	.0355	(3.21)	.0326	(2.83)	.0533	(6.15)
t	-.0219	(-.83)	.0080	(.26)	.0098	(.32)	.0073	(1.31)
t^2	.0011	(1.27)	.00002	(.03)	.00004	(.04)		
PREV			.0275	(1.77)	.0282	(1.81)	-.0002	(-.02)
AGE1			-.0026	(-.22)	-.0003	(-.03)	.0129	(1.47)
MARITAL			.1107	(1.54)	.1053	(1.46)	.0564	(1.05)
ABILITY			.0586	(4.77)	.0554	(4.44)	.0187	(1.96)
NJOBS			.0051	(.93)	.0051	(.93)	-.0045	(-1.10)
TRAIN			.0196	(.89)	.0211	(.96)	.0021	(.13)
CURRENT			.0108	(2.45)	.0115	(2.60)	-.0005	(-.14)
SIBLINGS					.0057	(.74)	.0041	(.73)
FATHER					.0079	(1.21)	.0059	(1.22)
MOTHER					.0079	(1.04)	.0002	(.03)
BROKEN					.0392	(.78)	.0062	(.16)
k_{oi}							-.5325	(-11.11)
$r_i t^2$							.0023	(2.97)
$r_i k_{oi} t$							.2580	(12.44)
v							.7833	(17.49)
R^2	.141		.209		.219		.574	

(continued on next page)

TABLE 6 (concluded)

Variable	Coeff. (1)	t	Coeff. (2)	t	Coeff. (3)	t	Coeff. (4)	t
				C. Black Men				
CONSTANT	5.6995		5.3345		5.2603		5.7753	
s	.0368	(6.31)	.0210	(3.06)	.0190	(2.68)	.0289	(5.31)
t	.0009	(.04)	.0054	(.23)	.0081	(.34)	-.0145	(-3.30)
t^2	-.00003	(-.04)	-.0003	(-.35)	-.0003	(-.45)		
PREV			-.0248	(-2.37)	-.0229	(-2.17)	-.0105	(-1.28)
AGE1			.0087	(.88)	.0070	(.71)	-.0010	(-.13)
MARITAL			.1056	(2.51)	.1118	(2.64)	.0873	(2.67)
ABILITY			.0413	(5.02)	.0411	(4.94)	.0243	(3.75)
NJOBS			.0091	(1.93)	.0110	(2.28)	.0059	(1.57)
TRAIN			-.0090	(-.35)	-.0094	(-.37)	.0001	(.00)
CURRENT			.0097	(2.67)	.0100	(2.76)	.0064	(2.24)
SIBLINGS					.0026	(.61)	-.0013	(-.39)
FATHER					.0014	(.24)	-.0020	(-.45)
MOTHER					.0096	(1.58)	.0063	(1.34)
BROKEN					-.0473	(-1.42)	-.0263	(-1.01)
k_{oi}							-.2855	(-7.27)
$r_i t^2$							-.0012	(-2.23)
$r_i k_{oi} t$							.1644	(8.46)
v							.5559	(15.47)
R^2	.105		.196		.207		.531	

marginally significant. But the introduction of the ability variable detracts from the education variable and does not provide an independent explanation.

We believe it is fair to conclude from Tables 5 and 6 that background, especially family characteristics of persons, affect their schooling attainment quite significantly, but have little if any effects on postschool investments, or on earnings, holding investment variables and parameters constant. Their indirect effects work almost wholly through educational attainment and almost not at all through postschool investment behavior or efficiency.

The human capital model which served as a guide appears to have survived the reported experiments. There does remain a challenge of measuring behavior expressed by the variables k_o, r, and v, whose role in earnings is undiminished even after the application of so many rarely available personal characteristics to the earnings function.

V. Summary

1. In this paper we analyzed the distribution of earnings histories of 884 men aged 30-39 in 1968. On average, the longitudinal profiles of earnings covered the first sixteen years of work experience. Deflated for price-level changes and for economy-wide growth, the profiles showed pronounced individual growth as well as individual differences in the growth of earnings. Typically, the profiles were concave with respect to experience, confirming the general shape suggested by cross-section data.

