A FORMULATION OF THE EARNINGS FUNCTION USING THE CONCEPT OF OCCUPATIONAL INVESTMENT*

KATHRYN L. SHAW

ABSTRACT

Standard models of income determination specify income to be a function of two variables that measure postschool investment—the years of labor market experience and the years of employer tenure. This investigation develops a better proxy for general human capital investments by hypothesizing that the intensity of investment varies by occupation and that a proportion of the occupational skills are transferable with occupational change. After developing exogenous measures of these features, the occupational investment variable is calculated for the young men of the National Longitudinal Survey. Empirical work demonstrates that occupational investment is a strong determinant of income—far superior to the experience variable.

Many studies of on-the-job training as a determinant of earnings growth have followed Mincer's [10] formulation of the theory of postschooling investment. Usually a distinction is made between the effects on earnings of age, per se, and experience, where experience is defined by a homogeneous measure of years of work in the labor force. In this paper I develop a new approach to measuring experience, defining "occupational investment" in a way that introduces heterogeneity in a worker's experience. By hypothesizing that occupations are characterized by different degrees of general investment, I can use an individual's history of occupational choices to calculate that individual's quantity of occupational investment at each time t of the wage profile.

The author is Assistant Professor of Economics, Carnegie-Mellon University.

* Research support from the National Council on Employment Policy, Dissertation Grant No. DD-25-80-023, and the National Science Foundation, Grant No. SOC78-04279, is gratefully acknowledged. I would also like to thank Zvi Griliches, Richard B. Freeman, members of the Carnegie-Mellon Empirical Workshop, and anonymous referees for their valuable comments. [Manuscript submitted April 1983; accepted February 1984.]

The Journal of Human Resources • XIX • 3
0022-166X/84/0003-0319 $01.50/0

There are two fundamental results. First, occupational investment is a significant and robust determinant of earnings growth, dominating the effect of experience. Second, the occupational investment variable reveals that general human capital and firm-specific human capital are skill substitutes rather than skill complements. Individuals tend to specialize in one or the other.

In the following section I present the theoretical model of occupational investment. Empirical measures are developed in Section II, and tests of the variable in wage regressions are discussed in Section III. The conclusions follow.

I. THE MODEL OF OCCUPATIONAL INVESTMENT

The Definition of Occupational Investment

Occupational investment is the accumulation of skills an individual acquires to perform work within an "occupation." An occupation is defined to be a homogeneous skill classification within which individuals are perfect substitutes in demand and/or have infinite cross elasticities of substitution in supply.[1] Cabinet makers and engineers, for example, have occupation-specific skills. In practice, the occupational classifications are not as homogeneous as would be desired, and in the empirical analysis in this paper 3-digit occupations will be used.

By definition, occupational skills are perfectly transferable across employers and, therefore, are a form of general human capital investment. It is useful to think of each individual as possessing a 2-dimensional vector of skills: their employer-specific skills and their general occupation-specific skills, which refer to skills utilized in their current occupation.[2] These two sets of human capital investment are separable, as will become apparent in the empirical work below.

Occupation-specific and firm-specific skills are quite similar in that changing occupations or employers reduces the return to the stock of investment in those skills. However, they also differ in that an employer-change eliminates all the employer-specific skills, whereas some portion of the occupational skills will be transferable to the new occupation. In the new occupation, the individual will begin with a quantity of invest-

1 This definition is representative of that found in the economics literature on occupational classification. See Dauffenbach [3] and Scoville [12].

2 In fact, an individual's vector of human capital investment is multidimensional, consisting of depreciated investment for all previous occupations and employers. At any point in time, only two skills are relevant—those for the current occupation and for the current employer. If individuals switch back to a previous occupation or employer, those skills would reappear.

ment equal to the value of his old occupational skills weighted by their degree of transferability. Transferability is always greater than zero because a portion of postschool investment is completely general (for example, learning to communicate with others).

Two examples serve to clarify the concept of occupational investment. First, assume an occupational change from engineering to management is made. If management is narrowly defined as the management of scientific personnel, a portion of the individual's engineering skills will be valuable as a manager. Perhaps 30 percent of the skills will be passed on. Compare this to the case of a worker moving from the position of forklift operator to bulldozer operator. In this case the skills are very similar and therefore more transferable. However, this does not imply that the operative is more skilled than the engineer-manager. Though the operative will transfer more of his previous skills, he will have less total skills to transfer.

This description can be formalized in the following manner. It is hypothesized that as a change from occupation i to occupation j is made, the individual will transfer γ^{ij} percent of his skills from occupation i to occupation j. While residing in i, the individual accumulated occupation-specific investment equal to $\tilde{K}^i$. Thus, combining the definitions of skill transferability and occupation-specific investment, the *individual's* accumulated quantity of *total occupational investment* at time t is defined as:

$$K_t^j \equiv \tilde{K}_t^j + \gamma^{ij}\tilde{K}_{t_j-1}^i + \cdots + \gamma^{gj}\tilde{K}_{t_h-1}^g \tag{1}$$

where $\tilde{K}^j$, $\tilde{K}^i$, . . ., $\tilde{K}^g$ represent stocks of occupational-specific investment for all current and previous occupations, j, i, . . ., g. Define $\tilde{K}_t^j \equiv \Sigma_{h=tj}^t k_h^j$, for $k_t^j \equiv$ the percent of full income invested in occupation j in year t, or the intensity of investment. The γ^{ij} and γ^{gj} are the percent of skills transferred from occupations i and g to j, respectively. The t_j and t_h are the years of entry into occupations j and h.

