Do Returns to Human Capital Equalize Across Occupational Paths?

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Abstract

This study estimates earnings function parameters across alternative occupational paths, with an emphasis on identifying rates of return to post-school human capital investment. Based on cross-sectional and synthetic cohort analysis using the 1973-2000 Current Population Surveys, estimates are obtained for men and women on the returns to schooling and the investment intensity, length, and returns from post-school training. Although the shapes of wage-experience profiles differ substantially across occupations and skill groups, evidence supports the theoretical prediction that rates of return are equivalent across alternative investment paths. Little evidence is found for an increase in returns to post-school training over time. By the 1990s, returns to schooling had risen to a level similar to the returns from post-school training.

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I. INTRODUCTION

One of the most consistent findings in labor economics is that wages grow with labor market experience. Although much literature is devoted to understanding why earnings rise over the lifecycle, the dominant explanation for an upward sloping wage profile remains the general human capital model. Individuals invest in worker-financed general (i.e., transferable) human capital, initially lowering the wage, but subsequently increasing productivity and wages. The shape of the earnings-experience profile reflects the intensity and time pattern of training investments, coupled with the rate of return from these investments (Ben-Porath, 1970; Mincer, 1974; Becker, 1993).

Testable implications of the general human capital model include: (1) there is a negative relation between a worker’s initial wage and wage growth, (2) market rates of return to post-school human capital investment will tend to equalize across alternative investment paths, and (3) rates of return to schooling and post-school training investments should tend toward equality (Weiss, 1986; Neumark and Taubman, 1995).

Early tests of the negative relation between initial wages and wage growth suffered from small sample sizes, unsatisfactory earnings measures and spurious negative correlation between initial wages and wage growth owing to measurement error (Hause, 1977, 1980; Kearl, 1988). More recently, Neumark and Taubman (1995) have provided a test of the theoretical implication of the human capital theory in which they correct for the negative bias that plagued previous studies.1 Neumark and Taubman (1995) use a sample of white males from the National Longitudinal Survey of Youth (NLSY) and correct for the negative bias using lagged wages as instruments for wages.2 After correcting for bias, they find a negative relation between the initial wage and wage growth. In addition, Neumark and Taubman find a ratio close to one when they compare the present value for a steep wage profile among highly-educated workers to that of a flat wage profile among less-educated workers. This finding suggests that rates of returns equalize over careers between workers with different education levels. In estimating the present values of their profiles, they

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1. A negative spurious correlation occurs between the wage level and wage change if wages are measured with errors. That is, if there are other variables that affect wages (independent of human capital investment) that are not perfectly correlated over time, then a measurement error is introduced in both the dependent and independent variable, leading to a negative bias. Random measurement error or response error on wages would have an identical effect.

2. Using lagged wages as instruments for wages gives consistent estimates because lagged wages are likely to be correlated with wages but not with the error terms, if one assumes that the error terms are not serially correlated.
assume equivalence in rates of return between schooling and post-school training, as theory would suggest.\textsuperscript{3}

This paper examines a) whether rates of return to heterogeneous post-schooling human capital investment (e.g., learning-by-doing or formal on-the-job training) differ across occupational paths, b) whether rates of return to schooling and post-school training are similar, and c) how rates of return have changed over time. The Mincer-Chiswick model of human capital is modified to allow investment in heterogeneous post-school human capital and to empirically examine differences across occupations in wage-experience profiles. Estimates are obtained using cross sectional and synthetic cohort microdata. The approach allows one to make inferences regarding the intensity, length, and rate of return on post-school investment across occupational paths. Even though the shapes of wage-experience profiles differ enormously across occupations (Moroney and Trapani, 1989) and between high- and low-skill groups, our evidence is highly consistent with the prediction from human capital theory that rates of return on alternative post-schooling investment paths are equivalent.\textsuperscript{4} Moreover, by the 1990s rates of return to schooling had risen to levels similar to returns obtained for post-school training.

**II. THE CANONICAL HUMAN CAPITAL MODEL**

The Mincer-Chiswick variant of the human capital model (see Mincer, 1974; Chiswick, 1974; Polachek and Siebert, 1993; Polachek, 1995) assumes a homogeneous stock of human capital that affects worker productivity equally in multiple lines of work. Following Becker (1993), workers bear the cost of post-school general human capital investment in the form of lower wages and reap the returns from their accumulated human capital through subsequent higher productivity and wages. Thus, the Mincer-Chiswick model of the human capital earnings function relates present net earnings in year $t$ after schooling to all past human capital investment, less any current human capital investment.\textsuperscript{5}

\textsuperscript{3} Neumark and Taubman’s (1995) estimates of separate rates of return to schooling and post-school training diverge substantially, a finding similar to that found previously by Hanushek and Quigley (1978).

\textsuperscript{4} As discussed in the concluding section, our results are consistent with the general human capital model, but do not allow us to reject alternative optimizing models of the earnings generation process (e.g., incentive pay models). A weaker interpretation of our results is that they support the hypothesis of an efficient labor market in which the net present value of alternative career paths are equalized.

\textsuperscript{5} Acemoglu and Pischke (1998) show how low levels of worker turnover, independent of skill specificity, lead employers to invest in general as well as firm-specific training. Likewise, much current research suggests that workers are willing to bear costs of specific training in return for back-loaded wages. Our subsequent estimates will reflect investment intensities and rates of return on worker-financed training. Hellerstein, Neumark, and Troske (1999) are
The post-training wage \( Y_N \) of an individual who invests \( K \) fraction of their potential earnings in year \( t \) in \( N \) periods of training is

\[
(1) \quad Y_N = E_0 \left[ \prod_{t=1}^{N} (1+r_t K_t) \right]
\]

where \( E_0 \) is the potential earnings of the individual who does not invest in human capital (the “raw” wage), \( r_t \) is the average rate of return on investment, and \( \Pi \) is a multiplier operator. It is assumed that all workers have identical lifetime investment profiles and realize equivalent rates of return. The observed or net wage of an individual who invests a fraction of their potential earnings in post-school training is

\[
(2) \quad Y = (Y_N - K_{N+1} Y_N) = E_0 \left[ \prod_{t=1}^{N} (1+r_t K_t) (1-K_{N+1}) \right]
\]

where \( Y \) is now the net wage in period \( N+1 \), \( E_0 \) is the raw earnings of the individual who has not invested in human capital, and \( K_{N+1} \) is the fraction of potential earnings invested in year \( N+1 \).\(^6\)

