The Career Decisions of Young Men

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This paper provides structural estimates of a dynamic model of schooling, work, and occupational choice decisions based on 11 years of observations on a sample of young men from the 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (NLSY). The structural estimation framework that we adopt fully imposes the restrictions of the theory and permits an investigation of whether such a theoretically restricted model can succeed in quantitatively fitting the observed data patterns. We find that a suitably extended human capital investment model can in fact do an excellent job of fitting observed data on school attendance, work, occupational choices, and wages in the NLSY data on young men and also produces reasonable forecasts of future work decisions and wage patterns.

This paper provides structural estimates of a dynamic model of schooling, work, and occupational choice decisions based on 11 years of observations on a sample of young men from the 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (NLSY). Our starting point is basic human capital investment theory, which we take seriously as a potential vehicle for explaining observed patterns of school attendance, work, occupational choice,

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and wages. The structural estimation framework that we adopt fully imposes the restrictions of the theory and permits an investigation of whether such a theoretically restricted model can succeed in quantitatively fitting the observed data patterns. We find that a suitably extended human capital investment model can in fact do an excellent job of fitting observed data on school attendance, work, occupational choices, and wages in the NLSY data on young men and also produces reasonable forecasts of future work decisions and wage patterns.

The structural approach provides rigorous interpretations for the parameters that are estimated, which has several important consequences. First, we estimate parameters that may be of interest in their own right, such as those of technology. In the current context, our framework isolates the quantitative importance of school attainment and occupation-specific work experience in the production of occupation-specific skills. Second, because we explicitly solve an optimization problem and thus determine decision rules, we can quantify the effect on decisions of altering specific parameters of the environment. In the present case, for example, we can alter the monetary incentives to attend college and thus assess how interventions such as college tuition subsidies would affect college attendance rates. Moreover, because schooling, work, and occupational choice are interrelated, we can estimate the impact of an intervention, such as a college tuition subsidy, on subsequent occupational choice decisions. Previous research has generally treated school and work decisions in isolation and therefore has been limited in its ability to address such questions. Finally, structural estimation permits welfare analysis, allowing us to calculate the distributional consequences of interventions on lifetime wealth and utility.

In order to understand the contribution of the present work, it is useful to set it within the context of the existing human capital investment literature. The general theory of human capital accumulation was developed primarily to interpret life cycle earnings profiles. From its inception (Mincer 1958; Becker 1964; Ben-Porath 1967), the theory has been related to observable measures of human capital investments, most notably school attainment. Consistent with the investment framework, the early empirical literature concentrated on estimating rates of return to schooling. On the basis of a straightforward comparison of age-earnings profiles among school completion groups, this early "rate of return" literature treated schooling as though it were exogenously assigned to individuals in the population.

These calculations ignored the implications for rate of return estimates of the fact that school attendance (human capital accumulation) is a choice. If individuals were identically endowed and faced the same loan market constraints, they would behave identically with respect to their choice of schooling (Rosen 1977). But if individuals differed in these characteristics, then rate of return calculations would be confounded by these population differences. The implication that self-selection on the basis of endowments or financing constraints or both is necessary to derive, and also to understand, the schooling-earnings relationship led to a more systematic treatment of the schooling decision process in the estimation of the schooling return (Willis and Rosen 1979).[1]

The treatment of work experience, that is, on-the-job training or learning by doing, as a behaviorally determined investment decision has received less attention empirically, although the same self-selection issues arise. Population differences in endowments or financing constraints will affect the interpretation of any cross-sectional relationship between earnings and work experience. While there is a considerable theoretical literature on the joint determination of human capital accumulation and labor supply (Blinder and Weiss 1976; Heckman 1976; Weiss and Gronau 1981), there are few empirical examples in which work experience is accumulated endogenously.[2]

For simplicity, much of the literature has assumed human capital to be homogeneous. This allows one to focus specifically on the work versus not work decision. However, there has been a parallel and complementary literature in which the multidimensional nature of skills is prominent.[3] In Willis (1986), skills are occupation-specific and are perfect substitutes over workers within occupations. Worker's self-select into occupations on the basis of the quantities of occupation-specific skills they have (their endowments) and skill rental prices, which together determine potential earnings in each occupation. As in the case of schooling and general work experience, comparing earnings of observationally equivalent individuals in different occupations will not provide an accurate assessment of the differential productivity of human capital investments among occupations

[1] There is also a large literature on schooling decisions that are less explicitly motivated by self-selection (e.g., Manski and Wise 1983).

[2] Eckstein and Wolpin (1989*a*), Shaw (1989), Altug and Miller (1992), and Wolpin (1992) are some exceptions.

[3] One line of research has taken a hedonic approach, where specific kinds of skills can be unbundled from workers and each type of skill has a market rental price (Tinbergen 1951; Welch 1969; Rosen 1974). Aggregates of each type of skill are inputs into output production functions. An alternative approach is that of Roy (1951) in which each individual's skill bundle maps into "task" units for which there is a market-determined price. Tasks may be sector-specific as in Heckman and Sedlacek (1985) or they may be occupation-specific as in Willis (1986). Aggregate task units enter as inputs into the output production function. We adopt this second approach, which is described in more detail below.

because of the self-selection mechanism that drives occupational choice.

This paper extends earlier work by considering self-selection in the three dimensions of schooling, work, and occupational choice. We combine features of the Heckman and Sedlacek (1985) and Willis (1986) models, each of which is an extension of the basic Roy (1951) framework. We extend the static deterministic setting of those models to one in which decision making is sequential and the environment is uncertain. Thus, for example, current school attendance decisions depend on the probabilities attached to future occupational choices.

The estimation of the model involves the repeated numerical solution of a discrete-choice, finite-horizon optimization problem, formulated as a dynamic programming problem.[4] Although the computational problem is substantial, it is made feasible by an approximate solution method for dynamic programming problems recently developed in Keane and Wolpin (1994). To implement the model, we follow approximately 1,400 white males from the NLSY from the ages of 16 to 26, assigning them in each year to one of five discrete, mutually exclusive, and exhaustive alternatives: attending school, working in a white-collar occupation, working in a blue-collar occupation, working in the military, or engaging in home production. In each period, the individual chooses one of these alternatives, endogenously accumulating schooling and occupation-specific experience, which thus affects the future rewards of the five alternatives. Individuals differ in their skill endowments among the occupations and in their schooling and home productivities. The current rewards associated with the five alternatives have stochastic elements that are drawn prior to the current-period decision but are unknown prior to the current period. Individuals take divergent schooling and occupation career paths because of the cumulative effects of the shocks and because they have heterogeneous skill endowments.

The paper is organized as follows: In Section I we describe the structure of the basic human capital model and discuss the solution and estimation method we employ. Section II describes the NLSY data on which we estimate the model and highlights the overall patterns in the data. Section III presents the estimates of a basic model and evaluates its ability to fit the data. Because the basic model fails to capture quantitatively some important features of the data, Section IV presents an extended version of the model, which is shown in Section V to conform substantially better to the data. Section VI

[4] See Eckstein and Wolpin (1989*b*) and Rust (1992) for recent surveys of solution and estimation methods for these models.

discusses the implications of our model in two important areas: (1) the importance of unobserved skill heterogeneity (endowments) in determining life cycle outcomes and (2) the impact of college tuition subsidies on life cycle outcomes. Section VII presents conclusions.

I. A Basic Human Capital Model

We begin with a basic human capital formulation. Each individual has a finite decision horizon beginning at age 16 and ending at age A. At each age a, an individual chooses among five mutually exclusive and exhaustive alternatives: work in either a blue- or white-collar occupation, work in the military, attend school, or engage in home production.[5] Let $d_m(a) = 1$ if alternative m is chosen ($m = 1, \ldots, 5$) at age a and zero otherwise. The reward per period at any age a is given by

$$R(a) = \sum_{m=1}^{5} R_m(a) d_m(a), \tag{1}$$

where $R_m(a)$ is the reward per period associated with the mth alternative. These rewards contain all the benefits and costs associated with each alternative.

A. *Working Alternatives* ($d_m(a) = 1$; $m = 1, 2, 3$)

The current-period reward for working in occupation m ($R_m(a)$) is the wage, $w_m(a)$. An individual's wage in an occupation is the product of the occupation-specific market (equilibrium) rental price (r_m) times the number of occupation-specific skill units possessed by the individual, $e_m(a)$.[6] The latter will depend on the technology of skill production. In a standard human capital formulation, the level of skill accumulated up to any age in an occupation depends on the number of years of schooling (successfully) completed, $g(a)$, and on work experience in that occupation, $x_m(a)$, which typically takes a quadratic form (Mincer 1958). Letting $e_m(a)$ be the number of skill units possessed at age a, $e_m(16)$ the skill "endowment" at age

[5] Primarily for computational reasons, we do not allow for joint activities, e.g., going to school and working.

[6] This formulation can be motivated by an aggregate technology in which within-occupation skill units are perfect substitutes. In that case the rental prices are equal to occupation-specific skill marginal products. See Roy (1951), Heckman and Sedlacek (1985), and Willis (1986) for further discussion.

16, and $\epsilon_m(a)$ a skill technology shock, we get

$$e_m(a) = \exp[e_m(16) + e_{m1}g(a) + e_{m2}x_m(a) - e_{m3}x_m^2(a) + \epsilon_m(a)],$$
$$m = 1, 2, 3;\ a = 16, \ldots, A. \quad (2)$$

This specification leads to a standard (ln) wage equation in which the constant term is $\ln(r_m) + e_m(16)$, the sum of the ln rental price and the age 16 skill endowment.[7]

B. Nonwork Alternatives: Attending School ($d_4(a) = 1$) or Remaining at Home ($d_5(a) = 1$)

In a pure human capital investment model, the current-period reward for school attendance would consist only of direct monetary costs such as tuition and books. The reward, $R_4(a)$, would be net earnings, and with perfect capital markets, the individual would maximize net wealth. We diverge from this setting in two ways. First, we allow for an indirect cost of schooling associated with effort. The current-period reward for school attendance ($R_4(a)$) is the effort cost at age a, which has a component that is a fixed endowment at age 16 ($e_4(16)$) and a component that fluctuates randomly with age ($\epsilon_4(a)$) minus direct schooling costs of attending college (tc_1) or of attending graduate school (tc_2). Although adding an effort cost implies that $R(a)$ is interpreted as utility, given the additive nature of rewards in (1), effort cost is denominated in wage units (dollars). Second, we allow for home production (leisure). The reward for remaining home ($R_5(a)$), which is also denominated in dollars, consists of the value of a fixed skill endowment at age 16 ($e_4(16)$) and a component that fluctuates randomly with age ($\epsilon_5(a)$).[8]

[7] Notice that the exponential form implies that the higher the endowment, the more skill units are ''produced'' per additional year of schooling or work experience.