Total occupational investment in occupation j is a weighted sum of the individual's accumulated quantities of occupation-specific investment, where the weights are the transferabiity parameters γ^{ij}, . . ., γ^{gj}. With measures of the transferability parameters and information on the individual's occupational history, K_t^j can be calculated for each individual, as will be done in the next section.

Occupational investment K^j is a heterogeneous measure of general human capital investment which replaces the homogeneous measure of years of experience in the labor market. It can capture the fact that production workers are less skilled than engineers at equivalent experience levels. By introducing occupational investment, the amount of otherwise unobservable heterogeneity in individuals' general postschool investment is reduced.

Income Determination

The standard earnings function of Mincer [10] can now be reformulated to include occupational investment. The natural log of income for an individual employed in occupation j at time t is:[3]

$$\ln Y_t^j = \ln E_0 + r^s S_t + r^e K_{t-1}^e + r^j K_{t-1}^j \tag{2}$$

The individual's intrinsic earnings capacity, E_0, is augmented by investment in schooling, S_t; employer-specific skills, K_{t-1}^e; and occupational skills, K_{t-1}^j. The K^e and K^j are in time-equivalent units of investment and equal the summation of the percent of time spent investing during each previous year.

When the definition of occupational investment (1) is inserted into equation (2), $\ln Y$ becomes:

$$\begin{aligned} \ln Y_t^j = {} & \ln E_0 + r^s S_t + r^e K_{t-1}^e \\ & + r^j \left[\tilde{K}_{t-1}^j + \gamma^{ij} \tilde{K}_{t_j - 1} + \cdots + \gamma^{gj} \tilde{K}_{t_h - 1}^g \right] + e_t \end{aligned} \tag{2'}$$

with error term e_t independently and identically distributed N $(0,\sigma)$ representing measurement error in Y_t (a covariance structure is added below). Income is a function of a weighted average of all current and previous occupational investment.

Equation (2′) implies that there are discontinuities in the investment-income profile, which can be clarified graphically (see Figure 1). Assume the individual changes occupations once, moving from occupation i to occupation j at time t_j. The move is motivated by a greater present value of income in j, or the returns of area (b) exceed the costs of area (a). The return-cost differential will be greater, the greater the transferability of skills and the steeper the growth path of income in the new occupation relative to the old. Given declining marginal productivities of investment and long work horizons, multiple occupational change may be optimal. The result is that investment and income will be discontinuous, particularly early in careers.

3 The log linear equation is derived from

$$Y_t^j = E_0(1 + r^s)^{S_t} + r^j \sum_{h=1}^{t-1} C_h^j + r^e \sum_{h=1}^{t-1} C_h^e - C_t^j - C_t^e$$

where C = the dollar costs of investment. Setting $k_t^j = C_t^j/E_t^j$ = the proportion of time spent investing, $K_t^j = \Sigma_{n-t_j}^{t} k_n^j$, and taking the $\ln(Y_t^j)$ with $\ln(1 - k_t^e - k_t^j) = 0$ will produce (2).

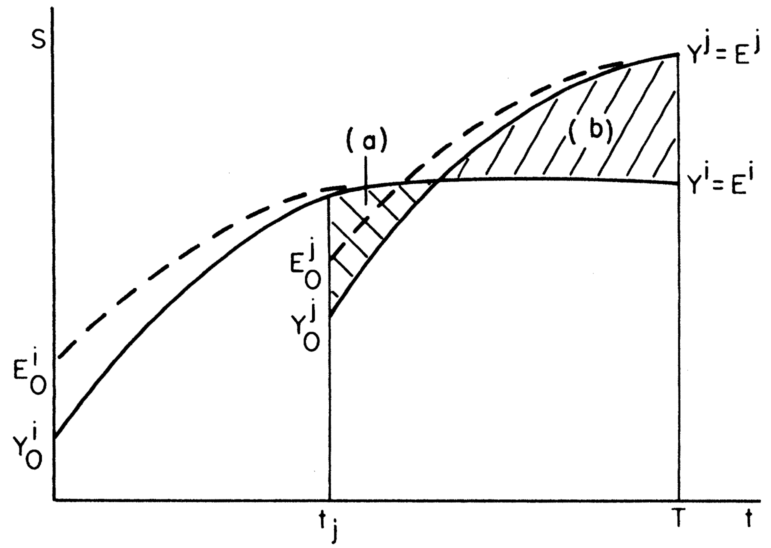

FIGURE 1

The Complementarity or Substitution of Postschool Investments

Researchers have generally hypothesized that schooling and postschool investments are complementary—that is, they are positively correlated. The explanation for this correlation is that the more able individuals will devote more resources to all forms of investment.

The model developed herein has two types of postschool investment, occupational and employer, which leads to the questions: Do more able individuals invest more in both types of investment? Or do individuals specialize in one type of investment, implying that these skills are substitutes rather than complements?

To answer these questions, picture the standard optimal human capital investment model (for example, Ben Porath [1]) for two types of investment. An individual will invest in greater amounts of *both* occupation-specific and employer-specific skills if either (1) the individual is innately very productive in producing both types of investment goods, and/or (2) each investment good is a powerful input in the production function of the other investment good. If these conditions are not met, the individual will tend to specialize in only one good. For example, if he is more talented at producing one good, or the firm's production technology limits his ability to produce both, he will specialize. The rising opportunity cost of investment with experience and a declining time horizon will also encourage greater investment in the skill in which the individual is marginally more productive, unless diminishing returns offset this effect.