To obtain an estimable function, Mincer takes the natural logarithm of both sides of (2) and decomposes the \( N \) years of training into years of schooling (\( S \)) and post-school training (\( N-S \)).\(^7\)

\[
(3) \quad \ln Y = \ln E_0 + r_s S + \sum_{t=s+1}^{N} r_t K_t + \ln (1-K_{N+1}).
\]

To evaluate post-school training, the Mincer-Chiswick model assumes that post-schooling investment declines linearly over time.\(^8\) Letting \( K_0 \) denote the fraction of potential earnings invested in post-school training at time \( t=0 \), then post-school investment \( K_t = K_0 (1-T/T^*) \), where \( T^* \) is the number of years of positive net investment and \( T \) is the number of years of post-school training. A number of assumptions and manipulation leads to the derivation of the following model (Mincer-Chiswick, 1972; Mincer, 1974):\(^9\)

\[
(4) \quad \ln Y = \left[ \ln E_0 - K_0 (1+K_0 /2) \right] + r_s S + [r_p K_0 + (1+K_0)/T^*]t + \left[ -(r_p K_0 T^* + K_0^2)/2T^{*2} \right] t^2 + \mu, \text{ or}
\]

\( \mu \) is the error term.

6. This assumes all training costs are opportunity costs and that investment in training is proportional to years working. If training costs include a substantial direct cost, especially during schooling, then net wages will be less than observed wages. However, direct costs are likely to be small compared to opportunity costs, even during formal schooling, when, on average, part-time summer employment plus scholarships, roughly offset direct schooling costs.

7. This derivation assumes that during the years of schooling opportunity cost and direct cost are approximately equal to the potential or gross earnings of students so that \( K=1 \), and that \( \ln(1+rK) = rK \), since \( r \) is roughly 10 percent and \( K \) is not likely to be greater than 1.

8. The profitability of human capital investment declines over time due to higher opportunity cost of time invested and fewer years to recoup one’s investment (Becker 1993; Mincer 1974; Chiswick, 1974).
\[ \ln Y = \alpha + r_s S + \theta_1 t + \theta_2 t^2 + \mu \]

where \( \ln Y \) is the natural log of earnings; \( \ln E_0 \) is the natural log of earnings for an individual who does not invest in any human capital, \( r_s \) is the rate of return to schooling; \( S \) is years of schooling completed; \( r_p \) is the rate of return to post-school investment; \( t \) (now in lower case) is years of potential experience or post-school training; and \( \mu \) is the classical error term. Equation 5 is the standard earnings function estimated in hundreds of studies, typically augmented by controls for worker, job, and labor market characteristics. Although studies often refer to the slope of the earnings profile (\( \theta_1 \) and \( \theta_2 \) evaluated at some value of \( t \)) as being the “return” to experience, it incorporates both the human capital investment path and the return on investment. We subsequently derive estimates of the earnings function parameters \( T^* \), \( K_0 \), and \( r_p \) based on the relationships shown in (4) and regression estimates from a variant of (5).

Rosen (1977) and Becker (1993) have pointed out that the Mincer-Chiswick model of human capital may imply a corner solution if rates of return to schooling are greater or less than the market rate of discount. Rosen (1977) shows that the corner solution can be avoided if one introduces individual variation in ability and in cost of financing human capital investment. Variation in individual ability can result in omitted-variable bias in estimated returns to human capital, while variation in the cost of financing helps identify the human capital demand curve and the marginal returns to investment (Becker, 1993; Card, 1995, 1999).

Willis (1986) develops a model of heterogeneous human capital where, as a special case, the Mincer-Chiswick (1972) model can be derived as an equilibrium wage profile. According to Willis (1986), if one assumes that workers embodying different human capital are imperfect substitutes in production, that individuals face the same market interest rate (equality of opportunity), that ability has a single factor which shifts productivity equally in all pursuits (equality of comparative ability), and that the opportunity of post-schooling investment is independent of schooling, then equation 5 can be derived as an equilibrium wage profile.10 Willis (1986, p. 565) also demonstrates that, under these assumptions, the Mincer-Chiswick human

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9. To derive equation (4) from equation (3), Mincer converted the post school training expression from discrete to continuous time, integrated over the years of post schooling training \( t \) and evaluated the term \( \ln (1 - K_{N+1}) \) by a second degree Taylor series expansion around \( T^* \), ignoring the remainder terms.

10. The assumption of “equality of comparative ability” can be relaxed. Equilibrium results are not affected as long as workers for whom ability is specialized by schooling level or occupation are inframarginal, while mobile workers with equivalent abilities determine equilibrium wage differentials at the margin (Willis 1986, p. 570).
capital function gives consistent estimates even if ability is unobserved. Moreover, Willis (1986, pp., 568-69) shows theoretically that although the human capital earnings function may vary in the short-run, it is remarkably stable in the long run as the technology, demand patterns, and stock of human capital changes.

III. A MODIFIED HUMAN CAPITAL MODEL

A limitation of the standard human capital model is that it assumes homogeneity in the type of human capital. Workers differ in the level and timing of investment, yet the effects of post-schooling investment are assumed identical across alternative occupational paths (for discussion, see Polachek, 1995). Of course, individuals differ in the types of skill they choose to acquire, limiting the usefulness of the standard model for many applications.\footnote{Polachek (1981) develops and estimates a model in which human capital type differs according to its decay rate. He then shows how the gender wage gap can be explained in part by differences in men and women’s choices regarding human capital type or occupation. Paglin and Rufolo (1990) likewise adopt a heterogeneous human capital framework to explain male-female differences in earnings. They provide evidence showing that differences in mathematical ability are associated with choice of college major and subsequent earnings. Moroney and Trapani (1989) provide evidences on differences in experience profiles by occupation, but do not calculate occupational rates of return.} Given heterogeneous human capital (and individuals), we expect that marginal rates of return should equalize across alternative investment types. Since different occupational paths have different cost and return structures, maximizing individuals exhibit different earnings-experience profiles even when rates of return are equal across alternative paths.