[8] If home-produced goods were tradable and capital markets were perfect, investment and consumption decisions would be separable. Given that home-produced goods are generally not tradable, the formulation is consistent with a utility function that is linear additive in a composite consumption market good and the home-produced good (or leisure); i.e., they are perfect substitutes. Consumption when working is equal to dollar earnings ($w(a)$) and when at home to the (dollar-equivalent) level of home production ($e_5(16) + \epsilon_5(a)$). The level of consumption (measured in units of the composite consumption good, i.e., dollars) while attending school is not separately identified from the effort cost of schooling. The model is silent as to the source of the consumption flows while attending school (or at home if viewed as leisure). Thus nonmarket skill endowments may reflect differences in abilities to maintain consumption levels while in school or at home as well as differences in effort cost or home production skills, and in this sense may reflect differential financial market constraints. Notice too that, in this formulation, while market skills may be acquired after age 16, learning skills and home production skills are immutable at their age 16 endowment levels.

Thus the structure of rewards is given by

$$\begin{aligned} R_m(a) &= w_m(a) = r_m \exp[e_m(16) + e_{m1}g(a) + e_{m2}x_m(a) \\ &\qquad\qquad - e_{m3}x_m^2(a) + \epsilon_m(a)], \quad m = 1, 2, 3, \\ R_4(a) &= e_4(16) - tc_1 \cdot I[g(a) \geq 12] \\ &\qquad - tc_2 \cdot I[g(a) \geq 16] + \epsilon_4(a), \\ R_5(a) &= e_5(16) + \epsilon_5(a). \end{aligned} \tag{3}$$

In (3), $I(\cdot)$ is an indicator function denoting that the expression in the parentheses is true. To close the model, productivity shocks are assumed to be joint normal, $N(0, \Omega)$, and serially uncorrelated. Initial conditions are the given level of schooling completed at age 16, $g(16)$, and the accumulated work experience at age 16 in each occupation, assumed to be zero ($x_m(16) = 0$). It is convenient to define the age 16 endowment vector $\mathbf{e}(16) = \{e_1(16), e_2(16), e_3(16), e_4(16), e_5(16)\}$, the work experience vector $\mathbf{x}(a) = \{x_1(a), x_2(a), x_3(a)\}$, and the technology shock vector $\boldsymbol{\epsilon}(a) = \{\epsilon_1(a), \epsilon_2(a), \epsilon_3(a), \epsilon_4(a), \epsilon_5(a)\}$. Further, we denote $\mathbf{S}(a) = \{\mathbf{e}(16), g(a), \mathbf{x}(a), \boldsymbol{\epsilon}(a)\}$.

At any age the individual's objective is to maximize the expected present value of remaining lifetime rewards. Defining $V(\mathbf{S}(a), a)$, the value function, to be the maximal expected present value of lifetime rewards at age a given the individual's state $\mathbf{S}(a)$ and discount factor δ, we get

$$V(\mathbf{S}(a), a) = \max_{d_m(a)} E\left[\sum_{\tau=a}^{A} \delta^{\tau-a} \sum_{m=1}^{5} R_m(a)\, d_m(a) \,|\mathbf{S}(a)\right]. \tag{4}$$

Note that $\mathbf{S}(a)$ contains the relevant history of choices that enter the current-period rewards, the endowment vector, and the realizations of all shocks at a, $\epsilon_m(a)$ for $m = 1, \ldots, 5$.[9] In addition, the individual knows all relevant prices and functions (occupation-specific rental prices, the reward functions, the skill technology functions, direct schooling costs, and the distribution of shocks). The maximization in (4) is achieved by choice of the optimal sequence of control variables $\{d_m(a)\colon m = 1, \ldots, 5\}$ for $a = 16, \ldots, A$.

The value function can be written as the maximum over alternative-specific value functions, each of which obeys the Bellman equation (Bellman 1957):

$$V(\mathbf{S}(a), a) = \max_{m \in M} \{V_m(\mathbf{S}(a), a)\}, \tag{5}$$

[9] Past realizations of the shocks are in the individual's information set but are not included in the state space because of the assumption of serial independence.

where $V_m(\mathbf{S}(a), a)$, the alternative-specific value functions, are given by

$$V_m(\mathbf{S}(a), a) = R_m(\mathbf{S}(a), a) + \delta E[V(\mathbf{S}(a+1), a+1) \,|\, \mathbf{S}(a), d_m(a) = 1], \quad a < A,$$
$$V_m(\mathbf{S}(A), A) = R_m(\mathbf{S}(A), A). \tag{6}$$

The expectation in (6) is taken over the distribution of the random components of $\mathbf{S}(a+1)$ conditional on $\mathbf{S}(a)$, that is, over the unconditional distribution of $\epsilon(a+1)$ given serial independence.[10] The predetermined state variables such as schooling and occupation-specific work experience evolve in a Markovian manner that is (conditionally) independent of the shocks, $x_m(a+1) = x_m(a) + d_m(a)$ $(m = 1, 2, 3)$ in the case of occupation-specific work experience and $g(a+1) = g(a) + d_4(a)$ in the case of schooling ($g(a) \leq \overline{G}$, where $\overline{G}$ is the highest attainable level of schooling).

The individual's decision process is described as follows: beginning at age 16, given $\mathbf{e}(16)$ and $g(16)$, the individual draws five random shocks from the joint $\epsilon(16)$ distribution, uses them to calculate the realized current rewards and thus the (five) alternative-specific value functions, and chooses the alternative that yields the highest value. The state space is then updated according to the alternative chosen and the process is repeated. The solution of the optimization problem at each age a can be represented by the set of regions in the five-dimensional $\epsilon(a)$ space over which each of the alternatives would be optimal, that is, would have the highest alternative-specific value function. There is no closed-form representation of the solution. Numerical solution is carried out by backward recursion using the approximation method developed and analyzed in Keane and Wolpin (1994) (see App. A).

The solution of the optimization problem serves as the input into estimating the parameters of the model given data on choices and possibly some of the rewards. Although the solution is deterministic for the individual, it is probabilistic from our view because we do not observe the contemporaneous shocks, that is, $\epsilon(a)$. Consider then having data on a sample of individuals from the same birth cohort who are assumed to be solving the model described above and for whom choices are observed over at least a part of their lifetimes. In addition, assume, as is the case, that wages are observed only in the

[10] Note that the alternative-specific value functions for this problem depend on all the state variables even though each of the reward functions depends on only a subset. This property is an important distinction between static and dynamic problems.

periods in which market work is chosen and only for the occupation that is chosen. Thus, for each individual, $n = 1, \ldots, N$, the data consist of the set of choices and rewards $\{d_{nm}(a),\ w_{nm}(a)d_{nm}(a)$: $m = 1, \ldots, 3\}$ and $\{d_{nm}(a)$: $m = 4, 5\}$ for all ages in the given range $[16, \bar{a}]$.[11] Let $c(a)$ denote the choice-reward combination at age a and let $\bar{\mathbf{S}}(a) = \{\mathbf{e}(16), g(a), \mathbf{x}(a)\}$ denote the predetermined components of the state space, that is, $\mathbf{S}(a)$ net of the technology shocks. Serial independence of the shocks implies that the probability of any sequence of choices and rewards can be written as follows:

$$\Pr[c(16), \ldots, c(\bar{a}) | g(16), \mathbf{e}(16)] = \prod_{a=16}^{\bar{a}} \Pr[c(a) | \bar{\mathbf{S}}(a)]. \quad (7)$$

The sample likelihood is the product of the probabilities in (7) over the N individuals. The solution to the individual's optimization problem provides the choice probabilities that appear on the right-hand side of (7). Thus, for example, the probability that an individual chooses to attend school at age a is $\Pr\{V_4(\mathbf{S}(a), a) = \max_m[V_m(\mathbf{S}(a), a)]\}$, which can be viewed, for the purpose of estimation, as a function of the parameters of the model conditional on the data. Estimation involves an iterative process: solving numerically the dynamic programming problem for given parameter values and then computing the likelihood function, and so forth, until the likelihood is maximized. The likelihood function involves the calculation of multivariate integrals as in general multinomial choice problems. Estimation is conducted using simulated maximum likelihood as described in Keane and Wolpin (1994).

The likelihood function using (7) applies to a sample that is homogeneous except for initial schooling. Clearly, the human capital investment process does not begin at age 16. The vector of age 16 endowments depends on prior human capital accumulation as well as innate talents. To allow for the possibility that individuals do not have identical age 16 endowment vectors, we define a type k individual, $k = 1, \ldots, K$, by an endowment vector $\mathbf{e}_k(16) = \{e_{mk}(16)$: $m = 1, \ldots, 5\}$. Thus individuals may have comparative advantages among the different alternatives, including in acquiring schooling and in home production, that are known to them. Thus each type solves the optimization problem with different initial (age 16) conditions.

We assume that while endowment heterogeneity is unobserved by us, we do know there to be K types. Denote π_k as the proportion of

[11] More generally, the observation set might begin at some age greater than 16. Below we discuss the problem of initial conditions that would pertain as well to this case.

the kth type in the population. In this case, the likelihood function is a mixture of the type-specific likelihoods, $\Pi_{n=1}^{N}\left(\sum_{k=1}^{K}\pi_k L_{nk}\right)$, where L_{nk} is the likelihood of person n's observed choice sequence and rewards if person n is of endowment type k, and the parameter vector is augmented to include the endowment vectors for the K types and the type probabilities.

