JOB MOBILITY AND EARNINGS OVER THE LIFE CYCLE

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Previous studies have shown that in the short run quits generally lead to wage increases on the next job and layoffs to no increase or to a wage cut. The author of this study argues, however, that the prospect of a job change for any reason creates a disincentive for a worker to invest in training that is specific to the current job, and therefore those who change jobs frequently may earn less over their life cycle than those who, other things equal, seldom change jobs. An analysis of data from the National Longitudinal Survey of Mature Men supports that expectation, showing that for white males job separations usually lead to wage gains in the short run but nonmobile workers tend to achieve significantly higher wages over the long run.

MANY recent studies have shown that the growth of earnings over the life cycle can be explained through a human capital model.[1] The hypothesis of this framework is that individuals are willing to forgo earnings today by investing in learning activities for the opportunity of increased earnings in the future. The objective of this paper is to extend the human capital approach to an analysis of the effects of job mobility on the cross-sectional distribution of earnings.

It will be argued that job mobility has two effects on earnings. First, it is likely to lead to changes in the wage rate an individual receives as he or she moves from one job to another. In other words, turnover will create shifts in the *level* of the experience-earnings profile across jobs—a relationship that has been well documented in the literature. Quits have generally been found to lead to wage increases and layoffs to wage decreases or at least no wage increase.[2] A second effect, however—that of mobility on the *slope* of the experience-earnings profile—has been ignored in the literature. It is hypothesized

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[1]See Jacob Mincer, *Schooling, Experience, and Earnings* (New York: National Bureau of Economic Research, 1974) for an exposition and application of the human capital model to 1960 U.S. census data. An excellent survey of the literature is given by Sherwin Rosen, "Human Capital: A Survey of Empirical Research," *Research in Labor Economics*, Vol. 1 (1977), pp. 3–39.

[2]See Ann P. Bartel and George J. Borjas, "Wage Growth and Job Turnover: An Empirical Analysis," in Sherwin Rosen, ed., *Studies in Labor Markets* (New York: National Bureau of Economic Research, forthcoming).

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here that the prospect of labor turnover will create disincentives for investing in on-the-job training as long as the training is partly specific to the current job. Since less investment is undertaken when a job separation is anticipated, earnings will grow at a slower rate while on a job that is not expected to be permanent. In other words, job mobility will tend to flatten the slope of the experience-earnings profile *within the job*.

This paper is an attempt to determine whether the "slope" effect of job mobility on earnings is empirically important. It presents a framework that allows for the estimation of this effect and empirical results from tests run on the National Longitudinal Survey (NLS) of Mature Men.

The Specification of Work History in the Earnings Function

It has been shown that the relationship between the individual's earnings capacity and his stock of human capital can be written as:[3]

$$(1) \qquad \ln E_t = \ln E_s + r \sum_{i=0}^{T} k_i$$

where:

- E_t = earnings capacity at time t, defined as what the individual's earnings would be if he did not invest in human capital;
- r = the rate of return to human capital investment;
- E_s = earnings capacity after completion of s years of schooling; and
- k_t = the ratio of dollar investment costs (C_t) to earnings capacity (E_t) or a measure of the fraction of time spent investing at time t.

Equation 1 can be interpreted as saying that the current earnings capacity of an individual can be decomposed into two parts: what the individual was worth prior to entering the labor market (E_s) and the returns to on-the-job training undertaken in the postschool period ($r \sum_{i=0}^{T} k_i$), where T measures the number of years of labor-force experience.

The main prediction of models of life-cycle allocation of learning activities is that the investment ratio—the proportion of time spent on human capital investment (k_t)—will decline over time.[4] This is predicted to occur because earlier investments have a longer payoff period and investments undertaken later in the life cycle are more expensive (due to the rising wage rate). This theoretical insight allows the transformation of the unobservable investment ratio into observable years of labor-force experience. For example, a simple functional form describing the path of investment over the working life would be:

$$(2) \qquad k_t = k_o - \beta t$$

where k_o is the initial level of the investment ratio (the proportion of time allocated to on-the-job training upon entering the labor force) and β is the rate of decline of human capital investment. Rewriting Equation 1 in continuous terms, substituting Equation 2, and integrating yields the simplest form of the earnings function:

$$(3) \qquad \ln E_t = \ln E_s + rk_o T - \frac{r\beta}{2} T^2$$

Note that Equation 3 reveals that individuals choosing to spend more of their time in learning activities (those having larger k_o) will have steeper rates of growth of earnings.

The functional form of this widely used earnings function arises from the assumption that investment declines linearly over the working life (Equation 2). For some groups of individuals (married women, for example) such an assumption is clearly

[3]See Mincer, *Schooling, Experience and Earnings*, pp. 11–19. To simplify the exposition, it has been assumed that the rate of return to human capital, r, is constant over time.