The evolution of the earnings equation literature has produced clear differences between the one-type and the two-type investment models. Willis and Rosen [16] elegantly elucidate one difference by characterizing ability as either hierarchical or multidimensional. Researchers initially treated ability as hierarchical, or one-dimensional, using IQ as one indicator of ability. Yet, if skills are truly multidimensional, individuals will favor investment in skills in which they have a comparative advantage. In the Willis-Rosen example, they find that some individuals have a comparative advantage in producing college skills and others have a comparative advantage in high school skills (shop classes, for example). The concept of hierarchical versus multidimensional ability refers to condition (1) above, concerning intrinsic talent or ability. However, the investment outcome is also a function of firms' production functions—condition (2)—and rising opportunity costs. The division of postschool investment into tenure and occupational skills is uniquely able to implicitly include both effects in testing whether postschool investments are complements or substitutes.

II. THE MEASUREMENT OF OCCUPATIONAL INVESTMENT

The cumulative investment in occupational skills, defined as K_t^j in equation (1), is translated into its measurable equivalent $OCCT_t^j$ for a given individual in the following way:

$$OCCT_t^j \equiv INT^j OEXP_t^j + d^{ij} INT^i OEXP_{t_j - 1}^i + \cdots + d^{gj} INT^g OEXP_{t_h - 1}^g \tag{3}$$

for current occupation j and all *past* occupations $i, \ldots, g$. The parameters d^{ij} and d^{gj} are direct proxies for γ^{ij} and γ^{gj}, and INT^j, INT^i, and INT^g are proxies for I^j, I^i, and I^g, developed below. The true intensity of investment I^j is hypothesized to fall with the individual's duration in the occupation. This will be captured by a nonlinear $OCCT^2$ term. Proxy measures of transferability and skill intensity from the individual's occupational history are developed next.

The Transferability of Occupational Skills

The probability of occupational change increases with the transferability of skills: the greater the transferability, the greater the incentive to change. This implies that measures of the probability of change, P^{ij}, will be closely correlated with transferability, γ^{ij}, after P^{ij} is adjusted for other determinants of movement.

The method of adjusting P^{ij} is the application of the theory of multidimensional scaling to transform the P^{ij} matrix into a distance matrix. Distance D^{ij} is defined as:

$$(4) \qquad D^{ij} = \sum_{k=1}^{J} |P^{ik} - P^{jk}| = (P^{ij} + P^{ji}) - (P^{ii} + P^{jj}) + \sum_{k=1}^{J} |P^{ik} - P^{jk}|$$

where P^{ik} = the probability of moving from occupation i to occupation k; P^{jk}, P^{ij}, and P^{ji} are defined equivalently, corresponding to the variation in their superscripts; and J is the set of all occupations. P^{ii} and P^{jj} are the probability of moving across detailed occupations within aggregate occupations i and j, respectively. The smaller the distance D^{ij}, the "closer" the occupations or the greater the transferability.[4]

The advantage of the use of distance is that it is a function of the probability of moving between occupations i and j, and also compares the probability of movement between i and j and *all other* occupations. For occupations i and j to be "close," or very "similar," they must have close equality of movement between i and k and between j and k. This would be the case if i and j belong to the same "mobility cluster," where the cluster is defined as a group of occupations among which intermobility is common.[5] Examples of mobility clusters are the groups formed by the sequences of (a) technician, engineer, manager; (b) laborer, mine operative, inspector; and (c) receptionist, typist, secretary. These are sequences that are likely to exhibit high degrees of transferability.

The use of D^{ij} reduces spurious effects that are likely to affect P^{ij} but not γ^{ij}.[6] Also, by adding P^{ij} and P^{ji} we eliminate the possibility that short-run demand shifts in the rates of return to human capital will influence the estimate of γ^{ij}.

---

4 Readers who are interested in more details about the distance function may write to the author for an appendix that provides more explanation and tables showing occupational change matrices based on the various survey files.

5 The use of distance as a means of measuring a mobility cluster was originated by Dauffenbach [3]. The mobility cluster is analogous to Dunlop's [6] job cluster in which jobs are linked by their similarity in technology, administrative organization, and custom.

6 Thus, the way in which D^{ij} eliminates the nontransferability determinants of P^{ij} is both by using the aggregate average of P^{ij} over individuals and time, and by including P^{ji}, P^{ik}, and P^{jk}. The aggregate average eliminates all the individual determinants of movement, so that the primary determinant across individuals is transferability. For further discussion of these properties of D^{ij} and an evaluation of alternative methods of estimating γ^{ij}, see Shaw [13] and write the author for the material mentioned in fn. 4.

Distance D^{ij} is calculated using several data sets. The proxy for γ^{ij} becomes:

$$d^{ij} = 1 - (D^{ij}/2) \tag{5}$$

so d^{ij} increases with the degree of transferability over the (0,1) range.

Three surveys asked individuals to provide information on their former occupation. The 1970 Census asked individuals their 1965 occupation. The January Current Population Survey (CPS) for 1966, 1973, and 1978 asked respondents their occupation "one year ago." The Occupational Changes in a Generation (OCG) survey asked for the occupation of respondents' first full-time job. The availability of these alternative surveys, which have varying time intervals, permits the calculation of several d^{ij} matrices to test the sensitivity of the estimates. The d^{ij} matrix based on the Census sample is presented in Table 1 for eight aggregate occupations, demonstrating that the estimates of skill transferability are generally consistent with one's intuition. (The P^{ij} and d^{ij} matrices for the various samples may be obtained from the author.)

