A Human Capital Model of the Effects of Abilities and Family Background on Optimal Schooling Levels

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Abstract

This paper develops a theoretical model of earnings where human capital is the central explanatory variable. The analysis and estimation strategy stems from the Mincerian (1974) simple schooling model. We incorporate human capital investments (i.e., schooling) into a model based on individual wealth maximization. From this model we can derive and utilize the conventional economic models of supply and demand. We use data collected from the NLSY79 to stratify our sample into one-year work-experience intervals for the years 1985-1989 to identify the "overtaking" cohort (i.e., the years of work experience at which an individual's observed earnings approximately equal what they would have

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been based on his schooling and ability alone). We find that the "overtaking" year of work-experience occurs for individuals who have 13 "FTE" years of work-experience, which is associated with an average 9.7 percent rate of return to the average optimal 11.4 years of schooling. Ultimately, we estimate an earnings transformation (production) function, a derived internal rate of return (demand) function, and a discounting rate of interest (supply) function to derive a reduced-form optimal level of schooling function for this "overtaking" cohort. Our estimation strategy employs the AFQT score as an ability proxy and also considers the possible endogenous nature of this variable (which we ultimately reject). This paper explores several estimation strategies including OLS, 2SLS, and NLSUR/NLOLS.

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I. INTRODUCTION

Becker's 1962 paper defines human capital investments to be any "activities that influence future real income through the imbedding of resources in people." (Becker, 1962, pp. 9) Human capital investments are of wide ranging interest because they can be used to explain income disparities across people, over space, and over time. Labor earnings are typically people's primary source of income. Human capital investments include schooling, on-the-job-training (OJT), routine medical exams, healthy diets, etc.-in other words, anything that can help increase worker productivity. Schooling is a unique type of investment in that it affects not only current day consumption but also future earnings potential as well. Individuals choose to invest in schooling until their marginal rate of return equals their discounting rate of interest. More practically speaking, they operate in such a way so as to maximize their expected (discounted) future earnings stream. Social and intellectual interest in income disparities, primarily stemming from differing schooling levels, has generated an enormous amount of attention across disciplines. There is a vast literature supporting/reflecting such an interest.

This paper specifies and estimates a human capital model that is based on individual wealth maximization. We use an earnings-schooling relationship to calculate individual marginal rates of return to schooling and discounting rates of interest. From these we can identify and estimate supply and demand functions for schooling-investment. We ultimately arrive at an optimal level of schooling equation that accounts for permanent family income levels, family size, and abilities. We consider two different proxies for ability, but ultimately confine our attention to just one. We consider the possible endogeneity of this variable as well. Our estimation strategy involves disaggregating our sample into one-year work-experience intervals for 1985-1989. We then estimate a log wage equation to identify the work-experience cohort which minimizes the estimated residual standard error and three other model selection criteria, namely the Akaike information criterion, the Schwarz criterion, and the Amemiya's prediction criterion. Once we have identified this group we proceed with the rest of our estimation. We employ the following estimation strategies in this paper: OLS, NLSUR/NLOLS, and 2SLS.

This paper is organized as follows: Section II provides the background and literature review. Section III discusses the conceptual framework that underlies the analysis. Section IV discusses the data used in the analysis. Section V presents the results and Section VI discusses them and provides alternative estimation strategies. Finally, Section VII concludes. A bibliography, appendices, and supporting tables and figures are provided at the paper's end. The Technical Appendix is available upon request from the authors.

II. Background and Literature Review

A tremendous amount of the economics literature has been devoted to studying human capital investments and the economic rates of return, particularly to education. Researchers have exploited the models and theories developed by Mincer and Becker in their attempts at getting purer, more accurate, and more sophisticated rates of return. Various econometric strategies have been developed and utilized to account for the potential measurement error, omitted variables bias, and selection bias of the traditional log wage model.

Becker's 1962 paper is one of the seminal works done on human capital investments. Becker provides the justification for an age-earnings profile that is both steep and concave. Its shape stems from the fact that such human capital investments lower observed earnings at young ages because any such costs are deducted from an individual's wage. However, observed earnings rise in later years because the returns to such investments are then added on to an individual's wage. Several years later

Willis and Rosen (1979) published a paper where they attempt to estimate lifetime earnings conditional on actual school choices (i.e., high school or college) that were purged of any selection bias. They estimate a structural probit for data collected from the NBER-Thorndike-Hagen survey of 1968 (i.e., male WWII veterans). Willis and Rosen do find that there is positive selection bias in observed earnings and estimate rates of return to be about 9 percent.

Some of the more recent studies on human capital investments and the associated rates of return to school have delved deeper into such econometric issues and also presented modifications to the standard Mincerian approach of explaining earnings. In 1983, Behrman and Birdsall extend the simple log wage model to incorporate not only school quantity but quality as well, as proxied by the years of schooling completed by a pupil's teacher. They argue that the omission of quality biases the traditional OLS estimates upwards. Behrman and Birdsall's analysis uses data collected from the 1970 Brazilian Census. Card and Krueger (1992) use an approach similar to Behrman and Birdsall in estimating the effects of school quality on rates of return to education. They proxy for school quality with various measures (e.g., pupil/teacher ratio, average teacher term length, relative teacher pay) found in the Biennial Survey of Education. Using the 1980 Census, Card and Krueger estimate earnings functions for white men born between 1920 and 1949. They find that men educated in states with higher quality schools, better-educated teachers, and a higher fraction of female teachers have higher rates of return to each additional year of schooling.

Another modification to the log earnings function comes from the work done by Altonji and Dunn in 1996. They incorporate parental education levels into their model by interacting them with their children's education levels. Using a fixed-effects estimation strategy, on data collected from the NLSY66 and PSID68, they find mixed evidence on the role of parental education in the human capital function. Ashenfelter and Zimmerman (1997) continue to investigate the effects of family background on the economic rates of return to education. Using data collected from the NLSY66, they gather information on father-son and sibling (i.e., brother-brother) pairings. They incorporate a family-specific fixed effect into the standard Mincerian log earnings function and ultimately arrive at a correlated random effects model. Ultimately, Ashenfelter and Zimmerman use a seemingly unrelated regressions approach and find an upward bias in the estimated rates of return from omitted variables. This bias is offset by a downward bias due to measurement error in self-reported schooling levels. Hence, controlling for omitted variables and measurement error yields results comparable to the conventional rates of return obtained from OLS.

Family background again comes to the forefront in Lang and Ruud's (1986) work. The approach taken by Lang and Ruud is similar to ours but differs on several important points. Like us, Lang and Ruud employ data collected from the NLSY (the 1966 wave instead) but they use potential, rather than actual work experience. They consider single, rather restrictive measures of socioeconomic status (i.e., the Duncan Index) and ability (i.e., IQ). Furthermore, their wage regressions employ an individual's hourly wage as the dependent variable which glosses over the well-known fact that individuals who have a higher hourly wage tend to work more because of their high opportunity costs to leisure. In spite of the paper's shortcomings they do find that their measures of individual discount rates, implicit in the education investment decision, do not vary with socioeconomic background. Family background does however help to explain differences in individual levels of education, primarily due to variation in their attainment speeds.

Ability measures have always received much attention in the human capital literature. Such unobservables have often posed problems for researchers. Researchers have most often proxied ability measures with IQ scores, or other such similar tests. However, in 1994, Ashenfelter and Krueger compile a unique data set consisting of twins (mostly identical) to address such issues. Using an instrumental variables technique, they do find significant evidence of measurement error that biases the rates of return down. When they adjust for such measurement error they find rates of return between 12 and 16 percent, much higher than the conventional estimates. Moreover, they conclude that any unobserved ability (i.e., omitted variables) does not bias the rates of return upwards.

Several of these different econometric estimation strategies are surveyed and summarized in Card's 1994 work. The studies he cites either use a fixed effects or instrumental variables method in accounting for the causal effect of schooling in the labor market. All but one of these studies find that the OLS estimates to rates of return are biased down (by about 10 to 30 percent). While many of these studies can be criticized for their identification strategy, imprecision, strict underlying assumptions, and unique samples, their similar findings do warrant careful rethinking.

III. CONCEPTUAL FRAMEWORK

Throughout this paper we will treat the schooling decision as an investment activity and focus solely on it. First, we posit the existence of an earnings transformation function[1,2] and define it as follows,

$$Y = F(S, A). \tag{1}$$

This function relates an individual's annual earnings, Y, to his/her years of schooling, S, and to his/her natural ability, A. For our earnings function to exhibit the conven-

[1]Burghardt and Oaxaca (1979) state that, "As Rosen (1973) points out, the transformation function is derived from a production function of knowledge whose arguments are schooling and ability. The units of knowledge (human capital) are multiplied by a constant market rental rate on human capital to yield earnings. The production function itself is derived from a learning function that governs the rate at which knowledge can be produced from prior schooling and ability." (Burghardt and Oaxaca, 1979, pp. 3)

[2]Lazear (1977) frames his discussion of education in the context of a production function.

tional positive, but diminishing marginal returns to schooling and positive returns to ability, we need the following inequalities to be satisfied,

$$F_S, F_A > 0 \text{ and } F_{SS} < 0. \tag{2}$$

We might also expect more able people to reap greater rewards (i.e., in the form of their resulting wage structure) to increased schooling levels and vice-versa as well[3]. Thus,

$$F_{SA} = F_{AS} > 0. \tag{3}$$

In the analysis that follows it is more convenient to think of our earnings transformation function in its log form,

$$\ln Y = \ln F(S, A). \tag{4}$$

Now, it is much easier to interpret and derive the marginal rate of return to schooling. Let us define the marginal rate of return to schooling, r, as follows,

$$r = \frac{\partial \ln F(S, A)}{\partial S}. \tag{5}$$

In order for the marginal rate of return to schooling to increase with ability (and hence for the demand for schooling to increase with ability) we need the following inequality to be maintained[4],

$$FF_{SA} > F_A F_S. \tag{6}$$

[3] For a general, perhaps dated, discussion of the effects of schooling and ability (and their interaction) on log earnings, see Hause (1972).

[4] The proof of this inequality is found in Appendix 1.

Next, we will assume that all relevant costs are just foregone earnings and that an individual seeks to maximize the present value, of his/her lifetime earnings over an infinite horizon[5] subject to the constraint imposed by (1). Formally speaking, we can mathematically represent an individual's maximization problem as,

$$\underset{S}{Max} V = \int_S^{\infty} Y e^{-it} dt \text{ subject to } Y = F(S, A), \tag{7}$$

where V is the present value of lifetime earnings, i is a fixed discounting rate of interest, and t is the index of integration.