[4]See Yoram Ben-Porath, "The Production of Human Capital and the Life Cycle of Earnings," *Journal of Political Economy*, Vol. 75, No. 4 (August 1967), pp. 352–65, and Gary S. Becker, *Human Capital*, 2d. ed. (New York: National Bureau of Economic Research, 1975).

false.[5] Less obviously, once specific training and job mobility are introduced in the analysis, the assumption of continuously declining investment is likely to be unrealistic even for men with a permanent attachment to the labor force. In particular, specific training and labor turnover are likely to create additional implications regarding the timing of investment activities over the life cycle. The major implications are:[6]

1. The experience-earnings profile is likely to be discontinuous across jobs, for two reasons. First, job mobility will probably result in wage gains if the job switch has been voluntary. These gains, in a sense, represent the returns to investments in job search. Second, the path of investment (k_t) over time will also tend to have discontinuities across jobs, primarily because different jobs provide different learning opportunities, and hence the fraction of time that can be invested is likely to vary among jobs.[7]

2. If investment declines over the life cycle, as the optimization models predict, then the proportion of time spent in training activities will probably decline as time elapses *within* a particular job. The reasons for this, of course, relate to the fact that given jobs of finite duration in a person's life cycle, the returns are greater to earlier than to later investments and the costs of investment are likely to increase over time. The decline of investment within the job is more likely to be observed on jobs of longer duration since at the beginning of the job, while the quality of the match is being investigated by both the individual and the employer, investment may increase or remain constant. A second implication of the analysis is that the proportion of time spent in human capital investments is likely to be higher the earlier the job occurs in the life cycle. That is, among jobs of the same duration, those that are held earlier in the life cycle are likely to have larger investment volumes than those held later in the cycle.

One way of introducing these effects into the earnings function is by incorporating the work history of the individual into the equation. Generally, suppose there are n jobs in the individual's working life up to time t. Then Equation 1 can be written as:

$$(4)\quad \ln E_t = \ln E_s + r \sum_{i=0}^{e_1} k_{i1} + \ldots + r \sum_{i=0}^{e_n} k_{in}$$

where e_j is the duration of the j^{th} job and k_{ij} is the investment ratio in the i^{th} year of the j^{th} job. As was argued earlier, the proportion of time spent on human capital investment will decline within the job. Thus:

$$(5)\qquad k_{ti} = k_{oi} - \beta_i t \qquad (i=1,\ldots,n)$$

where k_{oi} measures the proportion of time spent in investment activities during the first year of the i^{th} job and β_i measures the rate of decline of investment within the job.

We also expect the intensity of investment in the i^{th} job (as measured by k_{oi}) to be affected by the timing of the job in the life cycle. That is, more investment is likely to take place the earlier the job occurs. This, of course, follows from the fact that if some of the training is general (or useful in other jobs) the payoff is greater the earlier it occurs. If the training is partly specific, however, a more important prediction can be derived: the intensity of investment in the i^{th} job (k_{oi}) will be positively correlated with the completed duration of the job. This positive correlation arises because if specific training exists, higher volumes of investment imply lower turnover rates and, hence, longer job durations.

These hypotheses can easily be introduced into the earnings function if the relationships are linear. In particular, the

[5]Jacob Mincer and Solomon Polachek, "Family Investments in Human Capital: Earnings of Women," *Journal of Political Economy*, Vol. 82, No. 2, Part II (March 1974), pp. S76 – S108, argue that the discontinuity in labor-force participation experienced by married women creates discontinuities in both the experience-earnings profile and the investment path over the life cycle.

[6]See Solomon Polachek, "Differences in Expected Post-School Investment as a Determinant of Market Wage Differentials," *International Economic Review*, Vol. 16, No. 2 (June 1975), pp. 451 – 70, and Ann P. Bartel and George J. Borjas, "Specific Training and Its Effects on the Human Capital Investment Profile," *Southern Economic Journal*, Vol. 44, No. 2 (October 1977), pp. 333 – 41.