The standard model (equation 5), does not allow the intercept or the coefficients on experience and its square to vary across occupations, constraining earnings profiles to be equal among individuals having different combination of \( r_p, K_0, \) and \( T^* \).\footnote{This constraint can conceivably be non-binding since three coefficients (\( \alpha, \beta_1, \) and \( \beta_2 \)) constrain four parameters (\( \ln E_0, r_p, K_0, T^* \)). The special case in which all variation in these four parameters offset each other such that all occupational paths exhibit identical profiles is highly unlikely.} We allow \( r_p, K_0, \) and \( T^* \) to vary across occupational paths, but retain the assumption that they are identical for all individuals within occupations.\footnote{13} This leads to a modified human capital earnings function estimated for individuals, separately by gender, and over time (subscripts i and t are omitted).

\[ \ln Y = \alpha + r_s S + \sum_{j=2}^{k} \phi_j \text{Occ}_j + \sum_{j=1}^{k} \theta_j \text{Occ}_j t + \sum_{j=1}^{k} \theta_{2j} \text{Occ}_j t^2 + X \beta + \nu. \]

Here \( \ln Y \) is the log of hourly earnings; \( \text{Occ}_j \) is a set of occupational dummy variables equal to one if an individual is employed in occupation \( j \) and zero otherwise (for the intercept shifts \( \phi_j, j=2, \ldots, k \) since the
effect of an arbitrary reference occupation is reflected in \(\alpha\); and \(X\) is a set of controls for marital status, race, part-time status, large metropolitan location, region, and year; and \(v\) is a classical error term that now captures, among other things, intra-occupational differences in \(r_p, K_0,\) and \(T^*\). In equation (6), \(r_s\) now measures the average within-occupation rate of return to schooling, with the occupation dummies accounting for earnings shifts across occupations. That is, \(r_s\) does not measure returns to schooling resulting from greater access to higher-paying occupations.

The parameters \(r_p, K_0,\) and \(T^*\) cannot be directly retrieved from the coefficients of \(t\) and \(t^2\) from equation 6 since there are three unknowns and two equations relating \(r_p, K_0,\) and \(T^*\). However, if one makes an assumption about the positive net investment span \((T^*)\), one can solve for average rates of return to post-schooling investment \((r_p)\) and the fraction of potential earnings initially invested in post-schooling training \((K_0)\). Mincer (1974, pp. 20-23) shows that \(T^*\) corresponds to the unobserved peak of earnings capacity, and precedes the observed peak of earnings by \(1/r\), or about 10 years (coupled with a linear decline in \(K_t\), Mincer assumes a constant depreciation rate). Thus, one can obtain estimates of \(T^*\) by,

\[
T^* = t^* - 10 = -\theta_1/2\theta_2 - 10,
\]

where \(t^*\) is the peak of observed earnings (solved by setting \(\partial\ln Y/\partial t=\theta_1+2\theta_2 t=0\) and solving for \(t\)), where \(\theta_1\) and \(\theta_2\) are the coefficients on \(t\) and \(t^2\). Given any value of \(T^*\), the parameters \(r_p\) and \(K_0\) can be found as

\[
K_0 = \theta_1 T^* + 2 \theta_2 T^*^2 \tag{8}
\]

\[
r_p = \left[\theta_1 / K_0 - (1+K_0)/T^*\right] \tag{9}
\]

In the empirical work that follows, the coefficients on \(\theta_{1j}\) and \(\theta_{2j}\) from equation 6 are used to obtain estimates of \(T^*, K_0\) and \(r_p\) by occupation. This approach likewise can be used for other classifications in

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13. For an earlier attempt along these lines, see Hirsch (1978), who estimates a log earnings equation with separate occupational profiles using a sample from the 1970 Census of Population.

14. We obtain equations (8) and (9) as follows. We specify two equations, with the coefficients on \(t\) and \(t^2\) -- \(\theta_1\) and \(\theta_2\) -- set to equal the bracketed terms in equation (4). First using the \(\theta_2\) equation, we solve for \(r_p\) as a function of \(K_0\) and \(\theta_2\). That value of \(r_p\) is substituted into the \(\theta_1\) equation to solve for \(K_0\) in terms of \(\theta_1\) and \(\theta_2\), as shown in equation (8). Equation (8) is then substituted into the \(r_p\) equation and simplified to obtain equation (9). We have set up two equations with two unknowns (equations \(\theta_1,\) \(\theta_2\) with unknowns \(K_0\) and \(r_p\), and a specified value \(T^*\)). Equivalent results are obtained if we set up three equations and three unknowns (equations \(\alpha, \theta_1,\) and \(\theta_2\) set equal to the bracketed terms in (4), with unknowns \(E_0, K_0,\) and \(r_p\)). Since \(E_0\) enters only through the intercept \(\alpha\), it cannot be solved prior to calculation of \(K_0\).

15. We subsequently examine the sensitivity of our results to alternative assumptions about \(T^*\). A limitation of our work is that we are unable to account for the endogeneity of occupational choice, potentially leading to selectivity
which separate earnings profiles are estimated (e.g., education level, job skill requirements).

**IV. LONGITUDINAL PROFILES USING SYNTHETIC COHORTS**

Cross-sectional analysis may provide biased estimates of longitudinal earnings-experience profiles owing to cohort shifts. If the quality of birth cohorts is increasing over time or there exist economy-wide productivity shifts, cross-sectional estimates of earnings-experience profiles will be biased downward (i.e., too flat). In contrast, if quality declines over time or there are negative real wage shifts, cross-sectional estimates will be biased upward (too steep).

In addition to experience and cohort effects, year-specific effects can potentially bias estimates of earnings-experience profiles. If earnings shocks in the economy shift demand for all cohorts by equivalent amounts, cross sectional earnings profiles would not be affected. Longitudinal earnings-experience profile estimates, however, may be affected. Year effects cannot be readily disentangled from individual-year cohort and age (experience) effects since they are a linear combination of each other. But one can combine birth cohorts into multiple (say, five) year groupings and map out longitudinal profiles while controlling for year-specific shifts in earnings (Hanoch, 1980).