The Intensity of Occupational Investments

The intensity of occupational investment, l^j, is the proportion of potential working time spent investing in occupational skills. As a first approximation to l^j, there exist measures of the amount of on-the-job training "necessary for competence in an occupation." One measure, the *SVP* or Standard Vocational Preparation, is "a nine level scale indicating the amount of time required to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job" (Scoville [12, p. 387]). It is based on estimates made by researchers of the Bureau of Employment Security for the 4000 jobs of the *Dictionary of Occupational Titles*. The second measure is *TQ*, based on the Michigan Panel Study of Income Dynamics survey. *TQ* is the mean response for each occupation to the question, "On a job like yours, how long would it take the average new person to become fully trained and qualified?" (Duncan and Hoffman [5, p. 596]). As an approximation to l^j, it is hypothesized that *SVP* and *TQ* are proportional to the true average investment intensity. However, *SVP* and *TQ* are potentially biased by measurement error arising from differences between people's perceptions of the investment and the actual investment. For example, respondents are likely to presume that the more highly educated will invest more. Thus, an alternative estimation technique consists of letting the data themselves isolate estimates of l^j. Using the definition of *OCCT* in equation (3), we can calculate l^j by regressing

TABLE 1
PROXIES FOR OCCUPATIONAL PARAMETERS
Transferability Matrix d^{ij} (Census Data)[a]

	1	2	3	4	5	6	7	8
1. Professionals	.63							
2. Managers	.43	.65						
3. Clericals	.47	.59	.89					
4. Sales	.42	.74	.61	.77				
5. Craft	.32	.41	.49	.42	.48			
6. Operatives	.31	.42	.51	.43	.58	.80		
7. Service	.34	.43	.53	.45	.53	.59	.77	
8. Laborer	.35	.46	.57	.48	.65	.85	.66	.95

Intensity of Occupational Investment

	INT	*TQ*	*SVP*
1. Professionals	.49	.88	.88
2. Managers	.62	.90	.86
3. Clerical	.43	.46	.16
4. Sales	.52	.27	.11
5. Craft	.76	.86	.50
6. Operative	.47	.20	.20
7. Service	.24	.37	.14
8. Laborer	.20	.21	.09

a The diagonal elements measure the degree of transferability for movement across 3-digit occupations which are *within* the 1-digit occupation. All other movement is across 1-digit occupations. The numbered columns correspond to the occupations on the left.

$$\ln Y_t^j = X_t^j \Gamma^j + \alpha_1^j OEXP_t^j + \alpha_2^j \big[OEXP_{t-1}^i + \cdots + OEXP^g \big] + u_t$$

for each occupation j, where the X vector includes $\ln E_0$ and S. The coefficient on investment in the *current* occupation, α_1^j, equals $r^j I^j$ based on equation (3). Assuming constant r^j (= .10 for scaling) across all occupations, define

$$INT^j \equiv \hat{\alpha}_1^j / .10$$

INT^j is the proxy for intensity based on the wage regression.

Table 1 provides a comparison of the three estimates of intensity. Clearly the correlation between the ordinal ranking of occupational intensities is quite high, yet all three do differ considerably. *INT* is the preferred measure in the empirical work because the analysis requires a *cardinal* scale of intensity, which is endogenously provided by INT^j. All three are tested. (Further details about these estimates are available from the author.)

As an example of the valution of *OCCT*, I calculate the value of the variable for the hypothetical case in which a person with 10 years of experience has changed occupations three times evenly over the period. For upward occupational mobility, let the values of intensity rise from .30 to .60 and set transferability at .60. The value of *OCCT* based on equation (3) is

$$3.175 = (.6)(2.5) + (.5)(.5)(2.5) + (.6)(.4)(2.5) + (.6)(.3)(2.5)$$

Clearly, variation in intensity and transferability cause *OCCT* to diverge substantially from experience.

III. EMPIRICAL RESULTS

The data set chosen for estimation is the National Longitudinal Survey (NLS) of Young Men, aged 14–24 in 1966, surveyed yearly from 1966 to 1975, excluding 1972 and 1974. This young sample provides the extensive occupational history necessary for the calculation of occupational investment. Moreover, it covers the early labor market period when most occupational change occurs, when occupational decisions are likely to be most important, and when substantial investment in human capital is undertaken. The sample is restricted to men in order to avoid issues of occupational segregation and restrictions on choice.

The sample size is reduced from 5225 to 1447 with the restrictions that wage rates, occupational category, and schooling are reported in the years 1969 to 1975 and the individual is not a full-time student after 1969. When, in addition, I require reports of the Knowledge of the World of Work test score, the sample is reduced to 1410.

The occupational investment variable is calculated using the current occupational response for each survey year, not a retrospective job history. The occupational categorization used by the NLS is the 1960 3-digit occupational code of the Census Occupational Classification System. Examples of 3-digit occupations within the 1-digit craft occupation include carpenters, cement and concrete finishers, cabinet makers, etc. The 1960 classification has been criticized for its poor job of classifying occupations by skill homogeneity and its frequent use of "not elsewhere classified" (n.e.c.) categories. To address this issue, occupational change matrices were examined for movement across 3-digit occupations within each of the ten 1-digit occupational categories. Based on this examination, it was apparent that there is potential spurious movement in only one of the

1-digit occupational categories—operatives. However, the weighting of past occupational experience with d^{ij} counteracts this problem because the d^{ij} approaches one for close (possibly equivalent) occupations, and it is sufficiently aggregated so as to obscure detailed specious movement (see Shaw [13]).