[7]See Sherwin Rosen, "Learning and Experience in the Labor Market," *Journal of Human Resources*, Vol. 7, No. 3 (Summer 1972), pp. 326 – 42.

level of investment in the i^{th} job (k_{oi}) is given by:

$$(6) \quad k_{oi} = \alpha_i + \rho_i t_i^* - \sigma_i \pi_i \quad (i=1,\ldots, n)$$

where t_i^* is the expected completed duration of the i^{th} job and π_i is labor-force experience prior to starting job i.[8] The parameter ρ_i measures the importance of specific training on investment behavior, while σ_i measures the effect of aging on the distribution of lifetime investments.[9]

A problem immediately arises since the t_i^* are not observed. For all previous jobs (i=1,...,$n-1$), a first-order approximation is the actual completed job duration. For the current job we know that $t_n^* \geq e_n$. Specifically, $t_n^* = e_n + R$, where R represents the years remaining on the current job. An implication of the existence of specific training is that those men who have been longer at the job and invested more in specific training will have a lower probability of quitting (and of layoff) than other individuals.[10] Thus a first-order approximation would suggest:

$$(7) \qquad R = \lambda + \delta e_n$$

We can convert the unobserved completed duration of jobs (t_i^*) into observed job durations (e_i) by the following transformations:

$$(8) \quad t_i^* = \begin{cases} e_i, & i < n \\ \lambda + \gamma e_n, & i = n, \gamma = 1 + \delta. \end{cases}$$

Equations 5 – 8 provide the theoretical framework that allows the conversion of unobservable investment ratios into observable job duration variables. In fact, if we convert Equation 4 into continuous terms and use Equations 5 – 8, a "segmented earnings function" can be derived in which earnings capacity depends on the duration of each of the jobs in the life cycle and on quadratic and interaction terms. To illustrate, assuming there are two jobs in the life cycle, earnings capacity at time t can be written as:

$$(9) \ln E_t = \ln E_s + r\alpha_1 e_1 + r(\alpha_2 + \rho_2\lambda)e_2 + r(\rho_1 - \frac{\beta_1}{2})e_1^2 + r(\rho_2\gamma - \frac{\beta_2}{2})e_2^2 - r\sigma_2 e_1 e_2$$

The human capital framework, therefore, suggests that we estimate an earnings function in which there are three sets of independent variables: a linear term measuring duration for each job in the life cycle (e_i); a quadratic term for each of these job durations (e_i^2); and an interaction term between the duration of the i^{th} job and experience prior to the i^{th} job.[11] These three sets of variables roughly capture the expectation that earnings within the job will increase at a diminishing rate and the rate of growth of earnings in a job will be higher the earlier the job occurs in the life cycle.[12]

[8]Of course, $\pi_1 = 0$ since at the beginning of the first job no previous experience has been accumulated.

[9]Thus β_i measures the effect of aging within the job for given levels of previous experience.

[10]The fact that the probability of separation strongly diminishes with job tenure has recently been documented by Ann P. Bartel and George J. Borjas, "Middle-Age Job Mobility: Its Determinants and Consequences," in Seymour Wolfbein, ed., *Men in the Pre-Retirement Years* (Philadelphia: Temple University Press, 1977), pp. 39 – 97.

[11]The functional form for the earnings function with n segments can be shown to be:

$$\ln E_t = \ln E_s + \sum_{i=1}^{n-1} r_i \alpha_i e_i + r_n(\alpha_n + \rho_n \lambda)e_n + \sum_{i=1}^{n-1} r_i(\rho_i - \frac{\beta_i}{2})e_i^2 + r_n(\rho_n\gamma - \frac{\beta_n}{2})e_n^2 - \sum_{i=2}^{n} r_i \sigma_i \pi_i e_i .$$

A detailed discussion of the derivation and of identification problems can be found in George J. Borjas, "Job Investment, Labor Mobility and Earnings" (Ph.D. dissertation, Columbia University, 1975).

[12]Clearly Equation 9 cannot be estimated since the dependent variable is earnings capacity, which is unobserved. Net earnings can be defined as $Y_t = E_t - C_t$, so that $\ln Y_t = \ln E_t + \ln(1 - k_t)$. The variable Y_t is closer to the empirically observed earnings since most investment costs are likely to be forgone earnings. Assuming that k_t is a small number, $\ln(1 - k_t) \simeq -k_t$. Using Equations 5 – 8 leads to k_t being a function of job duration and previous experience. Thus the equation for observed earnings has the same form as Equation 9 but a slightly different interpretation of the coefficients in terms of the underlying parameters of the model. Details are available on request from the author.

The estimation of Equation 9 in principle allows us to use the estimated coefficients of the regression to solve for the underlying theoretical parameters. Given these calculations, estimates of investment ratios, k_{oi}, for each job could be obtained, but only by making assumptions concerning the magnitude of the rate of return to human capital investment, r, and the rate of decline of human capital investment, β_i, since the model is underidentified. Thus it is impossible to test *directly* the importance of specific training in the determination of earnings. It can be shown, however, that if t_n^* (the *completed* duration of the current job) were known, and if there were two jobs in the working life, the earnings function in terms of observed earnings, Y_t, could be written as:[13]

$$(10) \qquad \ln Y_t = f(e_1, e_2, e_1^2, e_2^2, e_1 e_2) + r\,\rho_2 R \cdot e_2 - \rho_2 R$$

Equation 10 says that (log) earnings are a function not only of the same variables that entered Equation 9 [i.e., $f(e_1, e_2, e_1^2, e_2^2, e_1 e_2)$], but also of R (the time remaining in the current job as of time t), and an interaction term between R and e_2 (the time already elapsed in the current job). The reason that R enters negatively into the determination of current earnings is that there exists a positive correlation between investment and job duration: the longer the time remaining in the current job, the higher the incentive to invest more in the current time period (since the payoff period to specific training is longer) and therefore the lower current earnings. The interaction between R and e_2 is positive because the theory suggests more investment in longer jobs. That is, the larger e_2, the more investment that has already taken place and the higher the returns the individual is collecting at time t.