To investigate how cohort effects influence estimates of earnings function parameters, we provide a synthetic cohort analysis using multiple cross-sections and estimate $T^*$, $K_0$, and $r_p$ for given cohorts over time. The simplest approach is to assume that intercepts but not slopes of occupational earnings-experience profiles differ across birth cohorts. This is done by estimating a modified version of equation 6 in which cohort dummies are included, along with year dummies (similar results are obtained when year dummies are excluded). This approach estimates separate profiles by cohort and occupation by following within-cohort earnings growth over time. That is,

\[
\ln Y = \alpha + r_s S + \sum_{h=2}^{\infty} \lambda_h \text{Cohort}_h + \sum_{j=2}^{k} \phi_j \text{Occ}_j + \sum_{j=1}^{k} \theta_{ij} \text{Occ}_j t + \sum_{j=1}^{k} \theta_{2j} \text{Occ}_j t^2 + \Sigma \beta + \nu
\]

bias in our parameter estimates (but see endnote 10). Given that we find highly similar rates of return across occupations, consistent with our simple model, selection bias may well be small. Were we finding highly different rates of return across occupational paths, failure to account for selectivity would preclude one from drawing strong inferences regarding market failure or the appropriateness of the human capital model.
where Cohort represents dummies equal to one if an individual is in cohort $h$ and zero otherwise.

Alternatively, one can allow both the intercepts and slopes of earnings-experience profiles across occupations to vary by cohort. A very general approach is to estimate equation 6 separately for each cohort, thus allowing all parameters to vary by cohort.

\[
\ln Y_h = \alpha_h + r_s h + \sum_{j=2}^{s_k} \phi_{jh} \text{Occ}_j h + \sum_{j=1}^{s_k} \theta_{1jh} \text{Occ}_j h \cdot t + \sum_{j=1}^{s_k} \theta_{2jh} \text{Occ}_j h \cdot t^2 + X_h \beta_h + \nu_h
\]

Here the subscript $h$ denotes a specific birth cohort. Equations 10 and 11 enable one to make inferences regarding the intensity, length and rate of return to post-schooling investment across occupational paths based on cohort-specific profiles. Although not a perfect substitute for panel data, the use of large synthetic cohorts is an attractive approach for tracking the wage profiles of representative birth cohorts.

V. DATA

The data set used in this paper includes the May 1973-78 Current Population Surveys (CPS) and the 1979-2000 CPS outgoing rotation group (ORG) earnings files (which include a quarter sample of all monthly surveys). Since the May CPS contains roughly a third of the CPS-ORG in a given year, to make our sample sizes comparable across years (and to ease computation), a random sample of a third of the CPS-ORG sample is used for the years 1979-2000. Time-consistent broad occupational categories, years of schooling, and other measures are constructed to allow comparability.

Real hourly wages on current occupation are constructed by dividing usual weekly earnings (inclusive of tips, commissions, and overtime pay) by usual hours worked in a week, and then deflated by the consumer price index (for years prior to 1983 we use the revised CPI-U incorporating current methods with respect to owner-occupied housing costs). Weekly and hourly wages for workers with top-coded earnings are calculated by assuming that the mean earnings of workers at or above the earnings cap follow a gender and year specific Pareto distribution. Estimated mean earnings are about 1.5 times the weekly earnings cap, or $1,500 for the $999 cap prior to 1989, $3,000 for the $1,923 cap during 1989-97, and $4,500 for the

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16. Beaudry and Green (2000) estimate longitudinal experience profiles using synthetic cohort analysis for Canada. They conclude that profiles have been shifting downward for recent cohorts, leading to an upward bias in cross-sectional profiles. They reject the hypothesis that experience profiles have steepened over time.
$2,883 cap since 1998. Estimated means above the cap increase slightly over time and are moderately higher for men than for women.\(^{17}\)

Our sample is restricted to wage and salary workers, ages 25-62, with hourly real earnings between $3.65 and $99.99 in 2000 dollars (the minimum corresponds to $1.00 in 1973 dollars), whose major activity was not attending school during the survey week, and who did not have missing information for any of the variables used in the earnings equations.\(^{18}\) Since earnings parameters differ between males and females, separate analysis is conducted by gender.\(^{19}\) The full sample used in the estimation consists of 615,485 men, and 522,254 women.

Mobility across occupations that is experience (age) related means that the experience-wage profiles measured in a particular occupation may differ from the experience-wage profile of workers who work in that occupation only a few years of their work life. Most job and occupational switching occurs at young ages (Bernhardt et al., 1999; Farber, 1999; Neal, 1999). To mitigate (but not eliminate) problems in interpreting the occupational earnings profiles as career paths, we use occupational categories that are not overly narrow and exclude very young and older workers (i.e., less than 25 and greater than 62).\(^{20}\)

**VI. EMPIRICAL RESULTS: CROSS-SECTIONAL PROFILES**

Investment parameters \(T^*, K_0,\) and \(r_p\) for men and women are calculated from the regression coefficients on the earnings functions shown in equations 5, 6, and 10. In addition to the variables shown in the text, each model controls for race, marital status, part-time status, large metropolitan area, region, and year. Equations 5 and 6 include year but not cohort dummies; equation 10 includes grouped cohort in addition to year dummies. Equation 5 constrains the earnings-experience profile to be equal across occupations, while equation 6 allows the profiles to vary across occupations. Regression coefficients from

\(^{17}\) These values are estimated and presented in Hirsch and Macpherson (2001, p. 6).
\(^{18}\) We exclude private household workers because of small sample sizes and our inability to include these workers in a similar occupational category.
\(^{19}\) Potential experience is a better measure of post-schooling training for men than women, since women are more likely to exhibit intermittent labor market participation and lower hours worked. Thus, estimates for women are probably less reliable than for men. Adjustments to female experience levels are discussed subsequently.
\(^{20}\) Occupational mobility does not bias estimates if workers at each age within an occupational category in a cross-section are equivalent (conditional on measured controls) to workers of the same age moving in and out of that occupation. Although such a condition is not literally satisfied, we suspect that our age restrictions and broad occupational categories allow us to closely approximate occupational returns.
equations 5, 6, and 10 used to calculate \( T^* \), \( K_0 \), and \( r_p \) are presented in the Appendix Table A-1. Coefficients (and standard errors) for the control variables are available on request.