It is unlikely that initial schooling (at age 16) is exogenous, in which case conditioning the likelihood on it as though it were nonstochastic is problematic. One remedy would be to specify the optimization problem back to the age at which initial schooling was zero for everyone (say, age 3) and solve for the correct probability distribution of attained schooling at age 16 (conditional on age 3 endowments). However, such a model would have to focus on parental decision making with respect to investments in children (including fertility decisions) and would be very demanding in many dimensions (modeling, computation, and data). The alternative we follow is to assume that initial schooling is exogenous conditional on the age 16 endowment vector.[12] The likelihood contribution for the nth individual is thus

$$\begin{aligned}&\Pr[c_n(16),\ \ldots,\ c_n(\bar{a})\,|\,g_n(16)]\\ &=\sum_{k=1}^{K}\prod_{a=16}^{\bar{a}}\pi_{k|g_n(16)}\Pr[c_n(a)\,|\,g_n(16),\ \text{type}=k].\end{aligned}\tag{8}$$

Note that the type proportions, treated as estimable parameters, are now conditioned on initial schooling, $g(16)$.[13]

II. Data

A. *Sample and Variable Definitions*

The data are taken from the 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (NLSY). The NLSY consists of 12,686 individuals, approximately half of them men, who were 14–21 years old as of January 1, 1979. The sample consists of a core random sample and an oversample of blacks, Hispanics, poor whites, and the military. This analysis is based on the white males in

[12] Another alternative is to treat the unobserved heterogeneity as an incidental parameters problem (Heckman 1981), i.e., to let the number of types equal the number of people ($K = N$). However, estimating individual-specific endowments is not computationally feasible.

[13] If our data began at age $a_0 > 16$, then the likelihood function would be conditioned on the relevant state at that age, namely, $g(a_0)$ and $x_m(a_0)$, and the type probabilities would have to be estimated separately for each state combination.

the core random sample who were age 16 or less as of October 1, 1977. Interviews were first conducted in 1979 and have been conducted annually to the present. We follow individuals from the first year they reach age 16 as of October 1 of that year through September 30, 1988. The sample consists of 1,373 individuals who first reach age 16 in the years 1977–81, with 98.4 percent of the first-year observations between 1977 and 1980.

The NLSY collects schooling and employment data as an event history retrospectively back to the preceding interview. Schooling data include the highest grade attended and completed at each interview date, monthly attendance in each calendar month (beginning in 1980), school leaving dates, and the dates of diplomas and degrees. Employment data include the beginning and ending dates (to the calendar week) of all jobs (employers), all gaps in employment within the same job, usual hours worked on each job, the usual rate of pay on each job, and the three-digit occupation for each job. In the 1979 interview, employment data were collected back to January 1, 1978.

The discrete decision period is assumed to be a (school) year.[14] Because the data provide weekly observations and individuals may actually be in several alternatives in a year, any rules used to create annual data on choices will be somewhat arbitrary. Mutually exclusive alternatives were assigned in a hierarchical fashion as follows.

1. *School attendance*.—To simplify the determination of school attendance, we looked at an individual's activity in the fortieth week of each year (October 1), the first week of each year (January 1), and the fourteenth week of each year (April 1), beginning with January 1, 1978. An individual is considered to have attended school during the year if the individual attended in any of the three weeks *and* the individual reported completing one grade level by October 1 of the next year.[15]

[14] We chose October 1 to September 30 as the decision period because it corresponds approximately to a school year. There is, of course, nothing about this calendar period that makes it particularly salient for the timing of employment and occupational choice decisions.

[15] There are a considerable number of observations (as many as 20 percent) with longitudinally inconsistent data on enrollment and highest grade completed. The records of all observations with inconsistent data were carefully scrutinized. In most cases we were able to reconstruct a reasonable history of school attendance and grade completion, or at least a partial history, based on the different pieces of information that are reported in the NLSY, i.e., the monthly attendance calendar; survey date attendance, highest grade attended, and highest grade completed; dates of school leaving; dates of diplomas; and the highest grade completed as of May 1 ''key'' variable created by the Center for Human Resource Research. In the determination of highest grade completed, an individual who obtained a general equivalency diploma was not considered to have completed 12 years of schooling; instead highest grade completed is the number of years that were actually attended and

2. *Work*.—The work assignment used data on work status in nine weeks, again to simplify the calculation, between October 1 and June 30.[16] An individual is considered to have worked during the year if the individual was not attending school and was employed in at least two-thirds of the weeks for at least 20 hours per week on average.[17]

a. *Occupation classification*.—A working individual is assigned to one of the three occupations: blue-collar, white-collar, or the military. The occupation that is assigned is the one in which the individual worked the most weeks during the year (based on the same nine weeks used to determine work status).[18] Aggregating civilian occupations into just two categories is consistent with the assumption that the disaggregated occupations within each category utilize the same type of skill units (mental skills vs. physical skills). Thus wage differences within the aggregates signify more or fewer units of the homogeneous skill. Although a finer disaggregation would probably be desirable, a nontrivial number of year-to-year transitions between finer occupational categories (even between one-digit occupation codes) appear to be spurious.[19] Moreover, the computational burden would increase significantly with more occupations.

b. *Real wages*.—Real (occupation-specific) wages are obtained by multiplying the average real weekly wage for the weeks worked in the occupation (assigned as above) times 50 weeks. The wage is therefore a ''full-time'' equivalent.[20]

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successfully completed. This treatment is consistent with recent work by Cameron and Heckman (1993). The rule for determining school attendance was a bit more complicated because of missing attendance data. If as many as two of the weeks were missing, then the only determinant of school attendance was whether or not a grade was completed. If highest grade completed was missing as of October 1 in any two consecutive years, then the observation is truncated at that period.

[16] The nine weeks were the first, the seventh, and the thirteenth of each of the three calendar quarters spanning the period. We ignored the summer quarter so as not to count summer jobs of those in school.

[17] If work status is missing for less than two-thirds of the weeks, then the work criterion is the same as the one based on the nonmissing weeks; otherwise, the observation is dropped from that point on.

[18] Occupational categories are based on one-digit census codes. Blue-collar occupations are (i) craftsmen, foremen, and kindred; (ii) operatives and kindred; (iii) laborers, except farm; (iv) farm laborers and foremen; and (v) service workers. White-collar occupations are (i) professional, technical, and kindred; (ii) managers, officials, and proprietors; (iii) sales workers; (iv) farmers and farm managers; and (v) clerical and kindred.

[19] With one-digit occupation codes, the transitions between the calendar quarters surrounding the interview date are significantly higher than those between any other quarters. Individuals, even those with the same employer, appear to report verbatim characterizations of their jobs that coders, who are trained to classify the verbatim responses into appropriate three-digit codes, interpret as occupation changes that are not real. This problem essentially disappears in the white- and blue-collar classification scheme.

[20] The wage is deflated by the gross national product deflator, with 1987 as the base year.

TABLE 1

CHOICE DISTRIBUTION: WHITE MALES AGED 16–26

	CHOICE					
AGE	School	Home	White-Collar	Blue-Collar	Military	TOTAL
16	1,178	145	4	45	1	1,373
	85.8	10.6	.3	3.3	.1	100.0
17	1,014	197	15	113	20	1,359
	74.6	14.5	1.1	8.3	1.5	100.0
18	561	296	92	331	70	1,350
	41.6	21.9	6.8	24.5	5.2	100.0
19	420	293	115	406	107	1,341
	31.3	21.9	8.6	30.3	8.0	100.0
20	341	273	149	454	113	1,330
	25.6	20.5	11.2	34.1	8.5	100.0
21	275	257	170	498	106	1,306
	21.1	19.7	13.0	38.1	8.1	100.0
22	169	212	256	559	90	1,286
	13.1	16.5	19.9	43.5	7.0	100.0
23	105	185	336	546	68	1,240
	8.5	14.9	27.1	44.0	5.5	100.0
24	65	112	284	416	44	921
	7.1	12.2	30.8	45.2	4.8	100.0
25	24	61	215	267	24	591
	4.1	10.3	36.4	45.2	4.1	100.0
26	13	32	88	127	2	262
	5.0	12.2	33.6	48.5	.81	100.0
Total	4,165	2,063	1,724	3,762	645	12,359
	33.7	16.7	14.0	30.4	5.2	100.0

NOTE.—Number of observations and percentages.

3. *Home*.—An individual is classified as being at home during the year if the individual neither was enrolled in school nor worked during the year, according to the definitions above.[21]

B. Descriptive Statistics

The basic human capital model provides a number of general qualitative implications that can be assessed with simple descriptive statistics from the data: (i) school attendance should decline with age, (ii) employment should increase with age, (iii) occupational choices should exhibit persistence, and (iv) occupation-specific wages should increase with age.

Table 1 shows the choice distribution by age. There are, as noted, 1,373 individuals in the sample at age 16; the number declines

[21] In actuality, some individuals would be classified as being at home if they were enrolled even for the full year but did not successfully complete a grade level, or if they worked during the year but did not satisfy the weeks and hours criteria.

slightly over the first eight years primarily as a result of sample attrition.[22] Over the last three years the sample size falls because part of the sample never reaches the older ages during the sample period. Overall, there are 12,359 person-periods in the data set.

As the table shows, the vast majority of the sample, approximately 86 percent, is in school at age 16. That proportion drops to 75 percent at age 17 and then falls to only 42 percent at age 18, the normal high school graduation age. School attendance declines steadily from there, with another discrete drop at age 22, reflecting the normal college graduation age. Less than 5 percent of individuals are still in school at age 25.

Paralleling the decline in school attendance, the propensity to work increases monotonically from less than 4 percent at age 16, to almost 37 percent at age 18, to 77 percent at age 23, and to 86 percent at age 25. However, the pattern differs considerably by occupation. Participation in both white- and blue-collar occupations increases monotonically, but at different rates. At age 18 there are four times as many individuals working in the blue-collar occupation as in the white-collar occupation, by age 22 there are twice as many, but by age 25 there are only one-quarter more. Moreover, participation in the blue-collar occupation is essentially unchanged after age 22, whereas white-collar participation almost doubles between age 22 and age 25. As one would expect, there is a close connection between leaving school at college-going ages and moving into white-collar employment. In contrast to the civilian occupations, participation in the military quickly increases to a peak, 8.5 percent at age 20, and then declines to about 4 percent at age 25.[23]

Given our definitions of employment and school attendance, a youth who is classified residually as being in the home sector may actually have been employed part of the year or attended school (without completing a grade level). Nevertheless, the prevalence of youths in the home alternative (neither completing a grade level nor working at least 20 hours per week and 35 weeks per year) as well as its age pattern is still surprising. The proportion of the sample at "home" rises from 10 percent at age 16 to over 20 percent at ages 18–21, falling after age 21 back to 10 percent at age 25.