We can then simplify the present value of lifetime earnings and take the log of the resulting expression to obtain,

$$\ln V = \ln Y - iS - \ln i. \tag{8}$$

Taking derivatives with respect to S we arrive at the following first order condition,

$$r = i. \tag{9}$$

Hence, the optimal level of schooling for an individual occurs at the point where his/her marginal rate of return to schooling exactly equals his/her discounting rate of interest.

We can now put the above analysis into a conventional supply and demand framework. We obtain an individual's demand for investment in schooling by taking the derivative of the log transformation function as defined in (4) with respect to schooling[6]. Hence, the demand for schooling can be expressed as,

$$r = r(S, A), \tag{10}$$

[5] This infinite horizon is imposed for mathematical simplicity. An infinite horizon model has been used by numerous other researchers as well. See Lang and Ruud (1986).

[6] For a given individual, his/her abiliity level is assumed to be fixed.

or equivalently as,

$$S^d = S^d(i, A),$$

where S^d is the level of schooling demanded at each discounting rate of interest for an individual with a given ability level A[7]. Thus, we allow the demand for schooling to be the marginal rate of return.

We can derive an individual's supply function for school investment from the present value function as defined in (8). Simple manipulation of this expression yields,

$$\ln Y = \ln(iV) + iS. \tag{11}$$

Differentiating this expression with respect to S yields an individual's supply curve. This establishes the relationship between the supply of schooling and the discounting rate of interest. It should be noted that an individual's discounting rate of interest, i, is uniquely fixed and does not vary with the level of schooling. However, since i can also be interpreted as the marginal opportunity cost of an additional year of school, it is reasonable to assume that i can vary across individuals. For example, we would probably expect the discounting rate of interest to be higher for children from poorer families than that of children from wealthier families. The same could be said of children from larger families as compared to children from smaller families. Hence, we can define i as a function of an individual's family characteristics,

$$i = i(X), \tag{12}$$

[7] The derivation of this equivalent expression is most clearly seen when we consider the stochastic estimation to equation (4) (i.e., equation (15)). Taking the derivative of the lnY with respect to S yields the marginal rate of return. Rearraning this expression and solving for S yields a level of schooling that is a function of r and A. Imposing the equilibrium condition that $r = i$ makes the demand for school a function of i and A.

where X denotes a vector of family background variables. In our analysis these include family size and permanent family income levels.

Combining (9), (10), and (12) we can simply define the optimal level of schooling as,

$$S^* = f(X, A). \tag{13}$$

We can graphically illustrate this optimal level of schooling using both a supply and demand framework and a framework relating the log earnings functions[8]. This can be seen in Figure 1. The top graph relates the log earnings transformation function to the log earnings present value functions as defined in (11). The log earnings transformation function is a concave curve reflecting the positive, but diminishing marginal returns to schooling. The log earnings present value functions are a series of straight lines relating lnY and S at a given discounting rate of interest, i. The optimal level of schooling, S^*, occurs at the point of tangency between these two curves-the point at which discounted lifetime earnings are maximized. The bottom graph tells the same story, just from a different viewpoint. This framework relates the downward sloping demand function, as defined in (10), to the infinitely elastic supply curve, as defined in (12). The intersection point between these two curves corresponds to the point where the discounting rate of interest exactly equals the marginal returns to schooling (i.e., the equilibrium as defined in (9)). This in turn establishes again, the optimal level of schooling, S^*. These two frameworks graphically establish the solution to the maximization problem as defined in (7).

We can now consider the situation in which ability levels and discounting rates of interest are allowed to vary across individuals. Figure 2 depicts this situation. Again in the top framework we see individuals' optimal schooling levels being established

[8] Becker and Chiswick (1966) give a very general discussion of how human capital investment can be nested in the context of a supply and demand curve analysis.

by the point of tangency between their log earnings transformation functions and their log earnings present value functions. The bottom framework achieves the same results, by utilizing the individual-specific supply and demand intersections instead. Hence, fitting a line through the set of tangency points in the top graph parallels the development of Mincer's simple schooling model[9] which is,

$$\ln Y_j = \beta_0 + \beta_1 S_j + u_j, \tag{14}$$

for individual j.

Next, we will discuss the empirical specification that underlies the econometric analysis. The stochastic approximation[10] to the transformation function as defined in (4) is,

$$\ln Y_j = \beta_0 + \beta_1 S_j + \beta_2 A_j S_j + \beta_3 S_j^2 + u_{1j}, \tag{15}$$

where j denotes the individual and u_{1j}[11] is an error term. To maintain the relationship as defined in (4), we would expect the following signs on the coefficients:

$$\beta_1, \beta_2 > 0 \text{ and } \beta_3 < 0. \tag{16}$$

The schooling-investment demand function is obtained by differentiating (15) with respect to S. Thus, obtaining,

$$r_j = \beta_1 + \beta_2 A_j + 2\beta_3 S_j, \tag{17}$$

[9] Burghardt and Oaxaca (1979) address the identification of this model. Since the model is not identified, β_1, has no economic meaning. However, its interpretation as an average rate of return to schooling is maintained throughout the analysis.

[10] See Heckman and Polachek (1974) for a discussion of the appropriateness of this functional form.

[11] We assume $u_{1j} \sim iid\, N(0, \sigma_1^2)$. The Bera and Jarque (1981, 1982) test confirms this assumption. The details of this test can be found in Appendix 2.

where $r_j = \frac{\partial \ln Y_j}{\partial S_j}$. We specify the schooling-investment supply function to be a linear function of various family background variables. Consider the following specification,

$$i_j = \theta_0 + \theta_1 S_{fj} + \theta_2 S_{mj} + \theta_3 (S_{fj} + S_{mj}) + \theta_4 DVS_{fj} + \theta_5 DVS_{mj} + \theta_6 N_j + \theta_7 N_j + u_{2j}, \quad (18)$$

where S_{fj} is the schooling level of an individual's father, S_{mj} is the schooling level of an individual's mother, N_j is the family size, and u_{2j}[12] is an error term. In the above construct, we have proxied permanent family income with the schooling levels of an individual's parents[13]. So as to not lose observations, and to maintain a constant sample size across regressions[14], we imposed an education level of zero years for any respondent's parent whose education level was reported as a missing value. We then constructed dummies indicating whether or not we imposed such a value. Hence, DVS_f takes on a value of "1" if we replaced a missing value for the respondent's father's education level with a zero. Similar reasoning applies for the dummy variable on a respondent's mother's schooling level, DVS_m[15].

The above construct allows for a nice interpretation of the coefficients. The θ_1 and θ_2 capture the pure wealth effects of family income on an individual's discounting rate of interest. Hence, we would expect these two parameters to have negative signs because an individual's discounting rate of interest (or alternatively, his/her

[12] We assume $u_{2j} \sim iid\, N(0, \sigma_2^2)$.

[13] We considered several other proxies of permanent family income, namely the Duncan Socioeconomic Index and variations of the parental schooling levels–the average level, the maximum level, and the head of the household's level. We abandoned such alternatives because we either lost too many observations or because we feared the bias that would result from a subjective judgement of the importance of parental schooling.

[14] The importance of maintaing a constant sample size across (15), (19), and (22) will become evident in the NLSUR estimations that follow.

[15] Of the 239 observations, only 26 (22) respondents did not report their father's (mother's) schooling level.

marginal opportunity cost of an additional year of schooling) decreases with his/her family wealth (i.e., the individual is more patient and can postpone earnings for more schooling). The θ_3 however captures the effect of family wealth on potential financial aid. Since financial aid offices base their decisions purely on family wealth, not individual parental contributions, we sum these two variables together and expect their common parameter, θ_3, to have a positive sign. Hence, children from richer families have less of a chance of receiving financial aid which in turn increases their discounting rate of interest. We can decompose the effects of family size on an individual's marginal opportunity cost of an additional year of schooling into two separate effects. The θ_6 parameter captures the pure income effect of family size. We would expect individuals from larger families to have increased opportunity costs to additional schooling, hence θ_6 should be positive. However, the larger a family, the more widely the (financial) resources are spread and hence the greater the opportunity for financial aid assistance. Thus, we would expect θ_7 to be negative.

Since the coefficients are not identified in the above specification, we collect terms and arrive at the following functional form,

$$i_j = \alpha_0 + \alpha_1 S_{fj} + \alpha_2 S_{mj} + \alpha_3 DVS_{fj} + \alpha_4 DVS_{mj} + \alpha_5 N_j + u_{2j}, \tag{19}$$

where,

$$\begin{aligned} \theta_1 + \theta_3 &= \alpha_1, \\ \theta_2 + \theta_3 &= \alpha_{2,} \end{aligned} \tag{20}$$

and

$$\theta_6 + \theta_7 = \alpha_{5.}$$

Hence, the above specification identifies the relative parental contributions on wealth effects, aside from the financial aid effects[16]. We can determine which of the effects are larger by noting the sign of the estimated coefficient.

The reduced-form optimal level of schooling equation is obtained by substituting (17) and (19) into the individual-specific equilibrium condition,

$$r_j = i_j. \tag{21}$$

When we do this and solve for S^*, we obtain,

$$S_j^* = \gamma_0 + \gamma_1 S_{fj} + \gamma_2 S_{mj} + \gamma_3 DVS_{fj} + \gamma_4 DVS_{mj} + \gamma_5 N_j + \gamma_6 A_j + u_{3j}, \tag{22}$$

where

$$\begin{aligned}
\gamma_0 &= \frac{\alpha_0 - \beta_1}{2\beta_3}, \qquad\qquad (23)\\
\gamma_1 &= \frac{\alpha_1}{2\beta_3},\\
\gamma_2 &= \frac{\alpha_2}{2\beta_3},\\
\gamma_3 &= \frac{\alpha_3}{2\beta_3},\\
\gamma_4 &= \frac{\alpha_4}{2\beta_3},\\
\gamma_5 &= \frac{\alpha_5}{2\beta_3},\\
\gamma_6 &= \frac{-\beta_2}{2\beta_3},\\
u_{3j} &= \frac{u_{2j}}{2\beta_3},
\end{aligned}$$

and

$$\sigma_3^2 = \frac{\sigma_2^2}{4\beta_3^2}.$$

The signs on the coefficients establish the net effect of the direct and indirect (i.e., through financial aid awards) wealth effects on schooling. The only coefficient that

[16]Specifically, this is because $\alpha_1 - \alpha_2 = \theta_1 - \theta_2$.

we could sign at this point would be that of ability. It is reasonable to expect that more able people would reap greater rewards from increased schooling levels. Thus, we expect γ_6 to be positive.