Prior to calculating the investment parameters, we examine whether the constraints imposed by equation 5 are valid by testing the null hypothesis that earnings profiles are equivalent across occupation (i.e., \( H_0: \phi_j = 0 \) (\( j=2, \ldots, n \)), \( \theta_{11} = \theta_{12} = \ldots = \theta_{1j} \), and \( \theta_{21} = \theta_{22} = \ldots = \theta_{2j} \), with the \( F \) value calculated by comparing the sum of squared residuals from equations 5 and 6). To test the null, we use a modified \( F \) test suggested by Leamer (1978, p. 114), which requires much larger critical \( F \) values to reject the null as sample sizes increase.\(^{21}\) Using either standard critical \( F \) values or those suggested by Leamer, we easily reject the null stated above, or the less restricted null of equal earning-experience profiles across occupations with intercept shifts by occupation (results not shown but provided on request). Rejection of the null is consistent with there being substantial variation in post-schooling investment and earnings growth across alternative occupational paths. Evident from the equation 6 regression coefficients is that occupations that require greater post-schooling investment or training (e.g., executive, administrative, and managerial, professional specialty, and technicians) tend to have the steepest and most concave earnings-experience profiles, while occupations requiring the least post-school investment have flatter profiles.

Table 1 presents estimates of the investment parameters \( T^* \), \( K_0 \), and \( r_p \) economy-wide and by broad occupation and gender. Among men, we estimate an initial investment intensity of .20, a net investment span of 22 years, and rate of return to post-school training of 9.1 percent. Among women, for whom potential experience overstates actual experience, estimates are .08, 21 years, and 9.6 percent. We examined the sensitivity of estimates to alternative assumptions about \( T^* \), which Mincer (1974, p. 22) suggests occurs \( 1/r \) or about 10 years prior to the peak of observed earnings. Letting \( T^* \) occur 12.5 years prior to the peak, based on an \( r \) of .08, we obtain estimates of \( K_0, T^* \), and \( r_p \) of .22, 20 years, and 6.9 percent among men, and .09, 18 years, and 7.5 percent among women. Letting \( T^* \) occur 8.33 years prior to the peak, based on an \( r \) of .12, estimates of \( K_0, T^* \), and \( r_p \) are .18, 24, and 11.3 for men and .07, 22, and 11.7 for women. That is, the

\(^{21}\) Leamer (1978) has shown that the classical hypothesis testing with a fixed level of significance increasingly distorts the evidence against the null hypothesis as the sample size increases. Thus, the significance level should be a decreasing function of the sample size. Using Leamer’s derivation, there is evidence against the null hypothesis if the \( F \) value is greater than \( [(N-k)/d] (N^{d/N}-1) \), where \( N \) is the sample size, \( k \) is the number of parameters estimated, including the intercept, and \( d \) is the number of restrictions.
estimated level of $r_p$ is sensitive to the value of $T^*$. However, the finding that $r_p$ is highly similar across alternative occupational paths, which we show subsequently, is not affected by the choice of $T^*$.

**TABLE 1 ABOUT HERE**

Evident from Table 1 is that the initial investment intensity ($K_0$) is greater in occupational categories that require greater training or skills (e.g., executive, administrative and managerial, and professional specialty, as compared to handlers, helpers, and laborers, and transportation and material moving). In contrast, the length of positive net investment tends to be longer in occupations requiring lower initial investment intensity, although this relationship has exceptions (e.g., protective services has low investment intensity and length). An inverse relationship between $K_0$ and $T^*$ is consistent with there being slower rates of human capital depreciation in less skilled occupations, as demonstrated by more concave profiles for occupations with greater initial investment intensity.

Occupational patterns are similar for women and men. Notable differences in the magnitude of parameters include substantially lower investment intensities for women and, in general, shorter investment lengths. These differences reflect in part the fact that the potential experience measure overstates actual participation and hours worked for women relative to men and thus lower prior investment. They may also reflect lower investment intensity among women for given work experience, although we can provide no direct evidence on this.

We experimented with several methods that adjust downward the female experience variable. Using the full CPS database, we measured by gender mean labor force participation rates and hours worked per week (the latter among employed participants), separately by year (25), schooling group (4), and age group (3), a total of 300 cells. As widely known, female participation has increased sharply over time and participation and hours worked are sharply higher for female college graduates relative to non-graduates. We then approximated actual experience by, alternatively, a) multiplying female potential experience by the cell-specific female-to-male participation ratio of participation times the ratio of hours worked; b) multiplying by the ratio of hours worked (but not participation); and c) multiplying by the ratio of each female’s individual hours worked to mean male hours in the year-schooling-age cell. All analyses in this
paper were estimated using the alternative experience measures. Although estimates of \( T^* \), and to a lesser extent \( K_0 \), differed with respect to the measure, there was surprisingly little effect on estimates of \( r_p \). Because no major conclusion in the paper is affected, we present only results using the unadjusted experience measure.\(^{22}\)

The principal focus of our paper is the difference in occupational rates of return to post-school investment. As seen in Table 1, results are clear-cut. Despite substantial differences in earnings profiles and estimates of \( T^* \) and \( K_0 \) across occupational paths, the returns to post-school investment vary remarkably little across occupations for either men or women. Estimates of \( r_p \) range from 8.6 to 9.7 percent among men, and from 9.2 to 9.9 percent among women. Although our approach has numerous limitations, particularly for women, the evidence is supportive of the proposition that investment rates of return tend to equalize across alternative occupational paths.

An alternative way to explore differences in rates of return across alternative investment paths is to segment the workforce by skill-related variables such as schooling or occupational skill requirements. The use of schooling allows us to track experience profiles with movement across broad occupational categories. To a lesser extent, the same is true based on segmentation by occupational skill requirements. For ease of presentation, we divide the sample into two groups for each characteristic. Low-schooling (Education-Low) and high-schooling (Education-High) groups are defined as those with high school or below versus those with some college or more. Segmentation on occupational training requirements (Train-Low and Train-High) divides the male and female samples by the median months of required training for occupational proficiency, as measured by the SVP variable in the *Dictionary of Occupational Titles* (DOT). Likewise, the groups Aptitude-Low and Aptitude-High are based on the gender specific medians of the \( q \) variable in the DOT, measuring required numerical, verbal, and spatial aptitudes.\(^{23}\)

\(^{22}\) Filer (1993) provides equations from the NLS that predict actual experience for women based on measured characteristics, including occupation. Because his sample period, 1966-84, is centered in the 1970s, use of these estimates would understate actual experience over our sample period.