The amount of occupational movement for these young men is substantial. On average, 54 percent of the sample changed their 3-digit occupation, and 41 percent changed their 1-digit occupation, over the two-year intervals (see Table 2). Over the nine-year period, 11.3 percent of the sample never changed occupations, 9.4 percent changed their 1-digit occupation seven times, and the majority (58 percent) changed three to five times. The extent and variability of movement is certainly sufficient for estimation of occupational investment, *OCCT*. Calculated for young men, occupational investment has a mean value of 3.49 years and a standard deviation of 1.16 (see Table 3 for mean values of sample variables).

The Wage Regression

Using ordinary least squares, estimation of equation (2) strongly indicates that occupational investment is an important determinant of income. It is highly statistically significant, and the .077 *OCCT* coefficient translates into an elasticity at the mean of .269, compared to .076 for *TENURE*. That is, a 10 percent increase in occupational investment at the mean increases wages by 2.69 percent, while an equal percent increase in tenure results in a wage increase of only .76 percent. Hypothesized to be measures of general and employer-specific investment, respectively, the results indicate that general postschooling investment is more than three times as effective as employer investment.

TABLE 2
PERCENT CHANGING 3-DIGIT OCCUPATION

		Over Two-Year Intervals		
1966–68	1967–69	1969–71	1971–73	1973–75
63.2%	60.5%	52.7%	48.2%	46.8%
		Over One-Year Intervals		
1966–67	1967–68	1968–69	1969–70	1970–71
55.2%	51.7%	47.0%	47.1%	43.8%

Notes: Note that about 75 percent of those who change 3-digit occupation also change 1-digit occupation. N = 1447.

TABLE 3
NLS VARIABLE LIST: 1975 VALUES

Variable	Definition	Mean (Standard Deviation)
LW75	Log(wage rate × 100) in 1975	6.22 (0.47)
WAGE	Wage rate	5.03 (0.38)
OCCT	$INT^j \cdot OEXP^j + d^{ij} \cdot INT^i \cdot OEXP^i + \ldots$[a]	3.49 (1.16)
OCCT2	*OCCT*OCCT*	12.18 (1.34)
TENURE	Years of tenure with current employer	4.74 (3.87)
SC	Years of schooling completed	12.20 (2.65)
EXPER	Years of labor market experience	10.06 (3.12)
OEXP	Years in current occupation	3.29 (2.67)
OCCJ	$INT^j \cdot OEXP^j$	1.80 (1.61)
OCCI	$OCCT - OCCJ$	1.69 (1.08)
LW73	Log(wage rate × 100) in 1973	6.03 (0.46)
AGE	Age in 1975	26.13 (2.20)
FOMY14	1959 median income for father's occupation when respondent was age 14	4957.6 (1775.9)
MED	Mother's years of schooling	9.94 (2.95)
FED	Father's years of schooling	9.49 (3.08)
CULTURE	Culture index for respondent at age 14	2.08 (1.01)
SIBLINGS	Number of siblings	3.35 (2.59)
TOGETHER	Parents together when respondent age 14	.82 (.38)
BLACK	Race is black = 1	.225 (.42)
MRT	Are or have been married = 1	.89 (.45)

TABLE 3 (Continued)

Variable	Definition	Mean (Standard Deviation)
IQ	IQ	94.59 (16.62)
KWW	Knowledge of the World of Work test score	34.10 (9.01)
SMSA	Live in SMSA = 1	.55 (.44)
RNS	Live in southern region = 1	.40 (.49)
B	Refers to the set of "background" variables which begin with *FOMY*14 above	

a See text for definitions of *INT* and d^{ij}.

The model of income determination, and the underlying model of occupational change, hypothesize a decline in the intensity of investment as the marginal cost of investment rises and the expected time horizon for returns falls. Parallel declines in investment occur. First, there is an overall decline in general investment with aging, which includes depreciation of past investment. This is commensurate with the widely tested results showing curvature in the experience variable. Second, the intensity of occupation-specific investment declines as the duration of the current occupation increases. The squared term *OCCT*2 picks up both of these effects; it has a significant negative coefficient (see Table 4, col. 2).

These regression results are for 1975, clearly a recessionary year. The results for 1973 actually are stronger: the coefficient (*t*-statistic) on *OCCT* is .096 (8.48) in 1973 compared to the 1975 coefficient of .077 in Table 4. The 1975 results are reported throughout because they maximize the available history of occupational experience for this sample.

It has been suggested that the occupational investment variable is a superior substitute for the labor market experience variable as a measure of the stock of general human capital embodied in the individual. Is this the case? Columns 4 and 5 of Table 4 report tests of the standard wage regression which includes experience. Experience is a significant determinant of income, but compared to *OCCT* in columns 1 and 2 it yields a lower R^2 and its elasticity at the mean is only .111—less than half that of *OCCT*.