Due to the fact that an individual's discounting rate of interest and marginal rate of return to schooling are not observable, we must estimate them in order to identify the supply and demand functions. Hence, in estimating the marginal rate of return to schooling, we use the estimated parameters obtained from the OLS estimation of (15). This then establishes an estimated marginal rate of return to schooling, $\hat{r}_j$, for each individual. We then impose the equilibrium condition as defined in (21) to get an estimated discounting rate of interest, $\hat{\imath}_j$. In other words, $\hat{r}_j = \hat{\imath}_j$. We use these estimated marginal rates of return and discounting rates of interest as the dependent variables in the demand of and supply for schooling investment functions, respectively.

The estimation strategy used here follows a procedure Mincer (1974) used when estimating the simple schooling model of equation (14). In this work he seeks to "gain understanding of the observed distribution and structures of earnings from information on the distribution of accumulated net investments in human capital among workers." (Mincer, 1974, pp. 2) He considers a theoretical model of earnings where human capital is the central explanatory variable. Mincer argues that experience, more than age, explains earnings differentials due to education. He argues that the correlation between log earnings and education is strongest in the first decade of work experience. Mincer introduces the notion of an "overtaking" year in which an individual's observed earnings are most reflective of his/her investment in school (and innate ability). At this particular point in time the distortion from post-schooling investments (i.e., OJT) is minimized and the return on an individual's prior investment (i.e., schooling) equals the cost of the current investment (i.e., OJT). An individual's earnings at this "overtaking" year provide the best test of the simple schooling model. This "overtaking" year is usually eight years after an individual has left school when an individual has between seven and nine "years" of work experience.

Goodness of Fit Measures

In our attempts to identify the "overtaking" year of work-experience, we considered five separate "goodness of fit" measures for the model as described in (15)[17]. The most typical and singular way of gauging the "goodness of fit" of a regression is the use of the R^2 measure. The R^2 measures the proportion of the total variance in the dependent variable that is explained by the model (linearly). Thus, we seek to maximize the R^2. This measure has been criticized for its obvious fault–it can be inflated just by including more regressors. Theil (1961) purported the use of an adjusted R^2 measure, $\overline{R}^2$, that corrects for the degrees of freedom. We chose not to include the adjusted R^2 measure because the number of regressors in (15) does not vary.

It is the belief of some that even the $\overline{R}^2$ does not impose a harsh enough penalty for the loss in degrees of freedom. Hence, the next three measures we consider attempt to correct this problem. All three of these selection criterion seek to minimize the mean-squared error (MSE) of prediction (as opposed to the residual standard error),

$$E(\ln Y_f - \widehat{\ln Y}_f)^2, \tag{24}$$

where $\ln Y_f$ is the future value of $\ln Y$ and $\ln \widehat{Y}_f$ is the predicted future value.

The first of these selection criteria is Amemiya's (1980) prediction criteria (PC). We seek to minimize the following,

$$PC = \frac{SSE(1 + \frac{k}{N})}{N - k} = \sigma_1^2(1 + \frac{k}{N}), \tag{25}$$

[17] All of these "goodness of fit" measures are based on the fact that we have a reasonably large sample (i.e., greater than 100 observations). This however is not really much of a concern for the earlier cohorts.

where SSE denotes the total sum of squared errors, k is the number of regressors (inclusive of the constant term), N refers to the sample size, and σ_1^2 is the error variance of u_1.

Another more general selection criterion is the use of Akaike's (1973, 1974) information criterion (AIC). It seeks to minimize,

$$AIC = \ln \frac{SSE}{N} + \frac{2k}{N} \approx \ln \sigma_1^2 + \frac{2k}{N}. \tag{26}$$

The third selection criterion was developed by Schwarz (1978). The Schwarz criterion seeks to minimize,

$$SC = \ln \frac{SSE}{N} + \frac{k \ln N}{N} \approx \ln \sigma_1^2 + \frac{k \ln N}{N}. \tag{27}$$

It should be noted that the three criterion discussed above are typically nested in discussions of regressor selection[18]. Typically researchers are testing different models using the same data set. We however, are testing a common model using different samples of our data to determine which work-experience cohort best suit its predictions.

The last "goodness of fit" measure we consider is simply the estimated standard error of the regression. We seek to minimize the estimated residual variance,

$$\widehat{\sigma}_1^2 = \frac{SSE_j}{(N-k)}, \tag{28}$$

(or alternatively its square root which is the estimated residual standard error). The estimated residual variance helps to explain all the variance in the model that has not been explained by the regressors. Thus, the smaller it is the more explanatory

[18] For nice discussions of these selection criterion see Greene (1997), Kennedy (1998), Maddala (2001), and Judge et al. (1988).

power we can attribute to our model.

IV. DATA

The data used in this paper is from the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 consists of 12,686 young men and women, living in the U.S., who were between the ages of 14 and 22 years when the first survey was conducted in 1979[19]. In 1998, the most recent wave of the survey, 8,399 civilian and military respondents were interviewed from the 9,964 eligible persons, hence yielding an overall retention rate of 84.3 percent.

The demographic variables for each respondent were collected from the 1979 interview. We confined our attention to include only white males. The resulting sample size is 4,393 persons. From this 1979 interview we were able to get several measures of a respondent's family background/income level. These measures include the respondent's family size and the highest grade completed by a respondent's mother and father. The NLSY79 provides three different measures used to gauge a respondent's ability. The first of these, which we chose not to use because of the small number of respondents, is the total Intelligence Quotient (IQ) score. The second of these is the Knowledge of the World of Work (KWW). The third is the Armed Forces Qualification Test (AFQT).

The educational attainment and enrollment status was available for each survey year. We have measures indicating both the highest grade completed by a respondent and his current enrollment status. When performing the econometric analysis, we do not include any respondent who is currently enrolled in school for that year because such individuals have not fully realized the gains to school in terms of their resulting wage structure yet. We also omit anyone who attended school after 1989 to ensure

[19] There is oversampling of the poor and people in the military.

that the wages we observe are truly reflective of final[20] schooling choices[21].

The income variables were collected from the main NLSY79 files as well. The dependent variable in the log earnings regression is the log of a respondent's total income from wages and salary in the respective year. Using the Consumer Price Index (CPI) for all urban consumers, as published by the BLS (Bureau of Labor Statistics), we deflated the income figures and express them in terms of 1985 dollars. In our analysis, we consider only people who earned at least $500 in nominal terms for a given year.

The variables used in the construction of the experience measures were collected from the supplementary NLSY79 work history file. Since each respondent is assigned a unique identification code, we were able to merge the two data sets. Due to this detailed collection of work experience variables, we do not have to use less accurate, potential work experience measures. A respondent's work experience for a given year is calculated by summing the hours worked in that year and all prior years (since 1979) and then dividing through by 2080. Taking account of the fact that many of our respondents were older than 18 years (the usual age that one graduates from high school in the U.S.) and had potentially been working for several years prior to the first survey in 1979, we constructed a variable to measure their experience prior to 1979. This variable is calculated as follows,

[20] The term "final schooling" is used somewhat loosely here because we can only observe individual schooling choices/enrollment through 1998, the most recent wave of the NLSY79 survey that we have.

[21] Including such individuals yields estimates of (15), (19), and (22) that are marginally more significant. By focusing on those individuals who have finished their educational investment through 1998, we only lose nine observations for the 13 year work-experience cohort. The earlier cohorts considered, the more observations lost. The figures in Table 4 do however support the choice of the 13 year work-experience cohort as the "overtaking" cohort.

$$Experience\ prior\ to\,1979 = (Age_{1979} - Schooling_{1979} - 6) * (Work\ Experience_{1979}/2080). \tag{29}$$

Hence, this gives us a measure of "full-time equivalent" (FTE) work experience[22].

Following Mincer's lead, we stratified our sample into one-year FTE work-experience intervals for the years 1985-1989[23]. Ultimately this procedure controls for experience without making it explicit in any of the equations. (15) is then estimated separately for each work-experience cohort. Running each regression separately allows for full interaction effects of work experience on each coefficient. The earnings data in the model as defined by (15), (17), (19), and (22) reflects not only ability and schooling-investment decisions but post-schooling investments (e.g., work experience, on-the-

[22] It should be noted that most often these "years" of work-experience do not coincide calendar years.

[23] We chose to confine our attention to the years 1985-1989 for several reasons. First, as previously stated, Mincer argues that the correlation between log earnings and education is strongest in the first decade of work experience. The NLSY79 began in 1979 and the latest year we chose to look at was 10 years later, in 1989. Second, Mincer finds that the "overtaking" year occurs eight years after an individual has left school and has acquired seven to nine "years" of work experience. In the first year of the survey, our respondents are between 14 and 22 years old. Roughly, half are under 18 years and it is reasonable to assume still enrolled in school. Using 1985 as a lower bound allows our youngest respondents to probably have acquired at least four years of work experience. We also do not, at this point, consider earlier years, like 1980 for instance, because the closer to the first survey year the cruder our approximations are of the respondents' true work experience. This is due to the fact that we had to estimate their work experience prior to 1979. Going as late into the survey as 1989 probably biases us towards finding a later "overtaking" year if anything. Furthermore, as a rough rule of thumb you can estimate the rate of return to education as the inverse of the overtaking cohort. Roughly speaking, in 1985, six calendar years have passed since the first survey year and we would calculate a 16.7 percent rate of return to schooling. This figure seems a bit high, but for 1989 we would get a 9.1 percent rate of return which seems more reasonable and is similar to rates previously found by other researchers.

job training) as well. Thus, ignoring the potential correlation between schooling and work-experience in cross-sections would bias the OLS estimates. By stratifying our sample into work-experience cohorts we purge the model of any post-schooling investment decisions. Thus, there exists an "overtaking" year in which an individual's earnings are most reflective of his/her natural ability and schooling levels alone. We reasonably assume that this "overtaking" year varies across individuals, even within a given work-experience cohort. Thus, we stratify our sample into one-year work-experience intervals for 1985-1989 so we can best identify the group whose earnings are "free" of OJT effects.

V. Estimation and Results

As mentioned above, our statistical estimation concerns white males who earned at least $500, in nominal terms, for a given survey year and who were not currently enrolled in school or anytime after 1989. Table 1 provides the descriptive statistics for each variable used in the analysis. The mean, standard deviation, maximum value, minimum value, and the number of cases are given for the overall sample. On average, our respondents are about 18 years old and seem to have the equivalent of a high school education while their parent(s) appear to have completed through their junior year of high school. On average, the respondents come from households with three other members. The ability measures indicate average intelligence levels. From these tables we can observe an upward trend in schooling levels, years of experience[24],

[24] At first glance the maximum values for the years of work experience may look quite peculiar. However, due to the construction of this variable it is quite possible for people to work the equivalent of several years within a given calendar year. This is the case for multiple-job holders and over-time workers. The maximum hours reported for any calendar year between 1979 and 1989 is 4992 (which corresponds to 57 percent of total annual hours and 2.4 FTE years). The reporting of such large values is relatively infrequent and the corresponding work-experience cohorts are rarely, if at all, used in the following analysis. The work-experience frequency distributions in Table 2 support this

and wages over time.