\(^{23}\) Each worker-year observation is sorted according to the DOT value for their current year occupation. DOT occupational descriptors are not gender specific. The DOT variables are from England and Kilbourne (1988), who map weighted averages of fourth edition DOT variables to 1980 Census occupation codes. To merge the England-Kilbourne data with the CPS, we first mapped 1970 and 1990 Census codes to time consistent 1980 Census 3-digit occupation codes; the latter mapping is straightforward while the former required probabilistic assignments based on information provided by the U.S. Bureau of the Census (1989). The training variable is based on the specific vocational preparation
TABLE 2 ABOUT HERE

Table 2 provides estimates of the investment parameters $K_0$, $T^*$, and $r_p$ for men and women by low and high investment groups based on education, length of post-school occupational training, and required occupational aptitudes. Results here reinforce the findings previously reported. Estimates of the investment intensity $K_0$ are higher among those with more schooling, in occupations requiring more training, and in jobs with a higher level of required aptitude. Differences in the length of the investment span by skill level are not clear, with $T$ somewhat lower for more educated workers, but higher for workers in occupations with high training and aptitude requirements. Our most important finding is that despite substantial differences in earnings profiles between high and low-skill workers, returns to post-school training are similar -- about 9 percent for all groups of workers. This finding is consistent with the prediction that rates of return to training tend toward equality across alternative post-school investment paths.

VII. CHANGES OVER TIME IN THE RETURNS TO SCHOOL AND POST-SCHOOL TRAINING

There exists strong evidence that returns to schooling increased during the 1980s and early 1990s (Levy and Murnane, 1992; Ashenfelter and Rouse, 1998), and mixed evidence that earnings profiles steepened during the 1970s and early 1980s (Levy and Murnane, 1992; Beaudry and Green, 2000). Higher returns to schooling have reflected both higher real earnings for those with high levels of education and declining real earnings for non-college-educated workers, in particular high school dropouts. Unexplored is whether or not there has been a secular increase in the rate of return to post-school training over the same period, or whether returns to training in high-skill occupations have risen relative to returns in low-skill occupations.

Table 3 provides regression estimates for 1973-2000 for the rate of return to schooling (approximated by the coefficient, $r_s$, on years of schooling) and the rate of return to post-school training, $r_p$, calculated as before from equation 9. Separate regression estimates are provided for the four-year time period 1973-76 and the eight three-year periods 1977-79 through 1998-2000 from standard log wage equations with largely “pre-market” or “choice” control variables (i.e., “outcome” variables such as (SVP) variable, measuring months training required for occupational proficiency. The required “intelligence” variable ($q$), measuring numerical, verbal, and spatial aptitude required for occupational proficiency, is scaled 1-4.
occupation, industry, and union status are excluded, while part-time status is included). Estimates of the returns to schooling mirror those provided in other studies. Rates for males are relatively low – about 6 percent – during the 1970s, and then rise steadily into the 1990s, with rates of return of 9.2 percent in 1995-97 and 1998-2000. Returns among women rise from 6-7 percent during the 1970s and early 1980s to just over 10 percent by the mid-1990s.

TABLE 3 ABOUT HERE

Table 3 also provides an estimate of changes over time in the slope of the earnings–experience profile, \( \varepsilon \), estimated in separate wage regressions by substituting the log of potential experience for experience and its square. Among men, the slope of the profile increases modestly during the late 1970s and early 1980s, changes little through the 1990s, and then drops during 1998-2000. Starting with an initial slope (i.e., earnings-experience elasticity) of .13 in 1973-76 the coefficient on log experience rises to .17-.18 during the late 1980s and 1990s, before falling to .15 during 1998-2000 (a period with a strong labor market for young workers). In contrast to men, the slopes among women rise steadily throughout the mid-1990s – from about .02 in 1973-76 to .10 in 1995-97 – before declining to .09 in 1998-2000. As emphasized by O’Neil and Polachek (1993), the increased slope of the earnings-age profile represents increased participation, hours worked, training investments, and a decline in discrimination, and not simply higher returns to human capital.

The most notable finding in Table 3 is that estimated returns to post-school training show no secular pattern. Among men, rates vary little, with a narrow range of estimates from 9.0 to 9.2 percent over the 1973-2000 period. We have less confidence in the results among women, but here there is also no evidence of an increase, with rates of return to post-school training falling slightly, from 9.9 to 9.4 percent between 1973 and 2000. In short, we find no evidence for a secular increase in returns to training investments on the

24. Ashenfelter and Rouse (2000) provide a time-series of annual estimates of \( r_s \) for the years 1979-93. They argue that standard OLS regression estimates closely approximate true rates of return, with the upward bias owing to omitted ability being roughly offset by downward bias from measurement error on the schooling variable. For an analysis of the theoretical and empirical issues surrounding estimation of the returns to schooling, see Card (1999) and Angrist and Krueger (1999). Note that changes in the CPS survey in 1994 appear to have had little effect on mean earnings (given consistent treatment of top codes), but resulted in estimates of somewhat larger inequality and increased returns to schooling (Polivka, 2000).

25. Experience is set to .25 (3 months) for workers with potential experience equal to zero. See Heckman and Polachek (1974) for a comparison of specifications using log experience versus its quadratic.
job. Rather, returns to schooling have risen from what were relatively low levels during the 1970s to rates of return about 9-10 percent, a level obtained for post-school training throughout the entire 1973-2000 period. Our results provide support not only for the proposition that rates of return tend to equalize across alternative occupational paths, but also across schooling and post-school training investments.

Brief mention of $K_0$ and $T^*$ estimates is also warranted. Among men, our estimates from the standard Mincerian quadratic specification of the human capital model implies initial investment intensities of about .20 of potential earnings, with investment intensity declining linearly over an approximately 20 year period $T^*$.

Estimates of $K_0$ for women is problematic, given that potential experience overstates actual experience and because the ratio of actual to potential experience has increased over time. Women have substantially lower estimated investment intensities, reflecting both fewer hours worked and lower intensity for given hours of work, and these rates have increased steadily over time as actual experience has increased. We obtain estimates of $K_0$ of only .02 for women in 1973-76, rising to .13 by 1995-97 (compared to .21 for men) and declining to .12 in 1998-2000. Such a substantial increase must reflect not only increases in work experience among women, but also increased training investments per hour worked.