Equation 10 also indicates that panel data can be used to test directly the importance of the specific training hypothesis as long as the individual is followed up for a long enough period of time to observe a job separation. Moreover, the estimation of Equation 10 unambiguously allows the identification of two important parameters of the model: the rate of return, r, and the parameter measuring the relationship between completed job duration and investment levels in the current job, ρ_n.

Empirical Analysis

The model outlined above is estimated using the 1966 National Longitudinal Survey of Mature Men.[14] In 1966, at the time of the survey, these men were 45 – 59 years of age. The NLS provides us with a retrospective working history for the men sampled. Because of the structure of the questionnaire, it is possible to get, at most, the duration of three jobs in the individual's working life: the first full-time job ever held after completion of schooling, the job held for the longest time, and the job held at the time of the survey (the "current" job). Since two or three of these jobs might be the same (that is, the first job could have been held longest) we have different numbers of jobs across individuals. The data also allow us to determine the time elapsed between jobs, such as that between the end of the first job and the beginning of the longest job (a "residual").

The earnings functions derived earlier require the same number of jobs across individuals. To provide this, the sample was broken up into four job mobility patterns:

Pattern 1: only one job has been held since the completion of schooling. Obviously, this pattern is composed of the least mobile individuals.

Pattern 2: the first job after the completion of schooling is different from the current job, which is also the longest job. We can identify the time elapsed between the first and current jobs (a residual). This pattern is therefore characterized by three segments.

Pattern 3: the first job was the longest job but it is not the current job. Again we can

[13]Equation 10 is derived in Borjas, "Job Investment, Labor Mobility, and Earnings." Details on the derivation are also available from the author on request.

[14]See U.S. Department of Labor, *The Pre-Retirement Years*, Vol. I, Manpower Research Monograph No. 15 (Washington, D.C.: G.P.O., 1970) for an extensive discussion of the survey.

identify a residual: the time elapsed between the first and current jobs. This pattern is also characterized by three segments.

Pattern 4: the first, longest, and current jobs are all different, providing two residuals—the time elapsed between the first and longest jobs and the time elapsed between the longest and current jobs. This pattern, which contains the most mobile individuals, is characterized by five segments.

In order to pool the samples, a simple method is used throughout. All individuals are assumed to have a current job. *FIRST* is defined as the first job after completion of schooling, if it is different from the current job; *GAPA* is defined as the residual following the first job; *LONGEST* is the job held longest, if different from both the first and current jobs; *GAPB* is the residual following the longest job; and *CURRENT* is the current job. If a job does not exist for a given individual, a zero is coded as his experience for that particular job.[15]

The sample was restricted to white men who were working in 1966, who were not self-employed, and for whom there were valid data for wage rates, working life histories, and the other key variables in the analysis. These restrictions simplify the study by avoiding the problematical interpretation of earnings for self-employed individuals and the effects of racial discrimination on wage rates. The dependent variable in the analysis is the natural logarithm of the usual wage rate in the job held during the 1966 survey week.

Table 1 defines the variables used in the study. Table 2 presents summary statistics for each of the mobility patterns and for the pooled sample. It shows systematic variations in earnings across mobility patterns. The least mobile men (Pattern 1) have wage rates 37.3 percent higher than the most mobile men (Pattern 4). The same finding holds when we compare Pattern 2 (where the current job is the longest held) to Pattern 4: those men who have held their current job longest have wage rates 16.3 percent higher. Moreover, Table 2 reveals that in comparing Patterns 2 and 4 (which jointly contain 89 percent of all observations), differences in personal characteristics, such as education and health, are too small to explain the sizable wage differential.

Table 1. List of Variables.

RATE	= Usual wage rate in 1966 job.
ANNUAL	= Annual earnings in 1965.
EDUC	= Completed years of education.
EXPER	= Experience since completion of schooling (in years).
FIRST	= Duration of first job after completion of school—if different from the current job (in years).
GAPA	= Residual experience following *FIRST* (in years).
LONGEST	= Duration of longest job ever—if different from first and current jobs (in years).
GAPB	= Residual experience following *LONGEST* (in years).
CURRENT	= Current job experience (in years).
INTER(i)	= Interaction term pertaining to the i^{th} job: tenure in i^{th} job times experience prior to the i^{th} job.
HLTH	= 1 if health is good or excellent; 0 otherwise.
TRAIN	= Number of years of formal post-school training.
MAR	= 1 if married with spouse present; 0 otherwise.