Are *OCCT* and *EXPER* proxies for equivalent or different determinants of income? Consider the wage regression estimated as a joint

TABLE 4
OCCUPATIONAL EFFECTS
(Dependent Variable *LW75*)

Variable	(1)	(2)	(3)	(4)	(5)	(6)
OCCT	.077	.174				1.65
	(8.58)	(4.70)				(4.65)
OCCT2		−.013				−.012
		(−2.69)				(−2.56)
SC	.036	.035	.037	.037	.037	.035
	(6.54)	(6.43)	(6.66)	(6.26)	(6.23)	(6.45)
TENURE	.019	.016	.017	.022	.022	.016
	(2.46)	(2.15)	(2.17)	(2.84)	(2.84)	(2.11)
TENURE2	−.0006	−.0004	−.0005	−.0007	−.0007	−.0004
	(−1.07)	(−0.74)	(−0.76)	(−1.12)	(−1.10)	(−0.73)
OCCJ			.128			
			(5.67)			
OCCJ2			−.008			
			(−2.42)			
OCCI			.099			
			(2.49)			
EXPER				.011	.045	.013
				(2.68)	(2.08)	(0.56)
EXPER2					−.002	−.0002
					(−1.60)	(−0.34)
S.E.E.	188.45	187.51	187.30	197.40	197.08	187.50
R^2	.380	.393	.394	.361	.362	.393

Notes: N = 1410. *t*-statistics in parentheses. Other variables in the regressions are background set *B*.

function of *OCCT* and *EXPER*. The inclusion of *OCCT* completely eliminates the effectiveness of experience (compare cols. 5 and 6, Table 4). An F-test strongly rejects the addition of *EXPER*; F(1,1392) = 0.78. *EXPER* is equivalent to *OCCT* only when all $d^{ij} = 1$ and all $l^j = 1$, or when considerable heterogeneity is eliminated by assuming that all occupational skills are perfectly transferable and all intensities of investment are equivalent. A plausible conclusion is that *EXPER* and *OCCT* are both proxies for the individual's stock of general human capital, but occupational investment is by far the superior measure.

Having substantiated the importance of *OCCT* as a determinant of income, I also examined the sensitivity of the estimated occupational investment coefficient to the underlying specifications of d^{ij} and l^j. Details of this examination are available from the author, and here I report only the type of tests undertaken.

There is no significant difference between the effect of *OCCT* on income when *OCCT* is calculated using d^{ij} matrices from the Census, the CPS, or the OCG samples. With regard to alternative measures of intensity, I^j, F-tests for the three measures tested here—the *INT*, *SVP*, and *TQ* (defined in Section II)—demonstrated that there is no significant difference between the three methods of calculating occupational experience, though coefficient estimates for *OCCT* based on *SVP* and on *TQ* are slightly lower than that based on *INT*.

These tests indicate that the effectiveness of *OCCT* is not sensitive to alternative specifications of d^{ij} and I^j. To substantiate further the importance of investment in previous occupations, *OCCT* is broken up into current and previous investment (col. 3, Table 4). Past investment, *OCCI*, is quite significant. The significance of *OCCT* is not a statistical anomaly; *OCCT* is a robust measure of occupational investment.

The Specialization Substitution of Postschool Investments

In Section I I question whether postschool investments are likely to be complements or substitutes—that is, whether employer-specific and occupation-specific investments will be positively or negatively correlated across individuals. They are likely to be positively correlated if the hierarchical view of skills is supported—more able individuals invest more in all skills. They will be negatively correlated if individual talents are multidimensional or if firms' production functions tend to induce specialization in one skill type.

The simplest way to resolve this question is to examine a correlation matrix for the investment vector. Table 5 presents the correlation matrix for five proxies for investment: *TENURE*, *OCCT*, *EXPER*, *TENURE/EXPER*, and *OCCT/EXPER*. Tenure, occupational investment, and experience are all positively, but weakly, correlated. This is to be expected since all increase with age. The weakness of the correlations with experience is quite noticeable: tenure and occupational investment are very different measures of postschool investment. To eliminate the aging effects, the correlation between tenure and *OCCT per year* of experience is examined. This correlation is weakly *negative*. Individuals are specializing in one form of investment or the other. Furthermore, there appears to be no real correlation between postschool investments and IQ or schooling (presented in Table 5).

A second method of testing for specialization is to estimate a varying parameters specification of the wage equation. The variables *TENURE* and *OCCT* are only proxies for individual investments, and there is likely to be considerable individual variation in investment that is unobserved. The wage equation can be used to test for systematic variation in unmeasured investment which reflects potential skill substitution.

TABLE 5
CORRELATION MATRIX[a]

	OCCT	*TENURE*	*EXPER*	*OCCE*[b]	*TENE*[b]	*SC*
OCCT						
TENURE	.23					
EXPER	.29	.20				
OCCE[b]	.45	.09	−.03			
TENE[b]	.04	.52	−.10	−.17		
SC	−.05	.09	−.41	.11	.04	
IQ	.12	.18	−.001	.19	.09	.63

a Simple correlation coefficient across individuals.
b $OCCE \equiv OCCT/EXPER$, $TENE \equiv TENURE/EXPER$.

Define four new variables:

$$OCCL = \begin{cases} OCCT & \text{if } TENE < \overline{TENE} \\ 0 & \text{if } TENE \geqslant \overline{TENE} \end{cases}$$

$$OCCH = \begin{cases} OCCT & \text{if } TENE \geqslant \overline{TENE} \\ 0 & \text{if } TENE < \overline{TENE} \end{cases}$$

$$TENL = \begin{cases} TENURE & \text{if } OCCT < \overline{OCCT} \\ 0 & \text{if } OCCT \geqslant \overline{OCCT} \end{cases}$$

$$TENH = \begin{cases} TENURE & \text{if } OCCT \geqslant \overline{OCCT} \\ 0 & \text{if } OCCT < \overline{OCCT} \end{cases}$$

where $TENE = TENURE/EXPER$ and $OCCE = OCCT/EXPER$ as in Table 5, and the overbars indicate mean values. These four variables are simply permitting the slopes of *OCCT* and *TENURE* to vary as a function of the quantity of investment in the *other* skill. For example, *OCCL* is equal to *OCCT* for all those individuals who have below-average levels of tenure, and *OCCH* is equal to *OCCT* for those who have above-average levels of tenure.