Although we do not observe any secular change in rates of return to post-school training based on estimates from the full wage and salary labor force, this does not rule out the possibility that $r_p$ rose for workers in relatively high-skill relative to low-skill occupational paths. This possibility is examined by estimating $r_p$ for each of our 9 time periods, separately by occupation and separately for those with low and high levels of schooling, non-school training, and required aptitude (as seen for the full 1973-2000 sample in Table 2). There is at most weak evidence of a slight decrease over time in rates for those in the lower skill categories and a slight increase in rates for those in the higher skill categories. But the principal conclusion from such analysis is that rates of return to post-school training varied little over the 1973-2000 period for

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26. A referee asks the question as to why there exists a discrete drop in $K_t$ from 1.0 during schooling to well below 1.0 following schooling. The “low” value of $K_0$ may be in part an artifact of the specification assuming a linear decline in $K_t$ (an exponential decline would permit a higher initial $K_t$). Discontinuity in $K_t$ moving from schooling to the workplace, however, is neither atheoretical nor surprising (Johnson, 1978). Schools specialize in provision of training while firms specialize in other marketable outputs, with job training a by-product of production. Schools and firms differ in the costs of providing various types of skills. Moreover, there is public subsidy of training in school (where $K_t=1.0$), but not in the workplace (where $K_t<1.0$). Thus, the optimal investment path may include a crossover point from full-time to part-time training (i.e., the move from school to work) involving a discrete drop in $K_t$. Johnson (1978) develops a human capital model in which there is a discontinuity in the investment path.
workers in both low- and high-skill occupational paths (these results available on request). Our results do not rule out the possibility that relative rates of return changed over time but, if so, such changes occurred within rather than across our broad occupational and skill categories.

VIII. EMPIRICAL RESULTS: LONGITUDINAL PROFILES

As discussed above, cross-sectional analysis may provide a misleading view of longitudinal wage profiles for any given birth cohort (Ruggles and Ruggles, 1977; Beaudry and Green, 2000). We calculate values of $T^*$, $K_0$, and $r_p$ based on “longitudinal” earnings-experience profiles estimated using synthetic cohort analysis that follows the same cohorts (but not individuals) over time. Observations for each calendar year 1973-2000 are placed into eleven birth cohort groups based on reported age and the year surveyed. The eleven groups are the five-year birth cohorts born in 1914-18, 1919-23, 1924-28, 1929-33, 1934-38, 1939-43, 1944-48, 1949-53, and 1954-58, plus birth cohorts born prior to 1914 and born after 1958.

We first estimate a form of equation 10, which adds cohort dummies to the wage regression, thus allowing different intercepts of the experience profile by five-year birth cohort, while continuing to include separate year dummies. This specification constrains the slope of the profile to be equivalent across cohorts. For men, cohort dummies decline with respect to birth year, indicating downward shifts in the earnings profile for more recent cohorts. Year effects relative to 1973 are increasingly negative, with improvement after 1996. Women exhibit somewhat high profiles (about .02) for the birth cohorts born between 1944-48 and 1954-58, as compared to both older cohorts and those born since 1959. There is little trend in year coefficients for women over most of the period, the exception being recent improvements since 1996, similar to that seen for men.

The longitudinal analysis, whose results are summarized in Table 4, suggests that the investment intensity and length of the net investment span are lower than implied by our cross-sectional analysis. For example, among men the estimated $K_0$ is .15 and $T^*$ is 18 years, as compared to the cross-sectional estimates of .20 and 22 years, respectively. Among women, the longitudinal estimate of $K_0$ is .05 and $T^*$ is 15 years, as compared to cross-section estimates of .08 and 21 years. Although longitudinal estimates of $K_0$ and $T^*$ are
low as compared to the cross sectional results, estimates of \( r_p \) change little, being .092 among men and .096 among women.

TABLE 4 ABOUT HERE

Table 4 also provides longitudinal estimates of the investment parameters by occupation. Although the longitudinal estimates are more volatile and possibly less reliable than cross-section estimates, we again find that returns to post-school training are highly similar across alternative occupational paths. In analysis not shown, longitudinal estimates of the investment parameters by low and high education, training, and aptitude requirements also produced similar \( r_p \) estimates across all groups, as did our previous cross-section analysis. Although observed earnings profiles differ substantially across alternative career paths and groups of workers, we find no evidence of substantial differences in the returns to training investments.

Because equation 10 constrains longitudinal profiles and other earnings function parameters to be equivalent across birth cohorts, we also estimate separate longitudinal earnings functions for three cohorts – those born in 1939-43, 1944-48, and 1949-53. This analysis follows the earnings of these three cohorts over the 1973-2000 period, and allows all earnings function parameters to vary by cohort.

TABLE 5 ABOUT HERE

Table 5 provides estimates of \( r_s, K_0, T^*, \) and \( r_p \) for these three birth cohorts. We continue to find a shorter investment span \( T^* \) in the longitudinal than in the cross-sectional analysis, implying a relatively rapid decline in the rate of human capital investment with respect to experience. For example, among men, \( T^* \) varies from 11½ to 13½ years for the three cohorts, as compared to 22 years estimated from the cross-section. Although we have little confidence in specific point estimates, longitudinal analysis clearly suggests that the number of years of positive net investment is not great, limiting productivity and earnings growth for senior workers.27 Returns to post-school training, however, are roughly similar across cohorts and by gender, although there is the suggestion that rates have fallen slightly for more recent cohorts. As expected, investment intensity increases sharply for more recent female cohorts, from .04 for those born 1939-43 to .12 for those born 1949-53.

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27. Longitudinal results in Hanushek and Quigley (1975) based on the PSID imply even shorter investment spans than obtained in our work. One interpretation is that the longitudinal results are consistent with recent literature.
 IX. CONCLUSIONS

We have developed a modified human capital earnings function in which post-school training investment parameters can vary across alternative occupational paths and over time. Using data from the 1973-78 May CPS and 1979-2000 CPS-ORG files, cross-sectional and longitudinal earnings profiles are estimated from which we extract occupation-specific estimates of the intensity, length, and rate of return to post-school investment. Our most important finding is that estimated rates of return to post-school investment are highly similar, about 9 to 10 percent, across alternative occupational career paths, for workers in occupations requiring low and high levels of training or low and high aptitude, and for workers with low and high education levels. These results are consistent across gender and hold using synthetic cohort as well as cross-sectional analysis. Finally, rates of return to post-school training appear to have changed little over the 1973-2000 period, while at the same time rates of return to schooling increased from roughly 6 to 9 percent. By the late 1990s, rates of return to training in school and post-school training were approximately equal, again consistent with theoretical expectations.