Table 3 gives the unsegmented earnings function derived in Equation 3 for the pooled sample and across mobility patterns, using the natural logarithm of the wage rate as the dependent variable. Note that the coefficients of the linear experience variable (which in the human capital model measure roughly the proportion of time spent investing in the early phases of the working life) are larger for the less mobile, Patterns 1 and 2. In other words, the experience-earnings profile is steeper for the less mobile men.

The individuals in Pattern 1 have had

[15] For example, in Pattern 2—where the first job is different from the current (longest) job—*FIRST*, *GAPA*, and *CURRENT* would exist, but *LONGEST* and *GAPB* would be coded as zero.

Table 2. Means of Variables.

Variable	*Pattern* 1	*Pattern* 2	*Pattern* 3	*Pattern* 4	*Pooled Sample*
EDUC	12.38	10.48	9.95	10.22	10.48
AGE	50.39	51.15	51.80	51.13	51.14
ANNUAL	9997.6	8286.4	6103.2	6863.7	7814.1
RATE	4.38	3.71	2.77	3.19	3.53
FIRST	—	3.20	17.91	2.98	3.79
GAPA	—	12.16	7.36	10.00	10.53
LONGEST	—	—	—	12.16	3.79
GAPB	—	—	—	5.21	1.62
CURRENT	25.36	18.21	5.75	3.99	13.46
HLTH	.86	.81	.80	.82	.81
TRAIN	.96	.82	.85	.83	.83
MAR	.93	.93	.89	.89	.92
Number of Observations	111	1136	113	616	1976

Table 3. Unsegmented Earnings Functions
(Dependent Variable = ln *(RATE)*; *t*-ratios are given in parentheses).

Variable	*Pattern* 1	*Pattern* 2	*Pattern* 3	*Pattern* 4	*Pooled Sample*
CONSTANT	.541	.171	−.0006	.716	.247
EDUC	.038**	.069**	.072**	.059**	.067**
	(2.8)	(15.3)	(5.1)	(8.1)	(18.6)
EXPER	.030*	.016	−.0009	−.017	.010*
	(1.6)	(1.0)	(−.04)	(−.7)	(1.3)
EXPER^2	−.0006*	−.0002	.0002	.0002	−.0001
	(−1.4)	(−.9)	(.4)	(.6)	(−1.1)
R^2	.120	.208	.211	.140	.181

*Significant at the .10 level in a one-tail test.
**Significant at the .05 level in a one-tail test.

only one job. Therefore the analysis of their earnings profile does not require any segmentation of their work experience history. The coefficients of experience can be used to calculate an estimate of k_o, the investment ratio measuring the fraction of time spent investing immediately after entering the labor force. If the rate of return is assumed to be 10 percent, the initial investment ratio is 18 percent.[16]

[16]To illustrate this calculation, consider Equation 3, which is written in terms of earnings capacity. To convert it to observed earnings, Y_t, note that $\ln Y_t = \ln E_t + \ln(1 - k_t)$, and assume $\ln(1 - k_t) \simeq -k_t$. Equation 3 can then be written in terms of observed earnings as:

$$\ln Y_t = (\ln E_s - k_o) + (rk_o + \beta)T - \frac{r\beta}{2}T^2$$

The segmented earnings functions for the pooled sample are presented in Table 4. As can be seen, the interaction terms between tenure in the i^{th} job and labor-force experience prior to the i^{th} job are mostly negative. The economic meaning of these negative interaction terms is that the rate of growth of earnings in the i^{th} job is smaller the later the job occurs. In terms of the human capital model, this implies that less is invested in jobs that occur later in the life cycle. Note also that the coefficients of the square of each job duration are generally negative. This implies that the rate of growth of earnings within the job diminishes as job tenure accumulates. The interpretation given by the human capital model would be that incentives for investment decline as tenure on the job increases. Finally, the coefficients of the linear job tenure terms tend to be positive or zero. We find, however, that among the coefficients of experience in jobs prior to the current job, the effect of experience in the longest job is by far the largest. This result, of course, highlights the importance of experience in determining current earnings in jobs held for a long time. The human capital interpretation is that relatively large investment incentives exist in jobs held longer, presumably due to the specificity of on-the-job training.