[22] Given the sample restrictions—namely, restrictions to respondents in the core component of the survey and to respondents who are male and white and are in a particular age group—there would have been at most 1,401 individuals observed at age 16 without any loss of observations due to missing data. Effective attrition is minimized in the NLSY by obtaining the retrospective employment and schooling information for respondents who return to the sample after an attrition spell.

[23] The fall to less than 1 percent at age 26 would appear to be an aberration of the small sample size.

TABLE 2

TRANSITION MATRIX: WHITE MALES AGED 16–26

	CHOICE (t)				
CHOICE ($t-1$)	School	Home	White-Collar	Blue-Collar	Military
School:					
Row %	69.9	12.4	6.5	9.9	1.3
Column %	91.2	32.6	2.5	14.2	11.2
Home:					
Row %	9.8	47.2	8.1	31.3	3.7
Column %	4.4	42.9	8.8	15.6	10.7
White-collar:					
Row %	5.7	6.3	67.4	19.9	.7
Column %	1.8	4.0	51.4	7.0	1.4
Blue-collar:					
Row %	3.4	12.4	9.9	73.4	.9
Column %	2.6	19.0	18.2	61.7	4.3
Military:					
Row %	1.4	5.5	3.1	9.6	80.5
Column %	.2	1.6	1.0	1.5	72.4

Table 2, which shows one-period transition rates, provides evidence on persistence. The first figure in each cell is the percentage of transitions from origin to destination (the row percentage) and the second the reverse, that is, the percentage in a particular destination who started from each origin (column percentage). Given the age of the sample, the strong state dependence in schooling is not surprising: 69 percent of the time, an individual who is in school one year stays in school the next year (row percentage), whereas 91 percent of those in school in any year came from school the previous year (column percentage). This latter figure implies that returning to school, after having left, is a fairly rare event.[24] There is also considerable immobility out of the home alternative. Almost one-half of the observations beginning at home are also at home the next period; about 60 percent of the remainder enter into the blue-collar occupation and about 20 percent return to school.

Table 2 also reveals substantial state dependence in occupation-

[24] Approximately 20 percent of those leaving school for at least one year return to complete at least one more grade level. However, this figure is likely to be overstated given our categorization rules. An individual who completes a year of college by going to school half-time in two years will be defined as having attended school only in the second year. The propensity to interrupt college is substantially greater than it is for high school. Only 5 percent of the sample ever left and returned to high school; of those who graduated from high school, 4.4 percent had left and returned.

specific employment. Over two-thirds of the white-collar observations in one year are in white-collar employment the next year. The comparable figure is around three-fourths for blue-collar employment and four-fifths for military employment. In addition, the transition rate from white-collar to blue-collar employment is about 20 percent, which is double the comparable transition from blue-collar to white-collar employment. However, the age pattern of these interoccupational transitions differs considerably (not shown). After age 21, transitions from white- to blue-collar occupations fall (from 25 percent at age 21 to 15 percent at age 25), and the reverse transition increases (from 8 percent to over 15 percent). This mobility pattern is consistent with an occupational hierarchy. For those leaving the military, the transition occurs mainly to blue-collar employment and to a lesser extent to home.

Table 3 explores further state dependencies in the data with respect to the alternatives other than home. The first row for each alternative lists the values of an alternative-specific state variable, the second row shows the proportion choosing the alternative (unconditionally), and the third row conditions on having chosen the same alternative in the previous period. With respect to the schooling alternative, the third row depicts school continuation rates for selected levels of school attainment from grade levels 9–17. As was evident in table 1, continuation rates fall abruptly at high school and college graduation.

The next three rows show the relationship between white-collar work experience (the number of years previously employed in a white-collar occupation) and the propensity to choose white-collar employment. Clearly, the likelihood of choosing white-collar employment increases rapidly with white-collar experience, reaching 75 percent after four years of experience, regardless of whether the individual chose white-collar employment the previous period. However, over 70 percent remain in white-collar employment even with only two years of experience if they were also in white-collar employment the previous period. The rise in blue-collar employment with blue-collar experience is even more rapid, reaching 75 percent after only three years of blue-collar experience. Having worked in a blue-collar occupation the period before has a smaller impact on the degree of state dependence with experience than was the case for the white-collar alternative, which is consistent with a smaller skill depreciation rate in blue-collar occupations. The same pattern is not, however, observed for the military occupation. The propensity to choose the military when the individual has one year of military experience exceeds the similar propensities in either of the civilian occupations, and the military is less frequently chosen as military experience in-

TABLE 3

Selected Choice-State Combinations

Highest grade completed	9	10	11	12	13	14	15	16	17
Percentage choosing school	26.9	59.8	49.1	13.5	45.1	44.8	62.5	13.5	42.5
If in school previous period	73.5	91.1	85.0	44.2	72.9	70.6	68.8	23.5	55.6
White-collar experience	0	1	2	3	4	5	6		
Percentage choosing white-collar employment	6.8	38.0	55.3	63.3	76.2	74.6	79.2		
If white-collar previous period	...	57.5	71.7	76.7	78.8	82.0	86.4		
Blue-collar experience	0	1	2	3	4	5	6	7	
Percentage choosing blue-collar employment	15.0	51.6	64.9	74.0	74.9	81.2	77.1	88.3	
If blue-collar previous period	...	62.0	71.4	78.7	81.7	85.3	78.7	85.4	
Military experience	0	1	2	3	4	5			
Percentage choosing military employment	1.5	68.0	56.6	44.6	32.7	61.9			
If military previous period	...	90.7	86.5	74.0	57.1	78.8			

TABLE 4

Average Real Wages by Occupation: White Males Aged 16–26

Age	Mean Wage: All Occupations	White-Collar	Blue-Collar	Military
16	10,217 (28)	. . .	10,286 (26)	. . .
17	11,036 (102)	10,049 (14)	11,572 (75)	9,005 (13)
18	12,060 (377)	11,775 (71)	12,603 (246)	10,171 (60)
19	12,246 (507)	12,376 (97)	12,949 (317)	9,714 (93)
20	13,635 (587)	13,824 (128)	14,363 (357)	10,852 (102)
21	14,977 (657)	15,578 (142)	15,313 (419)	12,619 (96)
22	17,561 (764)	20,236 (214)	16,947 (476)	13,771 (74)
23	18,719 (833)	20,745 (299)	17,884 (481)	14,868 (53)
24	20,942 (667)	24,066 (259)	19,245 (373)	15,910 (35)
25	22,754 (479)	24,899 (207)	21,473 (250)	17,134 (22)
26	25,390 (206)	32,756 (79)	20,738 (125)	. . .

Note.—Number of observations is in parentheses. Not reported if fewer than 10 observations.

creases beyond the first year, at least until the individual has five years of military experience.

Table 4 reports age-specific average real wages overall and by occupation. Real wages rise with age in all occupations. White-collar and blue-collar wages are very similar through age 21. However, after 21, white-collar wages are, on average, about 20 percent higher. Military wages are the lowest at all ages, about 20 percent lower than blue-collar wages. As can be seen by comparing the number of wage observations to the number of individuals who are working (table 1), there is considerable missing wage information, particularly at the younger ages and for blue-collar employment.[25]

III. Estimation Results of the Basic Model

The qualitative implications of the basic human capital model do not appear to be inconsistent with the descriptive statistics from the data. Therefore, we turn to a quantitative assessment, that is, to formal estimation. We fixed the terminal age (A) at 65 and the number of types (K) at four.[26] We also made one addition to the basic model;

[25] Moreover, wages span values that are clearly implausible. For this reason, all of the estimation allows for multiplicative (lognormal) measurement error in reported wages.

[26] Type proportions are conditioned on two values of initial schooling: $g(16)$ equal to grade 7, 8, or 9 and $g(16)$ equal to grade 10 or 11. Sixty-seven percent of the individuals had attained grade 10 by age 16, with an additional 7.5 percent attaining grade 11. Therefore, approximately one-quarter of the sample had completed less than 10 years of schooling by the time they had reached age 16 as of October 1.

namely, in keeping with the fact that the wage functions are occupation-specific, we allowed for linear cross-experience terms in the skill production functions. Specifically, military experience enters both civilian functions, and white- (blue-) collar experience enters the blue- (white-) collar function; otherwise the current-period rewards are as in (3).

In assessing the basic model, we consider three criteria: (1) the reasonableness of the parameter values, (2) within-sample fit, and (3) out-of-sample fit.

A. *Parameter Values*

The basic model generates parameter values (see App. B) that appear to be within reasonable ranges. For example, an additional year of schooling increases white-collar skill (and wages) the most, by 9.4 percent; it increases blue-collar skill by only 1.9 percent and military skill by 4.4 percent. The first year of white-collar experience increases white-collar skill by 11.7 percent, with little attenuation in the rate of increase at higher years of experience. The first year of blue-collar experience augments blue-collar skill by 14.3 percent; at 25 years of blue-collar experience, the additional year adds 9.8 percent. An additional year of white- (blue-) collar experience augments blue- (white-) collar skill by 6.7 (7.5) percent. The cost of a year of college is estimated to be \$3,000 and the cost of graduate school \$26,000. The discount factor is estimated to be .78.

B. *Within-Sample Fit*

Figures 1–5, based on a simulation of 5,000 individuals, graphically depict the fit of the basic model to the choice data of table 1. The largest discrepancies occur with respect to the schooling, military, and home alternatives, although the qualitative age patterns are replicated. The basic model predicts that only 63.9 percent will attend school at age 16, although 85.8 percent actually do, and there is no observable high school graduation effect at age 18 as there is in table 1. The basic model also understates the peak military participation (5.5 percent as opposed to 8.5 percent) and does not predict the steep increase in the percentage at home between ages 16 and 18 nor the sustained plateau between ages 18 and 21. More formally, table 5 presents within-sample χ^2 goodness-of-fit test statistics and

We also assumed that there was no skill endowment heterogeneity in the military occupation.