Table 2 provides the frequency distributions for the work-experience cohorts in 1985-1989. As would be expected, the cohort encompassing the largest percentage of respondents increases each year. However, as we move further in time we see a greater dispersion of respondents into each of the cohorts. In 1985, 14.7 percent of the sample had the modal experience that was about two years and in 1989, 9.3 percent of the sample had the modal experience of seven years.

Sample Stratification

As was previously mentioned, we chose to stratify our sample into one-year full-time equivalent intervals of work-experience for 1985-1989. Table 3 lists the number of people in each respective cohort and the corresponding percentage they comprise of the entire sample. The information contained in Table(s) 3 (and 4) correspond to cohorts in which the sample size was reasonable, i.e., above 100. The procedure for constructing the FTE work-experience intervals worked as follows: For example, in constructing the one-year work-experience cohort, we included individuals who reported having between one (inclusive) and two (not inclusive) years of work-experience at any time between 1985 and 1989. Obviously, in using such a decision rule we encountered the possibility of individuals who reported say, 1.2 years of work experience in 1985 and 1.9 years of work experience in 1986. To ensure that an individual entered the sample only once, we manually identified those individuals

latter claim. When one considers alternative work-experience measures, such as hours worked per week, one encounters indivuals who reported all possible hours. It is rarely the case however, that people report working the maximum weekly hours for more than a few weeks at a time. Individuals reporting such may include firefighters or physicials who are "on-call" but not necessarily actively or physically working. We did consider eliminating anyone who indicated working more than 16 hours a day but opted not to do so because we did not want to impose any artifical limitations.

who were double-, or even triple-counted. For these individuals, we chose to use the most recent year in which their work experience fell within the desired range (again subject to the constraint that their earnings were \$500 or above and that they were not enrolled in school for that particular year or any year after 1989). Once this year was identified, we chose their corresponding education and income levels.

We performed similar procedures for all other relevant work-experience cohorts and estimated the log earnings function, (15), separately for each cohort. Table 4 lists the selection criterion (AIC, SC, PC, $\widehat{\sigma}_1$, and R^2) for each regression done utilizing AFQT as the ability proxy. We get much stronger results, in terms of the appropriate signs and significance levels, on our regressors when using the AFQT score, as opposed to the KWW score. Hence, we have omitted the results from the regressions utilizing the KWW score as an ability proxy and only use the AFQT score in the estimations that follow[25].

13 Year-Work Experience Cohort

As can be seen from Table 4 the minimum values on the AIC, SC, PC, and estimated residual standard error are achieved for the 13-year work-experience cohort. The R^2 criterion reaches a maximum for the 14-year cohort. We however chose to work with the former work-experience cohort because it provides for a bigger sample and the regression yields coefficients that are of the appropriate sign and are all significant at the 10 percent level (the schooling and interaction term are significant at the five percent level as well). The estimated coefficients on the 14-year cohort are of the appropriate sign, but the only significant term (at the 10 percent level) is the schooling-ability interaction term. Thus, we can conclude that the "overtaking" year occurs for individuals with 13 FTE years of work experience.

[25]For an earlier discussion of the use of AFQT in the log earnings function, and the unique role that it plays, see Griliches and Mason (1972).

As was previously noted the AIC, SC, and PC criterion are typically nested in discussions of regressor selection. We however employ such criterion to determine which cohort (of varying sample sizes) best fits our proposed log earnings functional form (where the number of regressors is fixed). Thus, the differing degrees of freedom across our regressions are due to variations in the sample size as opposed to the number of explanatory variables. Holding other things constant (i.e., σ_1^2), the AIC, SC, and PC criterion would favor larger samples. Thus, the use of such criterion would bias our results towards finding earlier work-experience cohorts as the "overtaking" year(s). Due to the fact however that we determine the "overtaking" cohort to correspond to individuals with 13 FTE years of work-experience, we feel satisfied in our unconventional use of these "goodness of fit" criterion.

Table 5 lists the descriptive statistics for the 13-year work-experience cohort. The average age of our respondents is about 28.7 years (at any point between 1985 and 1989). The average annual income, in real terms, is about \$19,000, and \$25,000, in nominal terms. The respondents have completed through their junior year of high school and have been out for about 11.4 years. The average experience level is 13.5 years, so we can conclude that many of these individuals are either working over-time or are dual-job holders. 1989 was the most recent year in which 49.1 percent of these individuals had between 13 and 14 FTE years of work-experience. Similarly, it was 1988, 1987, 1986, and 1985 for 27.8, 0.4, 15.2, and 7.4 percent of the sample, respectively. As reported by the NLSY79, the parents have completed through their sophomore year of high school. However, when we adjust our figures for missing values, as was previously described, the average parental level of schooling falls by about one year. The average family size is 3.7 persons.

Overall

From this point onward, we will base the rest of our estimation on the "overtaking" cohort, i.e., the 13-year work-experience cohort. Table 6, column 2, lists the OLS results of (15) for this cohort. The strong performance of this cohort is evident from the table. As theory predicts, the schooling and schooling-ability interacted variables are positive while the schooling squared term is negative. The results are all significant at the five percent level.

Table 6, column 1, lists the results from the simple schooling model (14). We can compare the coefficient on the schooling variable in this model to the estimated marginal rate of return to schooling evaluated at the sample mean which is 9.7 percent. As expected, the rate of return, as estimated from the simple schooling model, is greater than that which is calculated directly from (15). The simple schooling model predicts a rate of return of 15.3 percent.

The results from the schooling-investment demand function are presented in Table 6, column 3. The coefficients on the demand function are taken directly from (15)'s coefficients. As expected, ability is positive and schooling is negative.

VII. DISCUSSION OF ESTIMATION STRATEGIES

There are a few estimation strategies we consider in this paper.

Unrestricted/OLS

1. Reduced-Form Optimal Level of Schooling

The first few estimation strategies are based on the assumption that A_j is exogenous, i.e., uncorrelated with u_{1j} and u_{3j} (and hence u_{2j}), and that S_j is also uncorrelated with u_{1j}. Our first estimation strategy involves the direct estimation of the schooling-investment supply function (19) by OLS. Since our estimation procedure constrains the model to be in equilibrium, the marginal rates of return we calculated from (15) are directly imposed as the left-hand side variables for (19) (i.e., the discounting rates of interest). Table 6, column 4, lists these results. The negative sign associated with the permanent family income proxies–the parental education levels–imply that children from wealthier families (as indicated by higher educated parents) have lower discounting rates of interest. Referring back to the conceptual framework, the negative sign on these coefficients implies that the pure wealth effects of increased parental schooling levels outweigh the indirect effects that family wealth has on the propensity to receive financial aid. Furthermore, we see that the dummy variables on parental schooling levels are negative, but only significant for the father. Thus, by us imposing a zero for missing father education levels, an individual's marginal opportunity cost of an additional year of schooling is lowered. The coefficient estimate on family size is also negative but insignificant. Again, referring back to the empirical section of the paper, this implies that the pure wealth effects of family size completely offset the indirect wealth effects on financial aid.

Now, once we have the estimated coefficients from (15) and (19) we can use them to derive the parameters in (22). Thus,

$$\hat{\gamma}_0 = \frac{\hat{\alpha}_0 - \hat{\beta}_1}{2\hat{\beta}_3},\ \hat{\gamma}_1 = \frac{\hat{\alpha}_1}{2\hat{\beta}_3},\ \hat{\gamma}_2 = \frac{\hat{\alpha}_2}{2\hat{\beta}_3},\ \hat{\gamma}_3 = \frac{\hat{\alpha}_3}{2\hat{\beta}_3},\ \hat{\gamma}_4 = \frac{\hat{\alpha}_4}{2\hat{\beta}_3},\ \hat{\gamma}_5 = \frac{\hat{\alpha}_5}{2\hat{\beta}_3},\ \hat{\gamma}_6 = \frac{-\hat{\beta}_2}{2\hat{\beta}_3}, \tag{30}$$

and

$$\hat{\sigma}_3^2 = \frac{\hat{\sigma}_2^2}{4\hat{\beta}_3^2}.$$

Table 6, column 7, lists these results. The standard errors, hence the t-statistics, have been computed using the Delta Method[26]. The optimal level of schooling is higher for more able individuals from smaller, richer families. The optimal level of schooling based on these coefficients for this work-experience cohort is 11.4 years.

2. Derived Supply Equation

Our second estimation strategy involves the direct estimation of the log earnings equation (15) and the optimal level of schooling equation (22) (i.e., the two equations in which we observe the dependent variable) by OLS and then uses the results to get consistent estimates of the coefficients on the supply equation (19). Hence,

$$\hat{\alpha}_0 = 2\hat{\beta}_3\hat{\gamma}_0 + \hat{\beta}_1,\ \hat{\alpha}_1 = 2\hat{\beta}_3\hat{\gamma}_1,\ \hat{\alpha}_2 = 2\hat{\beta}_3\hat{\gamma}_2,\ \ \hat{\alpha}_3 = 2\hat{\beta}_3\hat{\gamma}_3,\ \hat{\alpha}_4 = 2\hat{\beta}_3\hat{\gamma}_4,\ \ \hat{\alpha}_5 = 2\hat{\beta}_3\hat{\gamma}_5, \tag{31}$$

and

$$\widehat{\sigma}_2^2 = 4\widehat{\beta}_3^2\widehat{\sigma}_3^2.$$

Table 6, column 6, lists the OLS results for (22). The signs and magnitudes on the coefficients are similar to those derived above based on the OLS estimates of α and β[27]. The magnitudes of the parental schooling levels, the parental schooling dummies, and the family size variables are a little smaller while the AFQT variable is a bit larger. All of the variables, except for the mother's schooling dummy and the family size, are significant at the five percent level.

Table 6, column 5, lists the derived results of (19). Again, we utilize the Delta Method to calculate the standard errors of the estimates. The signs on the coefficients are identical to those based on the OLS estimates, but the magnitude differs

[26] It is assumed that cov(β, α)=cov(β, γ)=0.

[27] Note that the OLS estimates and the derived estimates are similar but not identical. This is because our system is overidentified.

somewhat.