The estimated wage regression as a function of these four variables is

$$\ln Y = \underset{(10.62)}{.109}\ OCCL + \underset{(3.01)}{0.37}\ OCCH + \underset{(4.03)}{.086}\ TENL + \underset{(0.80)}{.007}\ TENH$$

plus all independent variables in Table 4, whose coefficients do not vary noticeably. These results are strongly supportive of skill substitution. The larger coefficient on *OCCL* compared to *OCCH* indicates that individuals with below-average tenure have much higher returns to, or quantity of investment in, occupational skills.[7] The same is true for tenure. These results are consistent with one's intuition and with regressions run by occupation. For example, when the wage regression is estimated for only craft workers, the coefficient on *OCCT* is .326 (9.81), and on *TENURE* it is .0001 (0.04), even though the mean value of *TENURE* is 2.51 years. Observed tenure is simply a limited byproduct of employment. Craft workers are not investing in employer skills. These individuals clearly specialize in occupational investment.

Alternative Hypotheses

The most serious criticism of empirical work that uses experience as a proxy for general human capital investment is that true unobserved *productivity* may not rise with experience. Alternative explanations for the experience-income correlation are available, in light of our inability to actually measure productivity. In this subsection I address two related issues. First, how does *OCCT* improve our understanding of the causality of the experience-income correlation, and second, is *OCCT* likely to be measuring the productivity of investment or something else?

Several researchers have questioned whether the estimated experience-income correlation truly reflects an investment-income correlation rather than equity considerations, for example.[8] The statistical significance of *OCCT* clearly demonstrates that income growth is not simply a result of years in the labor market. Holding experience constant, frequent *random* occupational change would reduce income significantly. While experience need not measure productivity, the significance of the more heterogeneous *OCCT* indicates that an investment process may be taking place.

There are several possible explanations for the significance of *OCCT*. The first is that it is simply measuring movement up the occupational ladder with the current employer, for those who have found "good" employers. This does not appear to be the case here, for when a variable *OCEMP* is formed, equaling occupational investment during the years with the current employer, its coefficient and t-ratio is about one-fifth that of *OCCT* (compare col. 1 of Table 6 to col. 1 of Table 4).

A second possibility is that *OCCT* is picking up an institutional relationship that causes wages to rise with seniority in the occupation. The wage regression is reestimated with *OEXP*, years in the *current* oc-

7 Given the unobserved nature of the intensity of investment and the returns, both become a part of the coefficient of *OCCH* and *OCCL*. Note that these coefficients were not significantly affected by IQ interactions (not shown). Thus, there is no evidence that hierarchical ability affects skill specialization.

8 See, for example, Medoff and Abraham [9] and Doeringer and Piore [4].

TABLE 6
ALTERNATIVE HYPOTHESES
(Dependent Variable *LW*75)

Variable	(1)	(2)	(3)
OCCT			.034
			(4.32)
TENURE	.010	.031	.018
	(0.98)	(5.47)	(2.76)
*TENURE*2	−.0001	.019	−.0007
	(−0.16)	(2.40)	(−1.38)
SC	.032	−.0004	.018
	(5.70)	(−0.68)	(3.82)
OCEMP	.017		
	(1.52)		
OEXP		.011	
		(2.77)	
*LW*73			.535
			(22.98)
S.E.E.	197.92	197.34	136.85
R^2	.359	.361	.557

Notes: N = 1410. Other variables in the regression are set *B*. *t*-statistics are in parentheses.

cupation, replacing *OCCT* (see col. 2 of Table 6). The weakness of *OEXP* indicates that *past* occupational investment is a strong determinant of income and leads to rejection of the institutional importance of occupational seniority (refer also to the earlier discussion of *OCCI* in Table 4).

Most serious is the last possibility—that heterogeneity or sample selection criteria biases the *OCCT* coefficient. I address these possibilities one at a time.

The omission of unmeasured individual heterogeneity may mean that the wage-occupational investment correlation spuriously results from the greater occupational investment of the more "able" people, or those lucky enough to obtain a high growth path. Assume there is an individual-specific parameter whose omission from the wage regression will bias the coefficients because of its correlation with the independent variables. The most direct method of controlling for this heterogeneity bias is the first-differencing of all variables, eliminating the fixed-effects parameter so that we are regressing only within individual records.

The results of the fixed-effects estimation, shown in Table 7, substantiate the stability of the occupational investment variable. Increases

TABLE 7
FIRST-DIFFERENCED WAGE REGRESSIONS

	Dependent Variables						
	LW73–LW71		LW75–LW71		LW75–LW73		Pooled (LW75–LW73) (LW73–LW71)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$OCCT_t - OCCT_{t-1}$	.041	.175	.019	.097	.010	.016	.094
	(2.15)	(4.52)	(1.47)	(3.35)	(0.65)	(0.43)	(2.79)
$OCCT2_t - OCCT2_{t-1}$		−.022		−.009		−.001	−.011
		(−3.97)		(−3.01)		(−0.17)	(−2.85)
$TENURE_t - TENURE_{t-1}$	.004	.003	.008	.008	.010	.010	.008
	(1.11)	(0.85)	(2.91)	(2.72)	(3.31)	(3.31)	(2.56)
$SC_t - SC_{t-1}$	.008	.009	.007	.007	.015	.016	.012
	(0.70)	(0.80)	(0.68)	(0.75)	(1.35)	(1.35)	(1.02)
R^2	.024	.035	.027	.033	.021	.021	.028

Notes: N = 1410. *t*-statistics are in parentheses.

in *OCCT* provide a potent explanation for income growth in 1971–1973 and for its weakening in 1973–1975. For the pooled sample, occupational investment is clearly a source of income growth when the individual component is held constant.