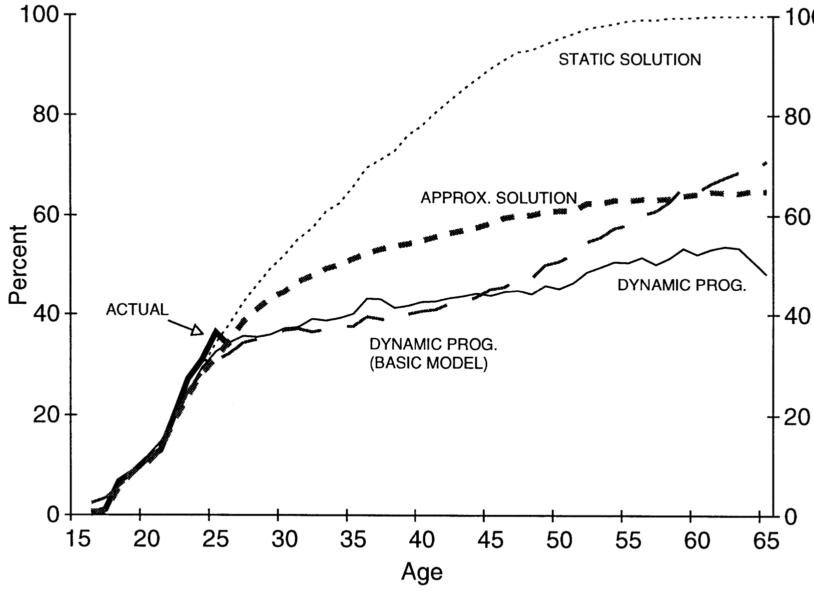

FIG. 1.—Percentage white-collar by age

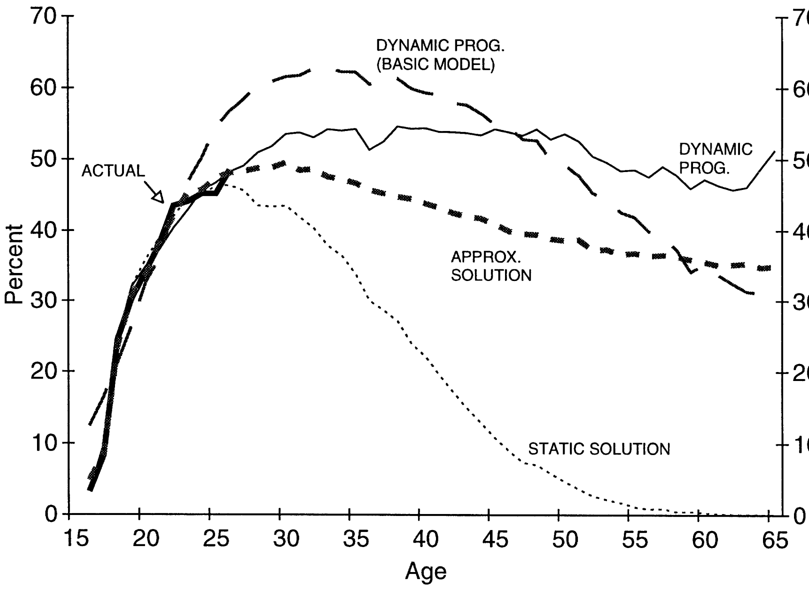

FIG. 2.—Percentage blue-collar by age

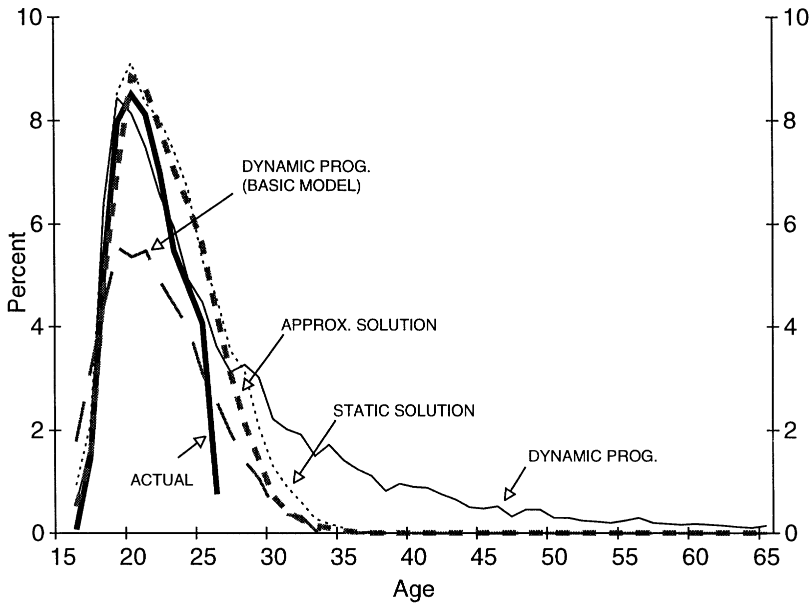

FIG. 3.—Percentage in the military by age

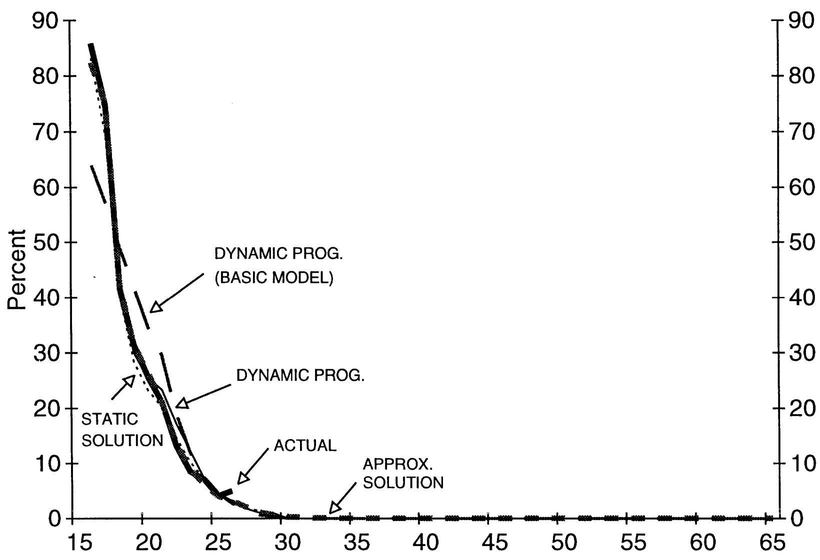

FIG. 4.—Percentage in school by age

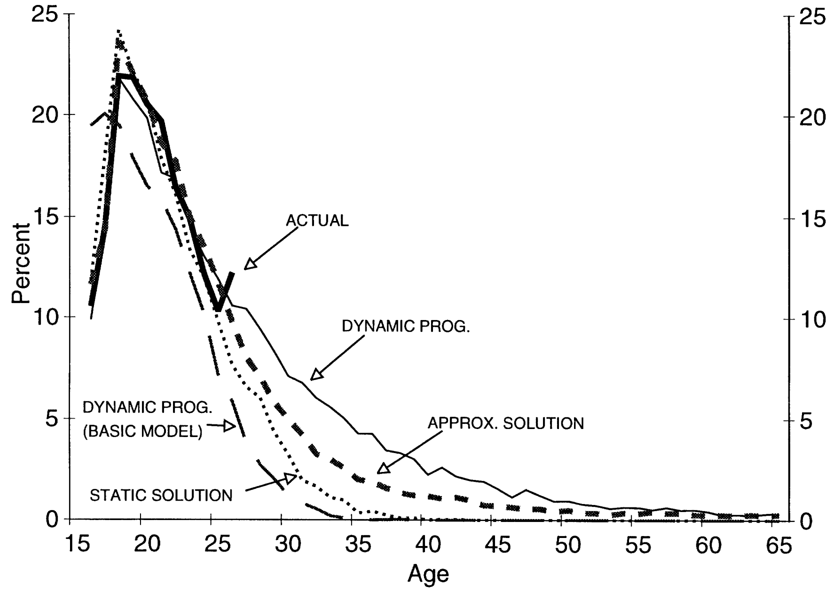

FIG. 5.—Percentage at home by age

confirms the impression of the figures.[27] Except at a few ages for the white- and blue-collar alternatives, the basic human capital model is clearly generating choice patterns statistically different from those that exist in the data.

The basic model also does not capture well the degree of persistence in choices that are observed in tables 2 and 3. The comparable diagonal elements of table 2 are 54.9 versus 69.9, 24.0 versus 47.2, 45.9 versus 67.4, 67.3 versus 73.4, and 47.6 versus 80.5. The model tracks more closely the effects of occupation-specific work experience on choices as in table 3, except for understating the impact of the first year of experience. The model predicts that the first year of white- (blue-) collar experience increases the probability of choosing the white- (blue-) collar alternative by 15 (27) percentage points versus the 31- (37-) percentage-point increase in table 3.

Table 6 presents evidence on the wage fit. The first two rows, comparing the predicted and actual mean and standard deviation of wages, do not reveal large discrepancies between the data and the model. However, a two-variate regression based on simulated data

[27] These χ^2 statistics have not been adjusted for the fact that the parameters of the model have been estimated.

TABLE 5

χ^2 Goodness-of-Fit Tests of the Within-Sample Choice Distribution: Dynamic Programming Model and Multinomial Probit

Age	School	Home	White-Collar	Blue-Collar	Military	Row
16:						
DP-basic	103.05*	17.10*	†	92.61*	†	213.2*
DP-extended	.00	.07	†	.15	†	.22
APP	2.00	.19	†	7.05*	†	9.24*
17:						
DP-basic	74.13*	7.37*	21.14*	54.63*	11.86*	169.15*
DP-extended	.95	.02	.28	3.31	.42	4.98
APP	.02	.00	1.78	.03	.00	1.84
18:						
DP-basic	15.02*	1.60	2.18	6.75*	1.71	27.26*
DP-extended	.03	.00	.93	.01	3.09	4.06
APP	.09	.94	3.03	.42	.17	4.65
19:						
DP-basic	35.83*	5.04*	.26	7.23*	14.41*	62.77*
DP-extended	.83	.51	.07	1.27	.34	3.02
APP	.00	.02	.01	.17	1.53	1.73
20:						
DP-basic	31.10*	6.24*	.14	.92	24.47*	62.86*
DP-extended	.16	.25	.24	.22	.22	.94
APP	.25	.01	.82	.06	.17	1.31
21:						
DP-basic	31.28*	6.54*	.01	1.46	16.61*	55.89*
DP-extended	2.91	3.50	2.45	.23	.72	9.81*
APP	.00	.65	.05	.03	.41	1.14
22:						
DP-basic	23.78*	2.94	1.01	.08	11.84*	39.66*
DP-extended	12.43*	.11	.61	3.04	.38	16.60*
APP	.12	1.49	.72	.64	1.21	4.19
23:						
DP-basic	12.63*	7.78*	2.99	2.00	3.15	28.56*
DP-extended	14.66*	.12	3.76	.42	.44	19.40*
APP	.23	.14	5.90*	.44	4.38	10.97*
24:						
DP-basic	.18	4.76*	2.28	4.61*	1.40	13.30*
DP-extended	.18	.99	.81	.04	.04	1.89
APP	1.21	2.77	2.20	.05	2.77	10.01*
25:						
DP-basic	.30	12.35*	6.21*	9.31*	1.84	30.01*
DP-extended	.14	3.45	2.71	.29	.23	6.82
APP	.01	2.98	5.00*	.61	2.56	11.16*
26:						
DP-basic	4.96*	38.64*	.17	3.13	†	46.90*
DP-extended	2.61	2.14	.45	.00	†	5.20
APP	2.84	4.95*	.10	.01	†	7.90*

Note.—The basic dynamic programming (DP-basic) model has 50 parameters, the extended dynamic programming (DP-extended) model has 83 parameters, and the approximate decision rule (APP) model has 75 parameters.