Table 4. Segmented Earnings Functions, Pooled Sample.
(Dependent Variable = ln *(RATE)*)

Variable	*Coefficient*	*t-ratio*
CONSTANT	.223	
EDUC	.061**	(18.0)
FIRST	– .0004	(– .05)
GAPA	.011*	(1.5)
LONGEST	.018**	(1.8)
GAPB	– .009	(– .6)
CURRENT	.028**	(3.4)
$FIRST^2$	.0007	(.3)
$GAPA^2$	– .0001	(– .8)
$LONGEST^2$	– .0004*	(– 1.3)
$GAPB^2$	– .0003	(– .07)
$CURRENT^2$	– .0004**	(– 2.5)
INTER2	– .0005*	(– 1.4)
INTER3	– .0007**	(– 2.4)
INTER4	.0005	(.9)
INTER5	– .0005**	(– 2.2)
R^2	.233	

*Significant at the .10 level in a one-tail test.
**Significant at the .05 level in a one-tail test.

By estimating the segmented earnings function within each mobility pattern, we can use the interpretation of the coefficients provided by the model (see, for example, Equation 9) to calculate k_{oi} for each job in each mobility pattern. Recall that k_{oi} measures the fraction of time spent in investment activities at the start of the i^{th} job. The estimated regressions are shown in the Appendix. As can be seen the coefficients are generally not very significant; this is mainly due to the large amount of multicollinearity among the variables. These estimated regressions were used to find the k_{oi} for each job in each mobility pattern (see Table 5).

Since the human capital earnings function is underidentified, assumptions regarding some of the parameters must be made in order to estimate the remaining parameters. In particular, the estimates presented in Table 5 are calculated by assuming that the rate of return, r, is 10 percent. Experimental variation of the rate of return to 5 and 15 percent did not affect the qualitative results of the analysis. Another assumption must be made about the rate of decline of human capital investment (β). It is assumed that β is the same across all jobs in the working life. Table 5 presents estimates of k_{oi} under varying assumptions about the magnitude of $r\beta/2$: .0010, .0015, and .0020.[17]

For the individuals in Pattern 2—where the first job was a short job different from the current (longest) job—investment was extensive. The estimate of k_{oi} for the cur-

The regression in Table 3 suggests $(rk_o + \beta) = .030$, and $r\beta/2 = .0006$. Using $r = .10$ and simultaneously solving these equations yields $k_o = .18$.

[17]These estimates cover the range of those found in the literature on unsegmented earnings functions. Mincer, *Schooling, Experience, and Earnings,* for example, p. 92, estimates $r\beta/2 = .0012$.

Table 5. Estimates of Investment Ratios.

Segment	$r\beta/2=.0010$ k_{oi}	$r\beta/2=.0015$ k_{oi}	$r\beta/2=.0020$ k_{oi}
Pattern 2			
FIRST	.159	.175	.191
GAPA	.098	.159	.220
CURRENT	.157	.198	.239
Pattern 3			
FIRST	−.204	−.114	−.025
GAPA	.032	.069	.106
CURRENT	.072	.045	.024
Pattern 4			
FIRST	−.279	−.265	−.250
GAPA	−.096	−.046	.004
LONGEST	−.023	.038	.099
GAPB	−.086	−.060	−.034
CURRENT	−.076	−.107	−.137

rent job is generally higher than the estimates for previous jobs, despite the fact that the current job started 15.4 years after the beginning of labor-force experience.

The estimates for individuals in Pattern 3—where the longest job was the first job—are very sensitive to the underlying assumptions. One reason for the instability of the coefficients might be the small size of this mobility pattern (113 observations). The results do indicate little investment in all jobs.

The results for the most mobile individuals—Pattern 4—show that little investment occurred in all jobs except the longest. Both the first and current jobs yield estimated k_{oi}s that are negative even though in the actual regression the current job coefficient was significantly higher than all the other coefficients. These estimates might be negative because they are ratios net of depreciation.

Summarizing, two important conclusions can be inferred from these empirical findings. First, the results indicate that longer job duration is associated with higher rates of growth in earnings. Second, the empirical evidence provides support to the hypothesis that mobile individuals have spent less time investing in on-the-job training. This, of course, will tend to depress the current earnings of men whose work histories have exhibited a substantial amount of labor turnover. Thus, the human capital hypothesis provides an explanation of why the current earnings of mobile individuals are lower than the earnings of "stayers."

As shown earlier, a more direct test of the specific-training hypothesis can be obtained if t_n^*, the completed duration of the current job, is observed. The National Longitudinal Surveys provide an excellent opportunity to test the hypothesis since individuals were re-interviewed for several years after 1966. We estimated Equation 10, using a small sample of men who, before 1969, left the job they held in 1966 (thus enabling us to observe the completed duration of the current job). These results are presented in Table 6. The coefficient of time remaining in the job as of 1966 (*REM*) is negative and marginally significant. In terms of the human capital model this coefficient suggests $\rho_n = .0620$. Recall that ρ_n measures the effect of completed job duration in the current job on the fraction of time spent in training activities in that job (see Equation 6). The coefficient of the interaction term (*REM* x *CURRENT*) is positive and significant, so that in terms of the model $r\,\rho_n = .0087$. The implied estimate of the rate of return to on-the-job training is 14 percent.