Restricted/NLSUR

3. NLSUR

Another estimation strategy involves the following recursive, constrained system of equations,

$$\begin{aligned} \ln Y_j &= \beta_0 + \beta_1 S_j + \beta_2 A_j S_j + \beta_3 S_j^2 + u_{1j} \\ S_j^* &= \gamma_0 + \gamma_1 S_{fj} + \gamma_2 S_{mj} + \gamma_3 DV_{fj} + \gamma_4 DV_{mj} + \gamma_5 N_j + \gamma_6 A_j + u_{3j} \end{aligned} \tag{32}$$

subject to

$$\gamma_6 = \frac{-\beta_2}{2\beta_3}.$$

We used a nonlinear seemingly unrelated regression (NLSUR) strategy[28] to estimate this restricted recursive system. The equations were stacked with the OLS estimates providing the starting values for the iterative estimation strategy. We imposed two alternative variance-covariance matrices, Σ, that allowed us to test the following hypothesis,

$$H_0 : \Sigma \text{ is diagonal; } H_1 : \Sigma \text{ is not diagonal.}$$

Thus, under the null hypothesis there is no correlation between the two errors, u_{1j} and u_{3j}, and hence each equation could just be estimated separately by non-linear

[28]This estimation strategy requires the sample sizes to be equal across the regressions. This helps justify our imposition of zero values for missing parental education levels and the subsequent indicator variable construction.

OLS (NLOLS). We obtained the estimated residual variances and covariances from the separate OLS estimates of (15) and (22).

We were able to test the null hypothesis using the following Breush Pagan test which is just a lagrange multiplier (LM) test,

$$LM = N \sum_{m<j} \sum_{j=1}^{M} r_{mj}^2 \rightarrow \chi^2_{\frac{M(M-1)}{2}}, \tag{33}$$

where M represent the number of equations in the system and r^2 is the simple squared correlation between the residuals, u_1 and u_3. The LM test is based on the restricted model where Σ has non-zero off-diagonal entries. For our two-equation system, the test statistic reduces to,

$$LM = 215 \left[\frac{\widehat{\sigma}_{13}}{\sqrt{\widehat{\sigma}_1^2}\sqrt{\widehat{\sigma}_3^2}} \right]^2 \rightarrow \chi^2_{\frac{2(2-1)}{2}}. \tag{34}$$

Our test-statistic is equal to .227 which is less than the critical $\chi_1^{2,.95}$ value of 3.84. Hence, we can accept the null hypothesis at the 95 percent confidence level and conclude that these is no covariance between the error terms and each equation could have been estimated separately by non-linear OLS (NLOLS) producing consistent but biased results with no loss in efficiency.

Next, we turn to testing the restriction. The hypothesis we test is,

$$H_0 : \gamma_6 = \frac{-\beta_2}{2\beta_3};\ H_1 : \gamma_6 \neq \frac{-\beta_2}{2\beta_3}. \tag{35}$$

We were able to test the null hypothesis using a likelihood-ratio test. We maintained the imposition of a diagonal variance/covariance matrix throughout. We calculated a test statistic of .357 which is again less than the critical $\chi_1^{2,.95}$ value of 3.84. Hence, we can accept the null hypothesis at the five percent level and conclude that this system of equations is in fact constrained.

Table 6, columns 8-11, provide the restricted NLSUR results for (15), (17), (19), and (22). All of the estimates from (15), with the exception of the schooling and ability interaction term, increase in significance. This rise in significance is due to the fact that the estimation of this set of equations by NLSUR imposes cross-equation restrictions that tighten up our standard errors and make our estimates more precise. Overall, the coefficient estimates increase in magnitude. The imposed estimates on (17) maintain appropriate signs and reflect the increased significance levels. The coefficient estimates from (19) maintain the same signs as those from the unrestricted OLS but vary somewhat in magnitude. The t-statistics are a bit peculiar here as we lose some significance on all the coefficients. Perhaps the somewhat odd results obtained here stem from the fact that (19) is not directly part of the constrained system of equations[29]. Lastly, the estimates from (22) are nearly identical to those obtained from unrestricted OLS.

A Last Thought

4. Endogenous Ability?

[29] We also considered estimating a three-equation system (i.e., equations (15), (19), and (22)) by NLSUR. This strategy was inoperable due to the fact that the variance/covariance matrix is not positive definite.

[30]Measures of ability pose continuing problems for researchers, labor economists in particular. The importance of incorporating such a measure is well documented in the literature, however choosing an appropriate measure to proxy such abilities poses a persistent challenge. "First, even our cognitive abilities as adults are heavily influenced by the social environment that we experienced during childhood, making it hard to discern any influence of preexisting genetic differences. Second, tests of cognitive ability (like IQ tests) tend to measure cultural learning and not pure innate intelligence, whatever that is." (Diamond, 1999, pp. 20) Some researchers have devised clever ways of overcoming such problems[31] but most are left using various potentially err-ridden proxies in their analysis.

We are fortunate that the NLSY does provide some measures of ability–the question however remains as to what type of ability is actually being measured. It is reasonable to question just how well the KWW[32] and AFQT scores used in this paper proxy for "true, innate" ability. Both of these tests were administered in the teenage or early adult years of our respondents' lives and are also quite particular as to what they are

[30]Kelejian's 1971 article outlines an estimation procedure for structural equations that are linear in parameters but whose regressors are nonlinear functions of endogenous and predetermined variables. At first glance some might think that the endogenous nature of the schooling variable, S_j, in (22) could warrant a closer look at its role in our original log wage equation (15). For us to employ Kelejian's nonlinear 2SLS (N2SLS) strategy we would need S_j to be correlated with u_{1j}. Due to the fact that u_1 and u_3 are uncorrelated (see arguments given in estimation strategy #3), we have a recursive, not simultaneous, system of equations and hence OLS is fine.

[31]See Ashenfelter and Krueger (1994) and Card (1994).

[32]Lazear (1977) attempts to purge the use of the KWW in his NLSY66 study by instrumenting for it with the following variables: schooling, schooling squared, parental education levels, a race dummy, and the median income for the father. In an earlier version of this paper, we similarly attempted to "purge" our ability measures of any outside influences. We did not pursue this avenue due to the poor results obtained using such a method.

testing. The AFQT score comes from the ASVAB test, which was administered in 1980, and used by the Armed Forces to assess a respondent's measure of trainability. Accounting for these and other facts (to be discussed below), we propose instrumentation for AFQT in the optimal level of schooling equation (22). We try the following set of instruments which help to identify the simultaneous system of equations: the inverse of a respondent's age in 1980 (the year in which the test was administered), the respondent's family size and a set of occupational dummies for the adult present in a respondent's home when he was 14 years old. Using the inverse of the respondent's age in 1980 allows ability to be concave with respect to his age. Thus, we are expecting ability to increase, but at a decreasing rate, as a person ages given their family background characteristics. The positive relationship between a child's ability and his/her family's resources (financial and time equivalents) is well-known across disciplines.

The occupational dummies were constructed based on the respondent's answers to the questions the NLSY posed in regard to with whom he lived when he was 14 years old. If there was an adult male present in the household, we took this individual's occupation. If there was no adult male present, but an adult female was present, we took her occupation. Individuals with other arrangements, those who lived by themselves, and those with no adults present were coded as missing values. We constructed a set of 12 occupational dummies based on the 1970 Census of the Population's Occupational Classification System. Regressing AFQT on these instruments yielded significant results for the most part (the exceptions are for a few of the occupational dummies). As expected, the inverse age and family size yielded negative effects and the occupational dummies were all positive.

When we instrumented for AFQT in (22) we got pretty poor results. All of the variables, with the exception of the constant term and AFQT, became insignificant. Due to the poor performance of the 2SLS estimation method, we decided to test the endogeneity of ability (i.e., the potential correlation that exists between $AFQT$ and u_3) in (22) by performing a Hausman test. We test the following hypothesis,

$$H_0 : p\lim\left(\hat{\gamma}^{OLS} - \hat{\gamma}^{2SLS}\right) = 0;\ H_1 :\ p\lim\left(\hat{\gamma}^{OLS} - \hat{\gamma}^{2SLS}\right) \neq 0. \tag{36}$$

Thus, under the null hypothesis OLS and 2SLS produce consistent estimates of γ but OLS is asymptotically efficient. Thus, we have no simultaneity because ability is exogenous. Under the alternative hypothesis, OLS is not consistent but 2SLS is. Here, ability is in fact endogenous to this system of equations. The Hausman test consists of the following regression and tests for the significance of γ_7,

$$S_j^* = \gamma_0 + \gamma_1 S_{fj} + \gamma_2 S_{mj} + \gamma_3 DVS_{fj} + \gamma_4 DVS_{mj} + \gamma_5 N_j + \gamma_6 A_j + \gamma_7 \hat{A}_j^{IV} + u_{3j}^*. \tag{37}$$

Based on the results for this regression, we can reject the null hypothesis because $\hat{\gamma}_7$ is insignificant at the five (and 10) percent level. Thus, we conclude that our ability proxy, AFQT, is in fact uncorrelated with u_3 and hence exogenous to the system.

Given that estimation strategy #3 concluded that we did in fact have a constrained system of equations (with no covariance existing between u_1 and u_3) we attempted to conduct a similar test using the NLSUR estimation. We believe that a test parallel to the above Hausman test in aforementioned context would lead to testing the significance of γ_7 in the following constrained system,

$$\begin{aligned} \ln Y_j &= \beta_0 + \beta_1 S_j + \beta_2 A_j S_j + \beta_3 S_j^2 + u_{1j} \\ S_j^* &= \gamma_0 + \gamma_1 S_{fj} + \gamma_2 S_{mj} + \gamma_3 DVS_{fj} + \gamma_4 DVS_{mj} + \gamma_5 N_j + \gamma_6 A_j + \gamma_7 \hat{A}_j^{IV} + u_{3j}^* \end{aligned} \tag{38}$$

subject to

$$\gamma_6 = \frac{-\beta_2}{2\beta_3}.$$

Like before, the estimated coefficient on $\hat{A}_j^{IV}$ is insignificant at the five (and 10) percent level. Thus, we conclude that ability remains exogenous even in the context of the constrained system of equations.