* Statistically significant at the .05 level.

† Fewer than five observations.

TABLE 6

WITHIN-SAMPLE WAGE FIT

	WHITE-COLLAR				BLUE-COLLAR			
	NLSY*	DP-Basic	DP-Extended	Static	NLSY†	DP-Basic	DP-Extended	Static
Wage:								
Mean	19,691	17,456	19,605	19,688	16,224	16,230	15,805	15,914
Standard deviation	12,461	10,324	12,091	13,664	8,631	8,437	8,431	9,837
Wage regression:								
Highest grade completed	.095	.033	.090	.091	.048	.006	.047	.056
	(.007)‡	(.007)	(.006)	(.007)	(.008)	(.006)	(.006)	(.007)
Occupation-specific experience	.103	.017	.080	.123	.096	.082	.078	.108
	(.009)	(.011)	(.012)	(.010)	(.005)	(.004)	(.004)	(.005)
Constant	8.33	9.15	8.44	8.22	8.80	9.25	8.84	8.54
	(.102)	(.087)	(.080)	(.100)	(.096)	(.069)	(.078)	(.082)
R^2	.213	.021	.182	.172	.150	.117	.104	.142
Observations	1,509	1,605	1,685	1,698	3,143	4,013	3,761	3,772

* Three wage outliers of over $250,000 were discarded. The only important effect was to reduce the wage standard deviation significantly.
† Two wage outliers of over $200,000 were discarded. The only important effect was to reduce the wage standard deviation significantly.
‡ Heteroskedasticity-corrected standard errors are in parentheses.

produced from the estimates of the basic model, including school attainment and occupation-specific work experience, shows that the basic model does not replicate the wage-education relationship for either occupation or the wage-experience relationship in the case of white-collar employment.[28]

C. Out-of-Sample Fit

The impact on accepted wages of the steep wage offer–experience gradient is more apparent outside of the sample ages. In particular, by age 40 the average wage of white-collar workers is predicted to reach $77,241; by age 50, $181,834; and by age 60, $400,401. The average wages for blue-collar workers at those same ages would be $83,029, $169,376, and $309,368. These are not reasonable forecasts. Later, we use March Current Population Survey (CPS) data to compare the forecasts of the choice distribution outside of the sample ages.

IV. An Extended Model

The basic human capital model does not provide a good fit to the quantitative features of the NLSY data. To attempt to better fit the data, we extended the basic human capital model (the full mathematical representation is provided in App. C along with definitions) in directions motivated by its specific failures. The extensions serve to improve the overall choice distribution (table 1) and the pattern of persistence (tables 2 and 3).

A. Work Alternatives

Skill technology functions ($e_m(a)$).—The civilian skill production functions were augmented to allow for a skill depreciation effect (adding a dummy variable for whether or not the individual worked in the same occupation in the previous period), a first-year experience effect (a dummy variable indicating whether or not the individual had ever worked in the occupation), age effects (a linear age term and a dummy variable indicating that the individual was under 18), and high school and college graduation effects.[29]

Mobility and job search costs.—The reward functions for the civilian

[28] The difference between these estimates and the parameter values reported in App. B is not so much the result of the different specification, but rather reflects the difference between the wage offer function that corrects for self-selection and the ''accepted'' wage function that does not.

[29] The military skill function excluded the depreciation parameter.

occupations were augmented to include a direct monetary job-finding cost if one did not work in the occupation in the previous period and an additional job-finding cost if the individual had no prior work experience in that occupation. These additional state variables parallel the ones added to the skill functions.[30]

Nonpecuniary rewards plus indirect compensation.—The extended specification allows for nonwage aspects of employment. Specifically, an additive parameter was included in each civilian reward function reflecting the net (positive or negative) monetary-equivalent value of working conditions, indirect compensation, or fixed costs of working associated with that occupation.[31]

B. *School Attendance*

In the extended model, the schooling reward is more generally interpreted to include a consumption value of school attendance and is allowed to depend systematically on age. In addition, the reward associated with attending school includes a cost of reentry into high school (a dummy variable indicating whether one attended high school in the previous period) and a separate reentry cost into postsecondary school (a dummy variable indicating whether one attended college in the previous period).[32]

C. *Remaining at Home*

The payoff from remaining home is allowed to differ by age (dummy variables indicating whether the individual is in the age range 18–20 and 21 and over).

D. *Common Returns*

The extended model allows for a common set of rewards: a psychic value associated with earning a high school diploma and additionally with earning a college diploma. Also, there is a cost of leaving the military prematurely, that is, without having remained there for at

[30] The military reward function included the latter only (see below).

[31] The nonpecuniary reward associated with military employment is treated differently than for civilian occupations. We assume that the demand for military labor (skill units) is perfectly inelastic. In this case, nonpecuniary aspects of military employment must be fully compensated in its rental price (the parameter enters multiplicatively and the constant term in the log military wage function is net of the parameter).

[32] One possible reason for a reentry cost is that, because of knowledge depreciation, effort may have to increase if school attendance is not continuous. Alternatively, there may be a psychic cost of attending school with a younger school entry cohort.

least two years, which enters the rewards of all alternatives except the military (a dummy variable indicating one year of military experience).

V. Estimation Results for the Extended Model

We apply the same criteria for judging the success of the extended model as for the basic model.

A. Parameter Values

Tables 7–9 provide the parameter estimates and associated standard errors.[33] The occupation-specific parameters, shown in table 7, are divided into four categories: those corresponding to skill functions, to nonpecuniary values, to entry costs, and to exit costs. The skill functions have the following selected characteristics: (1) An additional year of schooling augments white-collar skill by 7 percent, blue-collar skill by 2.4 percent, and military skill by 5.8 percent. (2) Neither graduation from high school nor graduation from college has a substantive additional impact on skills in either the white- or blue-collar occupation over and above the completion of the additional year of schooling (there are no diploma effects on wages).[34] (3) An additional year of white-collar experience, independent of the previous period's choice, increases white-collar skill by 21.5 percent in the first year (2.7 + 18.8 − .04). After that, each additional year increases white-collar skill by $2.7 - .08 \times x_1$ percent, with peak earnings reached at approximately 38 years of experience (age constant). (4) Blue-collar experience, independent of the previous period's choice, increases blue-collar skills by 24.7 percent in the first year and by $4.6 - .16 \times x_2$ percent after that. Blue-collar earnings peak at 33 years of experience (age constant). (5) White-collar experience increases blue-collar skill by slightly less than blue-collar experience increases white-collar skill, 1.9 and 2.3 percent per additional year of experience, respectively. (6) Military experience increases military skill by 12 percent in the first year and by $4.5 - .10 \times x_3$ percent after the first year. Military earnings peak at 45 years of experience (age constant). An additional year of military experience increases skills in white-collar occupations by 1.3 percent and in blue-

[33] Standard errors are calculated using the outer product of numerical first derivatives. In our earlier paper (Keane and Wolpin 1994), we found that, on the basis of Monte Carlo simulations, these standard errors seemed to be downward biased.

[34] To interpret a diploma effect within the skill acquisition framework would require that courses taken in the last year of high school or college are somehow more job relevant than those taken earlier.

TABLE 7

Estimated Occupation-Specific Parameters

	White-Collar	Blue-Collar	Military
	1. Skill Functions		
Schooling	.0700 (.0018)	.0240 (.0019)	.0582 (.0039)
High school graduate	−.0036 (.0054)	.0058 (.0054)	. . .
College graduate	.0023 (.0052)	.0058 (.0080)	. . .
White-collar experience	.0270 (.0012)	.0191 (.0008)	. . .
Blue-collar experience	.0225 (.0008)	.0464 (.0005)	. . .
Military experience	.0131 (.0023)	.0174 (.0022)	.0454 (.0037)
"Own" experience squared/100	−.0429 (.0032)	−.0759 (.0025)	−.0479 (.0140)
"Own" experience positive	.1885 (.0132)	.2020 (.0128)	.0753 (.0344)
Previous period same occupation	.3054 (.1064)	.0964 (.0124)	. . .
Age*	.0102 (.0005)	.0114 (.0004)	.0106 (.0022)
Age less than 18	−.1500 (.0515)	−.1433 (.0308)	−.2539 (.0443)
Constants:			
Type 1	8.9370 (.0152)	8.8811 (.0093)	8.540 (.0234)
Deviation of type 2 from type 1	−.0872 (.0089)	.3050 (.0138)	. . .
Deviation of type 3 from type 1	−.6091 (.0143)	−.2118 (.0144)	. . .
Deviation of type 4 from type 1	−.5200 (.0199)	−.0547 (.0177)	. . .
True error standard deviation	.3864 (.0094)	.3823 (.0074)	.2426 (.0249)
Measurement error standard deviation	.2415 (.0140)	.1942 (.0134)	.2063 (.0207)
Error correlation:			
White-collar	1.0000	. . .	. . .
Blue-collar	.1226 (.0430)	1.0000	. . .
Military	.0182 (.0997)	.4727 (.0848)	1.0000
	2. Nonpecuniary Values		
Constant	−2,543 (272)	−3,157 (253)	−.0900 (.0448)
Age	. . .	. . .	−.0313 (.0057)
	3. Entry Costs		
If positive own experience but not in occupation in previous period	1,182 (285)	1,647 (199)	. . .
Additional entry cost if no own experience	2,759 (764)	494 (698)	560 (509)
	4. Exit Costs		
One-year military experience	. . .	. . .	1,525 (151)

Note.—Standard errors are in parentheses.
* Age is defined as age minus 16.

collar occupations by 1.7 percent. (7) White-collar skills depreciate much more rapidly than blue-collar skills. For the same level of experience, white-collar skill is 30.5 percent lower in the year following an absence from white-collar work, whereas blue-collar skill is only 9.6 percent lower under a similar circumstance. (8) Military wages are reported with the most error; measurement error accounts for

TABLE 8

Estimated School and Home Parameters

	School		Home	
Constants:				
Type 1	11,031	(626)	20,242	(608)
Deviation of type 2 from type 1	−5,364	(1,182)	−2,135	(753)
Deviation of type 3 from type 1	−8,900	(957)	−14,678	(679)
Deviation of type 4 from type 1	−1,469	(1,011)	−2,912	(768)
Has high school diploma	804	(137)	···	
Has college diploma	2,005	(225)	···	
Net tuition costs: college	4,168	(838)	···	
Additional net tuition costs: graduate school	7,030	(1,446)	···	
Cost to reenter high school	23,283	(1,359)	···	
Cost to reenter college	10,700	(926)	···	
Age*	−1,502	(111)	···	
Aged 16–17	3,632	(1,103)	···	
Aged 18–20	···		−1,027	(538)
Aged 21 and over	···		−1,807	(568)
Error standard deviation	12,821	(735)	9,350	(576)
Discount factor	.9363 (.0014)			

Note.—Standard errors are in parentheses.
* Age is defined as age minus 16.