In terms of the underlying economics

Table 6. Earnings Functions When Completed Duration of Current Job Is Known.[a]
(Dependent Variable = ln (RATE))

Variable	*Coefficient*	*t-ratio*
CONSTANT	.164	
EDUC	.055**	(5.7)
FIRST	− .0009	(− .04)
GAPA	.028*	(1.3)
LONGEST	.014	(.5)
GAPB	.018	(.5)
CURRENT	.004	(.2)
FIRST^2	.0003	(.5)
GAPA^2	− .0004	(− .9)
LONGEST^2	.0002	(.2)
GAPB^2	− .0005	(− .5)
CURRENT^2	.0001	(.2)
INTER2	− .0008	(− .8)
INTER3	− .0008	(− .8)
INTER4	− .0003	(− .2)
INTER5	− .0003	(− .5)
*REM*x*CURRENT*	.0087**	(2.3)
REM	− .0620*	(− 1.3)
R^2	.170	

[a]Number of observations = 350.
*Significant at the .10 level in a one-tail test.
**Significant at the .05 level in a one-tail test.

of the problem, the negative effect of *REM* on current earnings can only be explained by referring to the relationship among turnover, specific training, and investment incentives. If training were totally general, time remaining in the current job would have no effect on investment incentives and, hence, no effect on current earnings. Once specific training is introduced, however, the payoff period to that portion of the training that is firm-specific becomes the time remaining in the current job. The longer *REM*, the higher the incentive to invest in human capital and, hence, the more investment today. Since human capital investments are financed by forgone earnings, *REM* would have a negative effect on current earnings. Simultaneously, longer *REM* would also imply that more had been invested in each year already elapsed in the current job. Hence, an interaction term between *REM* and *CURRENT* would have a positive effect, since higher volumes of prior investments would imply higher levels of returns being received in the current time period.

One last piece of evidence on the validity of the specific training hypothesis is given by comparing the gain of the fine degree of segmentation used in this paper to the unsegmented earnings function or to a function that combines all previous jobs into one segment, *PREVIOUS*. These two-segment earnings functions are shown in Table 7 for the pooled sample and for the mobility patterns. When the results are compared to the full segmentation in the pooled sample (Table 4), the simpler two-segment earnings function does not fare badly. The $\mathbf{R}^2$ in the simpler equation is .223, while the explanatory power of the full segmentation is only slightly higher, .233.

Within mobility patterns, however, there are significant differences between the simple segmentation shown in Table 7 and the full segmentation in the Appendix. For example, no significant differences in explanatory power can be detected in the equations for Pattern 2 (where the current job is the longest). The $\mathbf{R}^2$ for the unsegmented equation is .208 (see Table 2); it increases to .232 with the two-job breakdown (Table 7) and to .234 with the full segmentation (see the Appendix). Thus the introduction of the current job, where most investment took place, is the factor behind the increase in explanatory power.

In Pattern 4, the results are quite different. The full segmentation gives a much better fit to the earnings profile in this mobility pattern: the R^2 for the full segmentation is .184 (see the Appendix), while the explanatory power of the simpler segmentation is only .142 (Table 7) and that of the unsegmented function is .140 (Table 3). Thus the increase in R^2 comes when we segment previous experience. This finding suggests that the more "homogeneous" previous experience, the better the fit of the simpler (two-job) segmentation. That is, in Pattern 4 we are combining the longest job and a series of short jobs into one segment of previous experience. The results discussed earlier indicate that some investment took

Table 7. Earnings Functions Using Two Segments.
(Dependent Variable = ln (RATE); *t*-ratios are in parentheses)

Variable	*Pooled Sample*	*Pattern 2*	*Pattern 3*	*Pattern 4*
CONSTANT	.264	.280	−.077	.715
EDUC	.061**	.065**	.072**	.058**
	(17.3)	(14.3)	(5.2)	(7.8)
PREVIOUS	.004	.006	−.020	−.018
	(.5)	(.4)	(−.9)	(−.7)
CURRENT	.023**	.016	.128**	−.002
	(2.6)	(1.0)	(2.6)	(−.1)
$PREVIOUS^2$	−.0001	−.0002	.0007*	.0002
	(−.4)	(−.6)	(1.5)	(.6)
$CURRENT^2$	−.0003**	−.0002	−.0030**	−.0001
	(−1.9)	(−.5)	(−2.0)	(−.1)
PREVIOUS x *CURRENT*	−.0003	−.0002	−.0023*	.0003*
	(−1.0)	(−.4)	(−1.5)	(1.3)
R^2	.223	.232	.276	.142