While not conclusive, our evidence is supportive of the general human capital interpretation of the lifetime earnings generation process. That being said, equal rates of return across career paths need not be inconsistent with alternative theories of earnings determination. A large body of theoretical and empirical work has emerged emphasizing how jointly maximizing wage contracts can lead to a divergence between the sequencing of wage payments and marginal products. These include not only variants of the human capital model (i.e., specific training) but a family of implicit contract models in which the present value of lifetime earnings equals the present value of marginal products but spot wages need not equal spot marginal products (e.g., Lazear, 1976, 1979; Salop and Salop, 1976; Loewenstein and Sicherman, 1991; Hellerstein and Neumark, 1995). In this case, estimates of investment intensity and the length of net investment reflect not just training and productivity profiles, but also implicit agreements over the sequencing of pay. As argued by Polachek (1995), implicit contracts need not be viewed as contradictory to human capital theory. Rather, a richer human capital model incorporating firm as well as worker optimizing decisions is required.

The more general inference that might be drawn from our results is that equivalent rates of return suggesting that much general training is firm financed (e.g., Acemoglu and Pischke, 1998). For direct evidence on how
across occupational paths are consistent with both the general human capital model and joint worker-firm optimization models of the earnings generation process that equate lifetime earnings and productivity. Rather than providing a conclusive test of any single theory of wage determination, the evidence in our paper fails to reject the human capital model, in particular, and the more general proposition that labor markets are approximately efficient, with equivalent net present values across alternative occupational paths.

productivity and earnings vary with age, see Hellerstein, Neumark, and Troske (1999).
REFERENCES


Table 1. Parameters of Male and Female Cross-Section Earnings Profiles, by Occupation

<table>
<thead>
<tr>
<th></th>
<th>T*</th>
<th>Male K₀</th>
<th>rₚ</th>
<th>T*</th>
<th>Female K₀</th>
<th>rₚ</th>
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<td>.091</td>
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<td>.092</td>
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<td>.093</td>
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<td>59.15</td>
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Parameter estimates are based on regression results from equations (5) and (6), estimated over the 1973-2000 period. K₀ is the initial investment intensity, rₚ is the rate of return to post-schooling human capital investment, and T* is the number of years of net positive investment. T*, K₀, and rₚ are calculated from equations (7), (8), and (9), respectively. The dependent variable in the earnings function is the natural log of real hourly earnings. In addition to schooling, potential experience, and occupation, regressions include controls for race, part-time status, marital status, regional location, large metropolitan residence, and year.

*a Coefficients on t and t² do not permit a reliable estimate of T*. 
Table 2. Parameters of Male and Female Earnings Profiles, by Education, Training, and Required Aptitude Levels

<table>
<thead>
<tr>
<th></th>
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<th>Female</th>
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<td>$T^*$</td>
<td>$K_0$</td>
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<td>All Workers</td>
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<td>Training – High</td>
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<td>Aptitude – Low</td>
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<td>Aptitude – High</td>
<td>21.78</td>
<td>.221</td>
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Parameter estimates are based on regression results from equation (5), estimated separately by skill group over the 1973-2000 period. $K_0$ is the initial investment intensity, $r_p$ is the rate of return to post-schooling human capital investment, and $T^*$ is the number of years of net positive investment. $T^*$, $K_0$, and $r_p$ are calculated from equations (7), (8), and (9), respectively. The dependent variable in the earnings function is the natural log of real hourly earnings. In addition to schooling and potential experience, regressions include controls for race, part-time status, marital status, regional location, large metropolitan residence, and year.
Table 3. Schooling and Post-School Parameters of Male and Female Cross-Section Earnings Profiles, by Time Period

<table>
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<td></td>
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<td>(K_0)</td>
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Parameter estimates are based on regression results from equation (5), estimated separately by time period. \(K_0\) is the initial investment intensity, \(r_p\) is the rate of return to post-schooling human capital investment, \(T^*\) is the number of years of net positive investment, \(r_s\) is the rate of return to schooling, and \(\varepsilon\) is the wage-experience elasticity, \(\partial\ln W/\partial\ln(\text{Exp})\). \(T^*, K_0,\) and \(r_p\) are calculated from equations (7), (8), and (9), respectively. The dependent variable in the earnings function is the natural log of real hourly earnings. In addition to schooling and potential experience, regressions include controls for race, part-time status, marital status, regional location, and large metropolitan residence.
<table>
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Parameter estimates are based on regression results from equation (10), estimated over the 1973-2000 period. K_0 is the initial investment intensity for occupation j, r_p is the rate of return to post-schooling human capital investment, and T* is the number of years of net positive investment. T*, K_0, and r_p are calculated from equations (7), (8), and (9), respectively. The dependent variable in the earnings function is the natural log of real hourly earnings. In addition to schooling and potential experience, regressions include controls for race, part-time status, marital status, regional location, large metropolitan residence, and birth cohort.

^ Coefficients on t and t^2 do not permit a reliable estimate of T*. 
Table 5. Parameters of Longitudinal Earnings Profiles by Birth Cohort

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<td>rₚ</td>
<td>rₛ</td>
<td>T*</td>
<td>K₀</td>
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Parameter estimates are based on regression results from equation (11), estimated separately by birth cohort over the 1973-2000 period. K₀ is the initial investment intensity, rₚ is the rate of return to post-schooling human capital investment, T* is the number of years of net positive investment, and rₛ is the rate of return to schooling. T*, K₀, and rₚ are calculated from equations (7), (8), and (9), respectively. The dependent variable in the earnings function is the natural log of real hourly earnings. In addition to schooling and potential experience, regressions include controls for race, part-time status, marital status, regional location, and large metropolitan residence.
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The source of the data is the 1973-78 May CPS and the 1979-2000 CPS ORG Earnings Files. The sample consists of wage and salary workers, ages 25 to 62. Sample sizes are 615,485 men and 522,254 women. Dependent variable is the natural log of real hourly earnings and standard errors are in parentheses. Regression models 5 and 6 include controls for year, race, part-time status, marital status, regional location, and large metropolitan residence. Controls for model 10 are identical, except that birth cohort dummies are included.