42 percent of the total (ln) wage variance. Measurement error accounts for 28 percent of white-collar (ln) wage variance and for 21 percent of blue-collar (ln) wage variance.

Working in a white-collar occupation reduces the current-period reward by $2,543 because of its nonpecuniary aspects or fixed (yearly) costs of working. In the case of blue-collar employment, the reward is reduced by $3,157. Note that these white-collar and blue-collar rewards are measured relative to the military payoff. It is thus plausible that both are negative, since the military payoff includes room and board.

The cost of finding a white- (blue-) collar job is $3,941 ($2,141) if the individual has no previous white- (blue-) collar experience and $1,181 ($1,647) if the individual has white- (blue-) collar experience but did not work in a white- (blue-) collar occupation in the previous period. The cost of entering the military is $560 if one has no previous military experience. Finally, the cost of exiting the military prematurely is $1,525 per year.

The estimated school and home parameters are shown in table 8. The reward per period associated with attending school has the following selected features: (1) The contemporaneous utility of attending schooling for a 16-year-old ranges from as low as the monetary equivalent of $5,763 (11,031 − 8,900 + 3,632) of the consump-

TABLE 9

Estimated Type Proportions by Initial Schooling Level and Type-Specific Endowment Rankings

	Type 1	Type 2	Type 3	Type 4
Initial schooling:				
Nine years or less	.0491 (· · ·)	.1987 (.0294)	.4066 (.0357)	.3456 (.0359)
10 years or more	.2343 (· · ·)	.2335 (.0208)	.3734 (.0229)	.1588 (.0183)
Rank ordering:				
School attainment at age 16	1	2	3	4
White-collar skill endowment	1	2	4	3
Blue-collar skill endowment	2	1	4	3
Consumption value of school net of effort cost	1	3	4	2
Value of home production	1	2	4	3

Note.—Standard errors are in parentheses.

tion good for a person of type 3 to as high as \$14,663 for a person of type 1. This value declines for each type by \$1,502 between the ages of 16 and 17, by an additional \$5,134 (3,632 + 1,502) between the ages of 17 and 18, and by a further \$1,502 for each additional year of age thereafter. (2) The contemporaneous utility of each alternative is augmented by \$804 when a high school diploma is received and by \$2,005 when a college diploma is received. (3) The net tuition cost, net of the differential utility of attending college relative to high school, is \$4,168; the net cost of attending graduate school relative to high school is \$11,198 (4,168 + 7,030). (4) The cost of attending high school (college) in a period followed by nonattendance is higher by \$23,283 (\$10,700).

With respect to the home alternative, the contemporaneous utility of being home is roughly constant with age, ranging from as low as \$5,564 for type 3 persons to as much as \$20,242 for type 1 persons. The discount factor is estimated to be .936.

Table 9 shows the estimated proportion of individuals of each of the four endowment types conditional on initial schooling. Approximately 60 percent of the individuals are either of type 2 or type 3 regardless of initial schooling. However, only 5 percent of those with less than 10 years of schooling are of type 1, whereas almost a quarter of those with 10 years or more of schooling are of that type. The table also shows relative endowment rankings: type 3's, the largest group in the population, have the lowest skill endowments in all the alternatives; type 1's are the most productive in white-collar occupations, in school, and at home; type 2's are the most productive in blue-collar occupations and second in the other alternatives except for schooling; and type 4's rank second in schooling and third elsewhere. The sample exhibits a complex pattern of comparative advantages.

B. *Within-Sample Fit*

As with the basic model, consider first figures 1–5. For comparison purposes we also show the predicted choice distribution of a static model, which is identical to our model in terms of the specifications of the reward functions, but in which the discount factor is set to zero, and of a model based on an approximation to the alternative-specific value functions. That is, denoting $S_m(a)$ as the state space associated with alternative m at age a, define the ''approximate'' value of alternative m as $V_m(a) = S_m(a)\,\alpha_m + \epsilon_m(a)$.[35] This approximation, as a linear in parameters function of the state variables, thus takes the form of a five-alternative panel probit model with unobserved heterogeneity introduced by allowing the intercept vector to have four possible values.[36] From the graphs, it is difficult to distinguish the within-sample fit of the three models, although it is evident that they all perform better than the basic human capital model.

Table 5 shows the within-sample χ^2 goodness-of-fit test statistics for both the dynamic programming and approximation models. The figures in the table confirm the impression of the graphs: the two do about equally well, with the fit being rejected in only a few periods. The static model, not presented, performs about the same using this metric. It should be recognized that although the dynamic programming model contains eight more parameters than the approximation model does, it is fitting the wage data as well as the choice data and is thus restricted in terms of how it can fit the choice data alone.

The extended model not only provides a much better fit of the pattern of choices relative to the basic model (table 5), but also more

[35] Not all state variables appear in all the approximate value functions; i.e., there are exclusion restrictions. Specifically, lagged choice variables appear only in their ''own'' value functions because lagged alternative choice variables do not appear in the reward functions. Note that there would not be exclusion restrictions for approximate decision rules based on the basic model.

[36] The approximation model is estimated (by simulated maximum likelihood) using only the choice data, i.e., ignoring the wage data. The static model uses both choice and wage data.

closely captures the features of the data presented in tables 2–4. While the basic model failed to capture the degree of persistence observed in the data, the diagonal elements of the transition matrix predicted by the extended model are 63.3, 38.9, 64.5, 72.4, and 59.0. In comparison with the data (table 2), the only significant deviation arises with respect to the military. The basic model also seriously understated first-year experience effects on the choice distribution. The first-year experience effect predicted by the extended model is 30.6 percent (31.2 percent in the data) for white-collar and 36.0 percent (36.6 percent in the data) for blue-collar. The fit to the wage data is also much improved. As table 6 shows, the basic and extended models fit the first two moments of the white- and blue-collar wage distributions with reasonably similar accuracy. However, the (partial) covariance structure of wages with schooling and work experience, as indicated by the two-variate regression estimates, is much more closely fit by the extended model.

C. *Out-of-Sample Fit*

Figures 1–5 also show the forecasts of the three models through age 65, well beyond the actual data. These out-of-sample forecasts diverge considerably. The static model predicts unrealistically rapid changes in the choice constellation with age, culminating in almost everyone opting for white-collar employment by age 50. Neither the approximation model nor the dynamic programming model (the basic and extended models) forecasts such extreme outcomes. However, the approximation model tends to extrapolate trends more closely in within-sample age profiles. This is most apparent in the forecasts for the military and home alternatives. The extended dynamic programming model forecasts less white-collar employment and more blue-collar employment over the life cycle than the approximation model does.

The static model and the dynamic programming model also differ substantially in terms of their forecasts about wages. For example, at age 50 the static model forecasts the mean accepted white-collar wage to be \$164,261, whereas the blue-collar wage forecast is \$93,390. The corresponding forecasts for the dynamic programming model are \$48,497 and \$42,222. Although we cannot judge the accuracy of the dynamic programming model's forecasts, the static model's forecasts (like those of the basic model) are clearly unreasonable.

It is, of course, not possible to extensively compare the forecast accuracy of the approximate and dynamic programming models with the NLSY cohort: its members will not be 40 years old until

TABLE 10

Model Predictions vs. CPS Choice Frequencies

Age Range	NLSY*	CPS (Year)†	DP-Basic*	DP-Extended†	Approximation*
			White-Collar		
16–19	.043	.064 (1981)	.052	.043	.041
20–23	.190	.187 (1985)	.176	.187	.180
24–26	.344	.345 (1989)	.307	.335	.332
24–27	⋯	.348 (1989)	.323	.343	.349
28–31	⋯	.384 (1993)	.365	.375	.443
30–33	⋯	.413 (1995)	.370	.388	.472
35–44	⋯	.449 (1995)	.405	.430	.547
			Blue-Collar		
16–19	.171	.265 (1981)	.199	.182	.176
20–23	.430	.432 (1985)	.416	.418	.434
24–26	.475	.472 (1989)	.544	.490	.498
24–27	⋯	.476 (1989)	.565	.494	.498
28–31	⋯	.465 (1993)	.616	.539	.495
30–33	⋯	.460 (1995)	.624	.547	.487
35–44	⋯	.423 (1995)	.595	.541	.440

* Military is excluded to facilitate comparison with CPS (which is a civilian sample).
† Choice frequencies pertain to whites in the March CPS from the years indicated. We classify a person as working if, over the previous calendar year, he worked at least 35 weeks and, in those weeks, he worked at least 20 hours per week on average. The occupation is that held longest in the previous year.

after the year 2000. However, we can use available CPS data to follow the NLSY cohort through age 33, and to the extent that there are not strong cohort effects for nearby cohorts, we can compare the forecasts to the outcomes of near cohorts. Table 10 reports the results of such a comparison. The table reports results for both the basic and extended dynamic programming models, but given the previous results, we shall restrict our discussion only to the latter. Note first that the within-sample match between the CPS and the NLSY is remarkably close except for the youngest age category. This discrepancy arises because the March CPSs do not report whether an individual is attending school, which takes precedence in our NLSY categorization. However, notice that the ratio of white- to blue-collar employment in that age range is very similar between the two surveys.