While fixed-effects estimation is effective in eliminating the individual-ability parameter, it also eliminates most of the variation in the variables. This is a particular problem for short time intervals. A second, less restrictive means of holding ability constant is to include a lagged dependent variable in the regression. Although adding lagged income should make it more difficult to obtain a significant effect of *OCCT*, we see that its significance prevails (col. 3, Table 6). Whether the adjustment is made by first-differencing or by adding a lagged dependent variable, differences in ability or the initial random success in finding a "good job" do not account for the explanatory power of *OCCT*.

The individual-specific effect may be given a more concrete interpretation. It may represent the selectivity bias arising from the individual's choice of his most optimal occupation. This sample selection bias can be addressed more directly using Heckman's [8] methodology. The probability of choosing occupation *j* is estimated in Shaw [14], based on the occupational choice model discussed in Section I. The probit results are used to calculate the inverse of Mill's ratio, which is inserted as a variable in the wage regression. This added variable has no effect on income, or no evidence of sample selection bias was found (not shown). Of course, this does not rule out the possibility of bias; we simply find none using a reasonable model of occupational choice.

Thus, there is no evidence that individual heterogeneity or the ability to secure a job with a high-wage employer or in a high-wage occupation can account for the significance of occupational investment. While the significance of *OCCT* cannot imply conclusively that occupational investment enhances productivity, a reasonable alternative explanation for its significance has not been found.

IV. CONCLUSION

Numerous authors have commented on the specific nature of occupational skills and their likely importance for income determination. Yet they have disregarded the information contained in the individual's occupational choice. Two important empirical results arise from the development of the model of occupational investment. First, investment in occupational skills is a strong determinant of income, empirically dominating the standard experience variable as a proxy for the stock of general human capital investment embodied in the individual. Second, the two forms of postschool investment, occupation-specific and firm-specific, act as substitutes, not complements. Individuals tend to specialize in one or the other. These results are unaltered after several tests for coefficient bias arising from heterogeneity and sample selection criteria.

The estimation of the effect of human capital investment on earnings is sharpened by the direct measurement of occupational experience. The implication that future wage regressions should include an *OCCT* variable is, unfortunately, difficult to implement because the calculation of *OCCT* requires a complete occupational history which is available in few data sets. For this reason it is difficult to discover whether the importance of occupational investment in the early experience of young men will also characterize their later experience.[9]

REFERENCES

1. Yoram Ben-Porath. "The Production of Human Capital and the Life Cycle of Earnings." *Journal of Political Economy* 75 (August 1967): 352–65.
2. Peter M. Blau and Otis Dudley Duncan. *American Occupational Structure.* New York: Wiley, 1967.
3. Robert Dauffenbach. "The Structure of Occupational Mobility in the U.S. Economy." Urbana: Center for Advanced Computation, University of Illinois, 1973.
4. Peter Doeringer and Michael J. Piore. *Internal Labor Markets and Manpower Analysis.* Lexington, MA: Heath, 1971.
5. Greg J. Duncan and Saul Hoffman. "On-the-Job Training and Earnings Differences by Race and Sex." *Review of Economics and Statistics* 61 (November 1979): 594–603.
6. John T. Dunlop. "The Task of Contemporary Wage Theory." In *New Concepts in Wage Determination*, eds. G. Taylor and F. Pierson. New York: McGraw-Hill, 1957. Pp. 117–39.
7. Sidney A. Fine. "Use of the Dictionary of Occupational Titles as a Source of Estimates and Training Requirements." *Journal of Human Resources* 3 (Summer 1968): 363–75.
8. James Heckman. "Sample Selection Bias as a Specification Error." *Econometrica* 47 (January 1979): 153–63.
9. James Medoff and Katharine Abraham. "Experience, Performance, and Earnings." *Quarterly Journal of Economics* 95 (December 1980): 703–36.
10. Jacob Mincer. *Schooling, Experience, and Earnings.* New York: Columbia University Press, 1974.
11. Sherwin Rosen. "Learning and Experience in the Labor Market." *Journal of Human Resources* 7 (Summer 1972): 326–42.

9 The perfect certainty model developed herein has ignored the possibility of returns to pure search or matching which would arise with occupational change, particularly for young men. Such returns were undetectable in tests made for alternative causes of occupation-employer change. However, the ability to isolate these returns in the NLS data is very weak.

12. James G. Scoville. "Education and Training Requirements for Occupations." *Review of Economics and Statistics* 48 (November 1966): 387–93.
13. Kathryn L. Shaw. "The Income Effects of Occupational Change and the Investment in Occupational Skills." Ph.D. dissertation, Harvard University, 1981.
14. ———. "A Theory of Occupational Change and Earnings Growth." Working paper No. 19–81–82, Carnegie-Mellon University, 1981.
15. W. Torgenson. *Theory and Methods of Scaling.* New York: Wiley, 1958.
16. Robert J. Willis and Sherwin Rosen. "Education and Self Selection." *Journal of Political Economy* 87 (October 1979): S7–S36.