Overall

In this paper we stratify our sample into one-year FTE work-experience intervals for 1985-1989 and estimate our log earnings equation separately for each cohort. We identify the "overtaking" cohort to be for those individuals who had 13 FTE years of work-experience anytime between 1985 and 1989. Mincer (1974) found that the best time to measure the effects of education on earnings is about 8 years after an individual leaves/completes school. At that point the distortion from post-schooling investment is minimized and the return on prior investments (i.e., schooling) equals the costs of current investment (i.e., OJT). Furthermore, Mincer argues that schooling best explains the earnings of individuals with 7 to 9 years of work-experience. While our results seem to over-shoot his findings, we would argue that it is most probably due to the way in which work-experience is measured and the five-year interval we chose to look at (which probably biases us towards finding a later work-experience cohort). Mincer was forced to use a crude approximation to measure experience where he said it was the difference between a person's age and the years of schooling he had completed. As we define it, a "year" of work experience may or may not (which is more likely) correspond to an actual calendar year. This is due to the full-time equivalent status that we impose in our construction of the work-experience intervals and because we know that there are many individuals who moon-light, work over time, or who only work part-time.

Moreover, the estimated rates of return to schooling for our "overtaking" cohort seemed reasonable and consistent with past findings at 9.7 percent. The coefficient on schooling in the simple schooling model of (14) tended to overstate the returns due to the fact that this equation does not include any other controls. Mincer purports that we can get a rough estimate of an individual's rate of return to education just by inverting the "overtaking" year. Applying similar reasoning, we estimate a rate of return of 7.7 percent.

The estimation strategies discussed above lead us to believe that we have a constrained system of equations whose error term in the log earnings function is normally distributed[33] and not correlated with the error term in the optimal level of schooling equation. Moreover, it is reasonable to think that ability exogenously enters our system of equations and is uncorrelated with u_1 (obviously) and u_3. Thus, the results found in Table 6, columns 8-11, are most applicable. Overall, our models perform very well as the estimated coefficients are of the theoretically predicted sign and most gain significance at the 10 percent level (or even the five percent level in most cases). The only variables that perform insignificantly throughout are the dummy variable for mother's education and family size. The latter could be due to its poor definition as was previously discussed. Lastly, the average estimated optimal level of schooling based on the sample means and using the OLS and NLSUR estimates is 11.4 years. These figures do not differ too much from the actual average schooling levels as reported by the NLSY.

VIII. CONCLUSIONS

This paper develops a theoretical model of earnings where human capital is the central explanatory variable. The analysis and estimation strategy stems from the Mincerian (1974) simple schooling model. We incorporate human capital investment (i.e., schooling) into a model based on individual wealth maximization while implicitly controlling for work experience. From this model we can derive and utilize the

[33] Departures from normality were tested using the Bera and Jarque (1981, 1982) test. See Appendix 2 for details.

conventional economic models of supply and demand.

Using data collected from the NLSY79 we stratify our sample into one-year FTE work-experience intervals for 1985-1989 and estimate a log earnings model that incorporates both schooling and ability for each cohort. Originally we considered two separate proxies of ability, namely the KWW and AFQT scores, but resign to using the latter. We even test for the endogeneity of this variable, but conclude that it is in fact exogenous. Based on this and the "goodness of fit" measures (and somewhat on the model's performance) we are able to identify the "overtaking" year of FTE work-experience from the estimation of (15). At this year, an individual's earnings most closely correspond to their natural abilities and schooling investments, which are purged of any OJT effects. The 13-year FTE work-experience cohort satisfies such criterion. We calculate the average estimated marginal rate of return to schooling to be 9.7 percent and an optimal level of schooling of 11.4 years. In the end we estimated a constrained system of equations with uncorrelated error-terms and are satisfied with the overall performance of each equation.

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Appendix 1

Proof of $FF_{SA} > F_A F_S$.

$r = \frac{\partial lnF(S,A)}{\partial S} = \frac{Fs}{F}$

$\frac{\partial r}{\partial A} = \frac{FF_{SA} - F_S F_A}{F^2} > 0$

$FF_{SA} > F_A F_S$.

Appendix 2

The Bera and Jarque (1981, 1982) test tests for departures from normality. The hypothesis we test is,

$$H_0 : u_1 \sim N(0, \sigma_1^2);\ H_1 : u_1 \nRightarrow\sim N(0, \sigma_1^2). \tag{39}$$

This test is based on the fact that a normally distributed error would be symmetric (i.e., its third moment or its skewness equals zero) and mesokurtic (i.e., its fourth moment or its kurtosis equals three). The standard measure of a distribution's symmetry is its skewness coefficient,

$$b_1 = \frac{E(u_1^3)}{(\sigma_1^2)^{3/2}}, \tag{40}$$

and the kurtosis is,

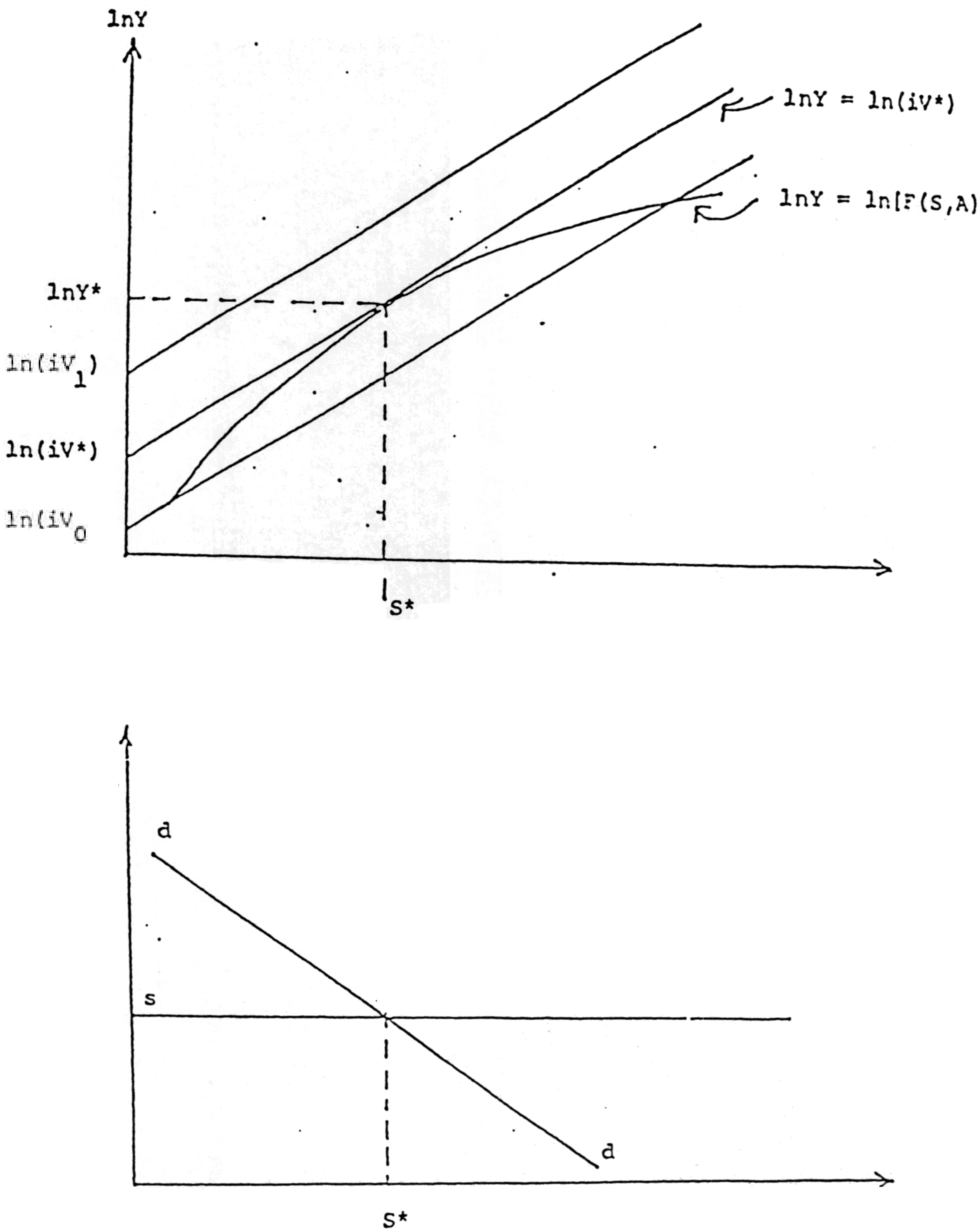
$$b_2 = \frac{E(u_1^4)}{(\sigma_1^2)^2}. \tag{41}$$

The test statistic is based on a Wald test,

$$W = N\left[\frac{\widehat{b}_1}{6} + \frac{(\widehat{b}_2 - 3)^2}{24}\right] \to \chi_2^2. \tag{42}$$

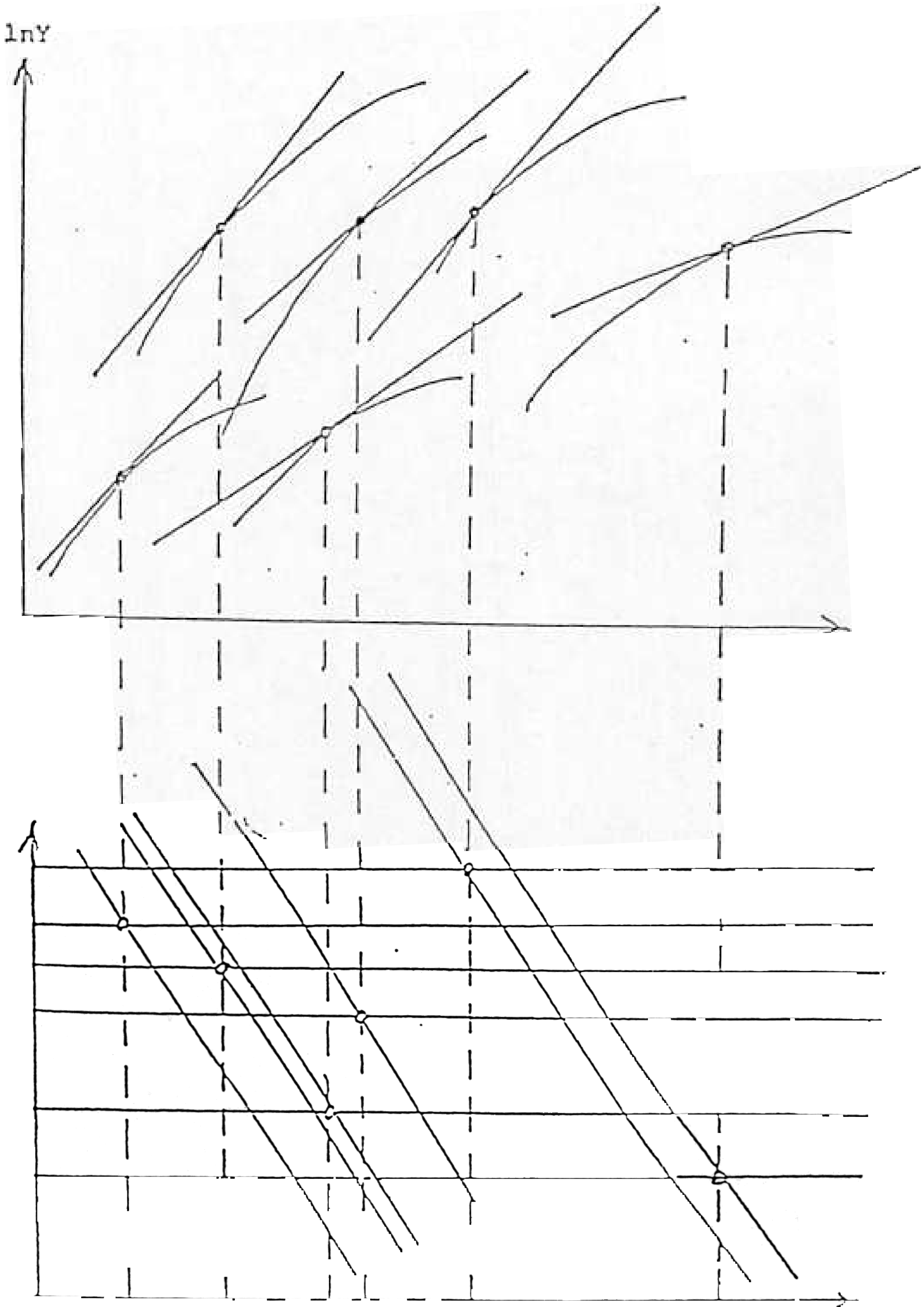
Performing this test on the residuals that result from (15), we get a test statistic of .176 which is less than the critical $\chi_1^{2,.95}$ value of 3.84. We can accept the null hypothesis at the five percent level and conclude that our errors are normally distributed[34].