2. The distribution of individual earnings profiles shows a great deal of variation in levels, slopes, and curvatures of this initial part (about one-third) of the earnings profile. The individual variation in

levels is interpreted in human capital terms as reflecting differential endowments at the time of entry into full-time work. These endowments consist of schooling levels, of rates of return to schooling, and of capacity levels independent of (or predating) schooling. The variation in slopes and curvatures reflects differential volumes, timing, and profitability of "postschool investments." These cover a broad range of activities such as occupational choice and progressions, job training and learning, job and geographic mobility, job search and acquisition of information, work effort, and the like. Since only variation in schooling and in years of work experience can be observed in cross-sections, analyses of the distribution of earnings miss a great deal of individual variation which we just described. In this paper we attempted to quantify this variation in a schematic fashion: (a) As variation in the coefficients (slopes, curvatures, and levels) of the earnings profiles, and (b) as variation in the parameters of the earnings function which represent postschool investment ratios, rates of return, and levels of endowment, aside from levels of schooling. The investment ratios and rates of return enter as multiplicative components of the coefficients of the earnings function and we attempted to decompose these coefficients in order to analyze the parameters.

We find that if slopes and curvatures of individual trajectories were available to analysts, an additional 20-25 percent of the relative variance of (monthly or weekly) earnings could be explained beyond the usual power provided by the cross-section earnings function approach. The decomposition of the slope and curvature coefficients into investment ratio and rate of return parameters provides a smaller increase in explanatory power because of errors introduced by the procedure. However, the estimated parameters are of reasonable magnitude and acquire the appropriate signs in the cross-section regressions.

We estimated individual capacities within schooling groups as the residual from the schooling regression at the "overtaking stage" (at about ten years of experience). We then find that individuals with greater investment ratios grow more rapidly than others, and--holding capacity constant--have lower initial earnings. Finally, in terms of the potential explanatory power, variation in earning capacity is at least as important as variation in slopes and curvatures of earnings in the residual left over by the usual earnings function in which only years of schooling and years of experience are specified.

3. Our next step was to explore which of the many personal and background characteristics of individuals appear to be related, perhaps as determinants, to the slopes, curvatures, and human capital parameters implicit in the individual earnings profiles. The characteristics were (a) education, "verbal ability" measured at time of interview, work experience prior to completion of schooling, training on the job, job mobility status, age, and marital status; (b) parental education, number of siblings, and whether or not both parents were present in the household at the age of 14. Set (a) may be viewed as additional measures of the person's human capital stock, set (b) as his family background variables.

We found that, overall, the individual coefficients and parameters of the earnings profiles are very weakly, if at all, associated with the personal and background characteristics. Education, verbal ability, and job training appear to be of some significance, but family background has no effect at all on the postschool earnings trajectory. In constrast, education of the respondent is quite strongly explained by the family background variables and by verbal ability which is probably more an effect than a determinant of schooling. In human capital terminology, family background appears to affect schooling but not postschool investments.

4. It is possible that postschool investment parameters are in fact affected by the background variables, but we find no relation because our estimates of the human capital parameters (k, r, v) are largely in error. If so, the personal and background variables would show up as "direct" determinants of earnings, without or with the (k, r, v) parameters in the earnings function. The results of the test are negative: While verbal ability, marital status, and job mobility appear to supplement experience coefficients prior to inclusion of k, r, and v, the family background variables have no effect before or after the inclusion of k, r, and v.

In sum, while the role of postschool investment parameters in earnings remains strong even after all the available personal information is utilized additionally, the latter show little or no relation to the personal accumulation of postschool human capital. Nor, less surprisingly, do they show "direct" effects on earnings. The indirect effects which do exist are almost entirely achieved via family investment in schooling of children. It is surprising, however, that no relation can be traced between (preschool?) earning capacity (v) and family background in our sample.

The findings and surprises in this study will call for replication on longitudinal data which are current rather than retrospective before they can be generalized.

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