*Significant at the .10 level in a one-tail test.
**Significant at the .05 level in a one-tail test.

place in the longest job, but little investment took place in the other previous jobs. If we combine these jobs into a single category of previous experience, we lose the information given by the relationship between job duration and the rate of growth of earnings. Therefore, the results point out the importance of the job held longest (regardless of when it occurred) in the determination of earnings.[18]

[18]Note that the analysis has concentrated on the effect of job experience on earnings; very little attempt has been made to include other variables in the equation. This was done to avoid the "kitchen-sink" tendency of many recent analyses using the earnings function. In addition, the analysis has focused on documenting the effect of job mobility on the slope of the earnings profile. As noted in the introduction, mobility also affects the level of the profile. A simple way of estimating this effect is to hold some measure of total on-the-job training constant and then insert variables that measure the extent of mobility. This can be done easily by adding mobility pattern dummies to the regression presented in Table 4. The coefficients of interest were:

Pattern	*Coefficient*	*t-ratio*
2	.050	(.9)
3	−.043	(−.5)
4	.160	(1.8)

The results indicate a shifting of the level of the earnings profile of about 16 percent for the most mobile individuals in the sample. A more detailed analysis of the level effects of job mobility can be found in Bartel and Borjas, "Wage Growth and Job Turnover."

Summary

This paper has analyzed the effect of job mobility over the working life on the earnings of middle-aged white males. An earnings function was developed that took into account the discontinuity of earnings across jobs, the decline in the proportion of time allocated to human capital investment within the job and over the life cycle, and the effect of the probability of job separation on the rate of growth of earnings *within* the job. Using this framework to analyze data from the National Longitudinal Survey of Mature Men, we obtained several empirical findings:

1. Individuals who have experienced a substantial amount of job mobility in their working lives tend to have smaller rates of growth of earnings *within* each job.

2. Although job separations lead to short-run gains in wage rates, the fact that

mobile men tend to have lower rates of growth in earnings within each job leads, in the long run, to a wage advantage in favor of the least mobile men. That is, labor turnover may lead to a significantly higher wage rate in the new job than in the old job, but by the time the men reach middle age, the short-run advantages of labor mobility are less important, leaving nonmobile men with significantly higher wage rates.

3. The explanatory power of the human capital approach was significantly increased by accounting for the effects of job mobility; this increase occurred when the duration of the job held longest (regardless of when it occurred) was introduced in the earnings function. This is due to the fact that most human capital investments take place on the job held longest.

The analysis in this paper provides a particular interpretation of the empirical results, namely, a human capital interpretation. It is very likely that the empirical findings are consistent with many alternative explanations. Perhaps the main contribution of the paper is simply to point out that job mobility is an important determinant of the wage structure and that it deserves much additional research.

Appendix

Segmented Earnings Functions by Mobility Pattern
(Dependent Variable = ln (RATE))

	Pattern 2		*Pattern 3*		*Pattern 4*	
Variable	*Coeff*	*t-ratio*	*Coeff*	*t-ratio*	*Coeff*	*t-ratio*
CONSTANT	.426		– .185		.505	
EDUC	.064**	(4.3)	.071**	(5.4)	.061**	(8.6)
FIRST	.007	(.4)	– .032*	(– 1.4)	– .025	(– 1.2)
GAPA	– .006	(– .4)	.042	(1.2)	– .013	(– .7)
LONGEST	—	—	—	—	– .007	(– .3)
GAPB	—	—	—	—	– .024	(– 1.0)
CURRENT	.007	(.4)	.153**	(3.1)	.057**	(2.5)
*FIRST*²	– .0006	(– 1.2)	.0010**	(2.3)	– .0000	(– .0)
*GAPA*²	.0001	(.5)	– .0010	(– 1.2)	.0005*	(1.3)
*LONGEST*²	—	—	—	—	.0002	(.4)
*GAPB*²	—	—	—	—	.0002	(.4)
*CURRENT*²	– .00003	(– .1)	– .0030**	(– 2.2)	– .0009**	(– 1.9)
INTER2	– .0005	(– .8)	– .00002	(– .00)	.0003	(.2)
INTER3	.0001	(.3)	– .0033**	(– 2.2)	.0002	(.3)
INTER4	—	—	—	—	.0010*	(1.4)
INTER5	—	—	—	—	– .0015**	(– 2.5)
R^2	.234		.313		.184	

*Significant at the .10 level in a one-tail test.
**Significant at the .05 level in a one-tail test.