[34]Greene (2000) warns that a failure to reject normality does not necessarily confirm it. He states that the Bera and Jarque test merely tests the symmetry and kurtosis of the underlying error distribution.



igL

Source data. Burghardt and Oaxaca 1979)



Source of data Burghardt and O (1979)

TABLE 1
DESCRIPTIVE STATISTICS FOR OVERALL SAMPLE

OVERALL SAMPLE

	Mean	Std.Dev.	Minimum	Maximum	NumCases
AGE 1979	17.948	2.336	14	22	4393
AGE 1980	18.906	2.320	15	23	4393
NOMINAL WAGE 1985	12717.900	10721.200	0	100001	3499
NOMINAL WAGE 1986	15394.900	12535.400	0	100001	3370
NOMINAL WAGE 1987	17553.200	13584.000	0	100001	3425
NOMINAL WAGE 1988	20892.900	32787.400	0	566028	3405
NOMINAL WAGE 1989	21992.500	18249.700	0	173852	3368
SCHOOLING 1985	12.525	2.354	3	20	3622
SCHOOLING 1986	12.636	2.455	3	20	3516
SCHOOLING 1987	12.747	2.510	3	20	3449
SCHOOLING 1988	12.812	2.594	3	20	3468
SCHOOLING 1989	12.848	2.621	3	20	3490
KWW	6.208	2.125	0	9	4393
AFQT	48.856	29.385	1	99	4087
EXPERIENCE 1985	4.073	3.071	0	23.9832	4393
EXPERIENCE 1986	4.748	3.350	0	25.3942	4393
EXPERIENCE 1987	5.443	3.638	0	25.3942	4393
EXPERIENCE 1988	6.162	3.941	0	27.5909	4393
EXPERIENCE 1989	6.908	4.256	0	29.9909	4393
MOTHER'S SCHOOLING*	11.186	3.152	0	20	4139
FATHER'S SCHOOLING*	11.396	3.944	0	20	3978
FAMILY SIZE 1979	3.992	2.162	1	15	4393

*=as reported by the respondent in the NLSY survey

Source of data: NLSY79

TABLE 2
WORK-EXPERIENCE COHORTS FREQUENCY DISTRIBUTION

	1985		1986		1987		1988		1989			
Years of Work Experience	*Frequency*	*%*	*Frequency*	*%*	*Frequency*	*%*	*Frequency*	*%*	*Frequency*	*%*	*Frequency Total*	*% Total*
0	123	2.80%	112	2.55%	108	2.46%	104	2.37%	98	2.23%	545	12.41%
1	522	11.88%	397	9.04%	324	7.38%	274	6.24%	250	5.69%	1767	40.22%
2	645	14.68%	473	10.77%	374	8.51%	303	6.90%	253	5.76%	2048	46.62%
3	604	13.75%	571	13.00%	454	10.33%	360	8.19%	289	6.58%	2278	51.86%
4	595	13.54%	534	12.16%	486	11.06%	421	9.58%	337	7.67%	2373	54.02%
5	507	11.54%	488	11.11%	456	10.38%	399	9.08%	333	7.58%	2183	49.69%
6	401	9.13%	465	10.59%	436	9.92%	419	9.54%	370	8.42%	2091	47.60%
7	291	6.62%	367	8.35%	427	9.72%	411	9.36%	408	9.29%	1904	43.34%
8	211	4.80%	279	6.35%	345	7.85%	370	8.42%	355	8.08%	1560	35.51%
9	155	3.53%	200	4.55%	272	6.19%	349	7.94%	360	8.19%	1336	30.41%
10	129	2.94%	167	3.80%	206	4.69%	262	5.96%	348	7.92%	1112	25.31%
11	71	1.62%	128	2.91%	157	3.57%	207	4.71%	252	5.74%	815	18.55%
12	49	1.12%	69	1.57%	127	2.89%	157	3.57%	210	4.78%	612	13.93%
13	41	.93%	48	1.09%	78	1.78%	130	2.96%	155	3.53%	452	10.29%
14	24	.55%	47	1.07%	46	1.05%	82	1.87%	130	2.96%	329	7.49%
15	6	.14%	19	.43%	41	.93%	45	1.02%	90	2.05%	201	4.58%
16	7	.16%	9	.20%	25	.57%	36	.82%	55	1.25%	132	3.00%
17	2	.05%	8	.18%	8	.18%	24	.55%	30	.68%	72	1.64%
18	4	.09%	2	.05%	10	.23%	17	.39%	29	.66%	62	1.41%
19	2	.05%	4	.09%	2	.05%	6	.14%	16	.36%	30	0.68%
20	1	.02%	1	.02%	6	.14%	4	.09%	6	.14%	18	0.41%
21	1	.02%	2	.05%	0	.00%	5	.11%	6	.14%	14	0.32%
22	1	.02%	0	.00%	2	.05%	3	.07%	4	.09%	10	0.23%
23	0	.00%	1	.02%	0	.00%	0	.00%	4	.09%	5	0.11%
24	1	.02%	1	.02%	0	.00%	2	.05%	0	.00%	4	0.09%
25	0	.00%	0	.00%	1	.02%	0	.00%	2	.05%	3	0.07%
26	0	.00%	1	.02%	2	.05%	1	.02%	0	.00%	4	0.09%
27	0	.00%	0	.00%	0	.00%	0	.00%	0	.00%	0	0.00%
28	0	.00%	0	.00%	0	.00%	2	.05%	1	.02%	3	0.07%
29	0	.00%	0	.00%	0	.00%	0	.00%	0	.00%	0	0.00%
30	0	.00%	0	.00%	0	.00%	0	.00%	2	.05%	2	0.05%

Source of data: NLSY79

TABLE 3
WORK-EXPERIENCE COHORT FREQUENCY DISTRIBUTION*

Years of Work Experience 1985-1989	*Frequency*	*% of Entire Sample*
0	221	5.03%
1	507	11.54%
2	763	17.37%
3	1039	23.65%
4	1208	27.50%
5	1272	28.96%
6	1243	28.30%
7	1107	25.20%
8	971	22.10%
9	833	18.96%
10	614	13.98%
11	446	10.15%
12	359	8.17%
13	230	5.24%
14	162	3.69%

note: sample is based on those individuals who additionally have wages >$500 and are not currently enrolled in school or anytime after 1989

Source of data: NLSY79

TABLE 4
EQ 15 LOG-EARNINGS FUNCTION
SAMPLE SIZE, AIC, SC, PC, ESTIMATED STANDARD ERRORS, AND R^2.
WORK-EXPERIENCE COHORTS

ABILITY MEASURE:	AFQT					
Work Experience Cohort	# observ.	AIC	SC	PC	std.error	R^2
0	206	0.267	0.332	1.307	1.132	0.046
1	483	-0.476	-0.442	0.621	0.785	0.174
2	728	-0.670	-0.644	0.512	0.713	0.193
3	997	-0.899	-0.879	0.407	0.637	0.228
4	1157	-0.963	-0.946	0.382	0.617	0.199
5	1221	-1.048	-1.032	0.351	0.591	0.183
6	1186	-1.051	-1.033	0.350	0.590	0.161
7	1060	-1.211	-1.192	0.298	0.545	0.175
8	916	-1.240	-1.219	0.290	0.537	0.200
9	786	-1.123	-1.099	0.325	0.569	0.184
10	584	-1.201	-1.171	0.301	0.547	0.212
11	422	-1.107	-1.069	0.330	0.572	0.136
12	342	-0.474	-0.430	0.622	0.784	0.083
13	215	**-1.461**	**-1.398**	**0.232**	**0.477**	0.299
14	149	-1.317	-1.236	0.268	0.511	**0.353**

AIC=Akaike Information Criterion
SC=Schwarz Criterion
PC=Amemiya's Prediction Criterion

BOLDED FIGURES CORRESPOND TO THE MINIMUM AIC, SC, PC, AND STD. ERROR.
BOLDED FIGURES CORRESPOND TO THE LARGEST R^2 AND ADJ. R^2.

note: samples are based on those individuals who additionally have wages >$500 and are not currently enrolled in school or anytime after 1989

Source of data: NLSY79

TABLE 5
DESCRIPTIVE STATISTICS 13 YEAR WORK-EXPERIENCE COHORT

<u>13 YRS</u>

	Mean	Std.Dev.	Minimum	Maximum	NumCases	%
AGE	28.652	1.783	23	32	230	100.000%
AGE IN 1980	20.691	1.425	16	23	230	100.000%
NOMINAL WAGE	25355.100	17159.600	1000	173852	230	100.000%
LOG REAL WAGE	9.869	0.603	6.908	11.924	230	100.000%
SCHOOLING	11.258	2.138	3	16	229	99.565%
AFQT	44.852	27.738	1	99	216	93.913%
EXPERIENCE	13.471	0.296	13	13.9981	230	100.000%
YEARS OUT OF SCHOOL	11.384	2.271	5	20	229	99.565%
MOTHER'S SCHOOLING*	10.529	2.950	2	18	208	90.435%
FATHER'S SCHOOLING*	10.108	3.834	0	20	204	88.696%
MOTHER'S SCHOOLING**	9.522	4.183	0	18	230	100.000%
FATHER'S SCHOOLING**	8.965	4.829	0	20	230	100.000%
MOTHER'S SCHOOLING DUMMY	0.096	0.295	0	1	230	100.000%
FATHER'S SCHOOLING DUMMY	0.113	0.317	0	1	230	100.000%
FAMILY SIZE 1979	3.696	1.856	1	10	230	100.000%
ESTIMATED r=I	0.095	0.033	0.007	0.216	215	93.478%
ESTIMATED OPTIMAL SCHOOLING	11.377	1.362	7.985	14.116	216	93.913%
1989 IS MOST RECENT YEAR	---	---	---	---	113	49.130%
1988 IS MOST RECENT YEAR	---	---	---	---	64	27.826%
1987 IS MOST RECENT YEAR	---	---	---	---	1	0.435%
1986 IS MOST RECENT YEAR	---	---	---	---	35	15.217%
1985 IS MOST RECENT YEAR	---	---	---	---	17	7.391%
RECENT YEAR	1987.961	1.333	85	89	230	100.000%
SINGLE COUNTS	---	---	---	---	225	97.826%
DOUBLE COUNTS	---	---	---	---	5	2.174%

note: sample is based on those individuals who additionally have wages >$500 and are not currently enrolled in school or anytime after 1989
*=as reported by the respondent in the NLSY survey
**=if a value was missing for these variables we imposed a value of zero

Source of data: NLSY79

TABLE 6

MODEL/ESTIMATION STRAGEGY:	UNRESTRICTED/OLS							RESTRICTED/NLSUR			
COHORT:	13 YRS	13 YRS	13 YRS	13 YRS	13 YRS	13 YRS	13 YRS	13 YRS	13 YRS	13 YRS	13 YRS
EQ:	14	15	17	19	19	22	22	15	17	19	22
DEP. VARIAB.:	ln(earnings)	ln(earnings)	estimated r	estimated I	estimated I	years of school completed	years of school completed	ln(earnings)	estimated r	estimated I	years of school completed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
CONSTANT	8.153	7.619	0.290	0.151	0.153	7.317	7.353	7.898	0.236	0.134	7.324
	(45.311)**	(14.426)**	(2.965)**	(14.764)**	(4.023)**	(13.449)**	(2.406)**	(35.786)**	(6.049)**	(8.086)**	(14.652)**
SCHOOLING	0.153	0.290	-1.871E-02	---	---	---	---	0.236	-1.395E-02	---	---
	(9.722)**	(2.965)**	(-2.056)**					(6.049)**	(-2.927)**		
AFQT*SCHOOLING	---	4.008E-04	---	---	---	---	---	4.229E-04	---	---	---
		(3.241)**						(3.119)**			
AFQT	---	---	4.008E-04	---	---	3.089E-02	2.14E-02	---	4.229E-04	---	3.089E-02
			(3.241)**			(6.738)**	(2.659)**		(3.119)**		(6.004)**
SCHOOLING^2	---	-9.356E-03	---	---	---	---	---	-6.977E-03	---	---	---
		(-2.056)**						(-2.927)**			
FATHER'S SCHOOLING	---	---	---	-2.442E-03	-1.975E-03	0.106	0.115	---	---	-1.494E-03	0.107
				(-3.717)**	(-2.064)**	(2.862)**	(1.455)			(-1.995)*	(2.840)**
MOTHER'S SCHOOLING	---	---	---	-3.092E-03	-2.757E-03	0.147	0.159	---	---	-2.071E-03	0.148
				(-3.494)**	(-1.919)*	(3.088)**	(1.580)			(-2.161)**	(3.882)**
FATHER'S SCHOOLING DUMMY	---	---	---	-2.851E-02	-2.499E-02	1.335	1.385	---	---	-1.879E-02	1.347
				(-3.062)**	(-1.856)*	(2.659)**	(1.496)			(-2.010)**	(2.904)**
MOTHER'S SCHOOLING DUMMY	---	---	---	-1.089E-02	-9.796E-03	0.523	0.693	---	---	-7.354E-03	0.527
				(-.945)	(-0.878)	(.855)	(0.772)			(-.872)	(.944)
FAMILY SIZE	---	---	---	-3.895E-05	-5.542E-04	2.962E-02	9.533E-03	---	---	-3.897E-04	2.793E-02
				(-0.0354)	(-0.0338)	(0.495)	(0.504)			(-.481)	(0.472)
R^2	0.294	0.299	---	0.235	---	0.446	---	0.297	---	---	0.446
adj R^2	0.291	0.289	---	0.216	0.281	0.430	---	---	---	---	---
resid. S.E.	0.507	0.477	---	2.912E-02	2.506E-02	1.544	1.562	---	---	---	---
# observ.	229	215	215	215	215	215	215	215	215	215	215
# of iterations	---	---	---	---	---	---	---	17 & 19	17 & 19	17 & 19	17 & 19
Estimated at sample mean r=i	---	---	0.097	0.097	---	---	---	---	---	0.095	---
Estimated at sample mean optimal years of schooling	---	---	---	---	---	11.377	11.377	---	---	---	11.400

t-values are in parentheses
** = significant at the 5% level for a 2 tailed t-test
* = significant at the 10% level for a 2 tailed t-test

note:
sample is based on those individuals who additionally have wages >$500 and are not currently enrolled in school or anytime after 1989
(5)= derived form
(7)=derived reduced form

Source of data: NLSY79

Technical Appendix

1. The interviewer established the respondent's sex and race. An interviewer only asked a respondent for his/her sex if it was not obvious by mere observation. Furthermore, the "white" classification was established via the interviewer remarks. The three choices available for race are white, black, and other. When the main data files were merged with files from the work history supplements, it was done according to the sex/race classifications as designated in the main files by the interviewer.

2. The family size is inclusive of the respondent and reflects his 1979 answers. Ideally we would have liked to use the respondent's family size when he was 14 years old (this is how the Duncan Indices are established). However, due to the fact that a large percentage of our respondents were between 18 and 22 years in the first year of the survey, it is reasonable to expect that many of them lived on their own and no longer took account of their family members when answering this question. We tried to construct a better measure by using information on a respondent's number of siblings in 1979 and with whom he resided (i.e., parental units) when he was 14 years old. The data provided by the NLSY for the number of siblings seems pretty unreasonable as it ranges from zero to 16. Most of the respondents report between zero and five siblings, but there is a large number who report between six and eleven siblings. Thus, when we calculate a respondent's family size based on these measures we get an average of 5.8 people, which is highly unlikely. We are left using the 1979 figures as reported by NLSY and concede that an average family size of 4.0 seems a bit high as well.

3. There are several other IQ scores available, but the Otis-Lennon Mental Ability Test was chosen because it had the most respondents.

4. The Knowledge of the World of Work (KWW) test was administered in 1979 and asks the respondents to pick which of three statements best describes a particular

job's duties. An overall score is calculated by assigning a value of "1" to a correct response and summing these for the nine questions.

5. The Department of Defense conducted the Armed Forces Qualifications Test (AFQT) in 1980 to get a measure of trainability. The AFQT score is a composite scored derived from select sections of the Armed Services Vocational Aptitude Battery (ASVAB) test. The AFQT80 was calculated by summing the raw scores from the arithmetic reasoning, word knowledge, paragraph comprehension, and one half the numerical operations scores. The NLSY79 User's Guide notes that the norms for the AFQT are based on people who are at least 17 years old. Hence, those individuals born in 1963 or 1964 were not used in this construction. They warn that while scores have been constructed for these younger respondents, they have not been adjusted to reflect their ages. But, the relative rankings of ability are maintained for all respondents, regardless of their birth year.

6. The enrollment status as of May 1 for a given survey year was used because it had the most observations available.

7. The NLSY79 reports these income variables for the past year. Hence, when conducting the wage regressions for 1985 we use the total income from wages and salary in the past year as reported in 1986.

8. The construction of the prior work experience inherently assumes that people's work experience in 1978 was similar to that measured in 1979.

9. There were two people in our sample who were 16 years old in 1979 and reported 12 years of schooling completed. There were five others who were 17 years old in 1979 and again reported having finished 12 years of school. All seven people reported positive hours worked in 1979. Since our method of calculating prior work experience would yield negative numbers for these individuals, we imposed a zero value instead. This may underestimate these individuals prior work experience but since this was so rare, we did not believe any serious bias would result.

10. For all the variables, except the hours worked, we left non-responses as missing values. Observations with missing values were omitted from the analysis. However, when considering the hours worked for a given year, we imputed a zero value for anyone who did not respond to the question for whatever reason. The justification for this is two-fold. First, we did not want a cumulative effect of missing observations. So for example, if a respondent did not know how many hours he worked in 1980 but did work 1,000 hours in 1981, we still wanted to consider him in our 1981 regressions. Imposing a missing value for his 1980 hours worked would have eliminated him from any future year analyses. Second, it seemed reasonable to assign a value of zero rather than a missing value because the potential existed for the inapplicability of this question for the respondent. This could be due to a person being unemployed but actively searching for employment, entirely out of the labor force, in school, etc. Thus any potential bias from this would be in the downward direction.

11. It was suggested that we randomly select samples of 157 observations from each work-experience cohort and re-run (15) to get more comparable measures of the "goodness of fit" criterion. Initially this sounded like a reasonable idea. Since the 14-year work-experience cohort corresponded to the smallest sample size (i.e., 157 observations), we would just randomly resample from each of the previous cohorts and see if the "overtaking" cohort did in fact change. However, upon greater reflection we realized that the actual implementation of such an idea would involve an almost prohibitively large number of regressions to run. Consider for example, how many unique samples of 157 individuals would come from say the five-year work-experience cohort of 1356 respondents! Moreover, it would be erroneous to use just *one* sample of 157 respondents from each work-experience cohort to see if the "overtaking" cohort changed based on the new selection criterion.

12. The occupational dummies used as instruments for $AFQT$ include the following: 1) professional, technical, and kindred workers; 2) managers and administrators,

except farm; 3) sales workers; 4) clerical and unskilled workers; 5) craftsmen and kindred workers; 6) operatives, except transport; 7) transport equipment operatives; 8) laborers, except farm; 9) farmers and farm managers; 10) farm laborers and farm foremen; 11) service workers, excluding private household; and 12) private household workers.