With respect to white-collar employment, the predictions of the dynamic programming model are very close to the true white-collar proportions for the NLSY cohort (as depicted in the CPS data), that is, through age 33, whereas the approximation model overstates white-collar employment. However, we observe exactly the opposite for the blue-collar predictions. The approximation model closely fits the data through age 33, whereas the dynamic programming model overstates blue-collar employment. The last row for each occupation shows proportionate employment of those aged 35–44 taken from the 1995 CPS, a group that is 5–15 years older than the NLSY cohort. The same pattern emerges. To the extent that the NLSY cohort will look like the 35–44-year-olds in 1995 when they reach those ages (in the years 1996–2007), the dynamic programming model closely forecasts white-collar representation, whereas the approximation model closely forecasts blue-collar representation. It would be difficult to choose between the dynamic programming model and the approximation model on the basis of their ability to accurately forecast the choice distribution.

VI. Discussion

A. The Importance of Unobserved Skill Heterogeneity

As seen in tables 7–9, there is considerable variation in type-specific endowments of civilian occupation skills and in school and home productivities. Table 11 presents selected characteristics at age 24, on the basis of a simulation using the estimates of the extended dynamic programming model. By age 24, age 16 endowment types differ substantially in their completed schooling levels, work experience, and current choices, with their schooling at age 16 held constant. Type 1's complete three and one-half to five more years of schooling than other types. Even given that by age 24 they have spent, on average, about six years in school out of the possible eight since age 16, those who had completed 10 years of schooling by age 16 had as much white-collar experience as any other type. Type 2's specialize in blue-collar employment and complete approximately 12 years of schooling. Type 3's are essentially the only individuals to accept military employment. However, because military employment is relatively short, these individuals also have accumulated significant white- and blue-collar experience by age 24. Type 4's spend the most time in home production and more time in school than all but the first type. At age 24, over 30 percent of those with the lower level of initial schooling choose to be at home, about five times more than the other types.

Specialization is even more apparent by age 40 (not shown): type 1's are predicted, on average, to have spent 94 percent of their years since (last) leaving school in white-collar employment and 5 percent in blue-collar employment; type 2's 69 percent of their years since leaving school in blue-collar employment and 25 percent in white-collar employment; type 3's 59 percent of their years in blue-collar employment, 25 percent in white-collar employment, and 9 percent

TABLE 11

SELECTED CHARACTERISTICS AT AGE 24 BY TYPE: NINE OR 10 YEARS INITIAL SCHOOLING

	Initial Schooling 9 Years or Less				Initial Schooling 10 Years or More			
	Type 1	Type 2	Type 3	Type 4	Type 1	Type 2	Type 3	Type 4
Schooling	15.6	10.6	10.9	11.0	16.4	12.5	12.4	13.0
Experience:								
White-collar	.528	.704	.742	.279	1.07	1.06	1.05	.436
Blue-collar	.189	4.05	2.85	1.61	.176	3.65	2.62	1.77
Military	.000	.000	1.35	.038	.000	.000	1.10	.034
Proportion who chose:								
White-collar	.509	.123	.176	.060	.673	.236	.284	.155
Blue-collar	.076	.775	.574	.388	.039	.687	.516	.441
Military	.000	.000	.151	.010	.000	.000	.116	.005
School	.416	.008	.013	.038	.239	.024	.025	.074
Home	.000	.095	.086	.505	.050	.053	.059	.325

NOTE.—Based on a simulation of 5,000 persons.

in the military; and type 4's 31 percent of their postschooling years at home, 51 percent in blue-collar employment, and 18 percent in white-collar employment.

Given the estimated parameters, the expected discounted present value of the utility stream (the expectation of [5]) as well as the expected alternative-specific value functions (the expectation of [6]) can be calculated at any feasible age-state combination. At age 16, the only relevant state is initial schooling and type. Table 12 compares the expected value functions by initial schooling and type at two ages, 16 and 26. At age 26, the expected value functions are averaged over all attained states using the probability of the attained states conditional on type and initial schooling.

The differences in lifetime utility due to variation in initial schooling are small relative to some of the differences due to endowment heterogeneity. For instance, the expected lifetime utility of type 1's with 10 years of initial schooling is \$28,000 larger than that of type 1's with nine or less, the largest difference for any type. On the other hand, when initial schooling is held fixed, the greatest difference in expected lifetime utility among the types is about \$185,000 (between types 1 and 3) for the higher level of initial schooling and \$175,000 for the lower level.

It is interesting that type 2's have much higher expected present values of lifetime utility than type 3's, even though both are essentially blue-collar types (although type 3's have their careers interrupted by military service, by choice). Type 2's are well endowed with blue-collar skill, and type 3's are poorly endowed with both white- and blue-collar skill. With respect to the alternative-specific valuations, at age 16 schooling has the highest expected lifetime reward for all types and initial schooling levels, whereas working has the highest valuation at age 26.[37]

The table indicates that skill endowment heterogeneity is potentially an important determinant of inequality in lifetime welfare. Indeed, on the basis of the simulated data, the between-type variance in expected lifetime utility is calculated to account for 90 percent of the total variance. It is especially troublesome, given this finding, that unobserved heterogeneity is usually left as a black box. However, we can determine some of the correlates of heterogeneity, if not its cause. Although we cannot determine each individual's actual type, we can use Bayes's rule to compute the probability distribution of the endowment types conditional on choices, wages, and initial schooling. Then, having calculated these endowment type probabili-

[37] The valuations at age 26 are not discounted back to age 16, which would require multiplication of the age 26 valuations by a factor of .516.

TABLE 12

EXPECTED PRESENT VALUE OF LIFETIME UTILITY FOR ALTERNATIVE CHOICES AT AGE 16 AND AT AGE 26 BY TYPE ($)

	All Types	Type 1	Type 2	Type 3	Type 4
	Initial Schooling 10 Years or More				
School:					
Age 16	321,008	415,435	394,712	228,350	289,683
Age 26	384,352	499,162	494,107	272,985	314,708
Home:					
Age 16	298,684	380,660	376,945	207,768	274,901
Age 26	426,837	611,167	516,547	291,932	338,653
White-collar:					
Age 16	293,683	372,544	372,733	207,586	262,370
Age 26	439,970	637,616	528,107	303,228	338,967
Blue-collar:					
Age 16	296,736	373,156	377,618	210,699	266,206
Age 26	438,240	617,873	534,578	305,641	342,195
Military:					
Age 16	285,686	350,655	356,202	210,461	261,944
Age 26	415,374	581,996	492,531	298,431	329,938
Maximum over choices:					
Age 16	321,921	415,503	396,108	229,265	291,122
Age 26	445,488	638,820	537,226	308,259	346,695
	Initial Schooling Nine Years or Less				
School:					
Age 16	273,186	387,384	371,369	211,942	276,040
Age 26	308,808	564,590	446,163	243,734	274,979
Home:					
Age 16	260,668	352,274	360,495	197,288	268,047
Age 26	334,643	578,637	468,465	268,815	305,262
White-collar:					
Age 16	253,764	342,833	354,261	196,294	253,686
Age 26	339,093	602,915	474,796	277,488	300,917
Blue-collar:					
Age 16	257,720	343,873	359,370	199,945	257,697
Age 26	344,179	583,895	486,456	282,223	305,520
Military:					
Age 16	251,710	322,293	340,126	199,737	254,386
Age 26	328,916	550,521	447,443	275,660	295,996
Maximum over choices:					
Age 16	275,634	387,384	374,154	213,823	286,311
Age 26	347,741	604,549	487,466	284,073	310,598

NOTE.—Based on a simulation of 5,000 persons.

ties for each individual, we can determine the extent to which observed family background characteristics are related to type.

The first row of Table 13 shows the baseline joint distribution of types and initial schooling in the sample. In comparison with the baseline, those individuals whose mothers had completed less than 12 years of schooling are substantially more likely to have completed nine years or less of schooling at age 16 and jointly to be of type 2, 3, or 4. The proportion of type 1's is only .04 for those whose mothers did not graduate from high school, .15 for those whose mothers were high school graduates with no college, .32 for those whose mothers had some college, and .39 for those whose mothers graduated from college. Further, as column 10 of the table indicates, having a mother who did not graduate from high school is associated with having an expected lifetime utility that is \$21,000 less than the average individual and \$53,000 less than a person whose mother was a college graduate.[38]

With respect to household structure, lifetime utility for a person who was living with both parents at age 14 is estimated to be between \$14,000 and \$20,000 higher than for a person who was living with only one or neither biological parent at age 14. Lifetime utility is also related to the number of siblings: individuals with only one other sibling have the highest lifetime utility, \$10,000 more than either only children or those with two siblings. Persons from families with five or more children have expected lifetime utility of almost \$25,000 less than those from two-child families.

Parental income in 1978, when the individuals in the sample were 14–17 years old, also is associated with endowment type. Those whose parents' incomes were below the median income of the sample have an expected lifetime utility that is roughly \$20,000 lower than those whose parents' incomes were above the median but less than twice the median, and over \$60,000 lower than those whose parents' incomes were at least twice the median.

We also estimated regressions of the expected present value of lifetime utility of each individual in the sample on family background characteristics. A regression that included father's and mother's schooling, family income, number of siblings, and whether the person lived with both parents at age 14 explained only 10 percent of the variance in the expected present value of lifetime utility. Ideally, one would like to relate endowments at age 16 to all the

[38] Expected lifetime utility is the weighted average of the type-specific expected present values of lifetime utility; the weights are the individual-specific type probabilities. Expected lifetime utility is thus a convenient summary measure of an individual's endowments.

TABLE 13

Relationship of Initial Schooling and Type to Selected Family Background Characteristics

	Initial Schooling Nine Years or Less and Person Is of Type				Initial Schooling 10 Years or More and Person Is of Type					Expected Present Value of Lifetime Utility at
	1 (1)	2 (2)	3 (3)	4 (4)	1 (5)	2 (6)	3 (7)	4 (8)	Observations (9)	Age 16 (10)
All	.010	.051	.103	.090	.157	.177	.289	.123	1,373	307,673
Mother's schooling:										
Non–high school graduate	.004	.099	.177	.161	.038	.141	.276	.103	333	286,642
High school graduate	.011	.043	.086	.071	.143	.210	.305	.131	685	309,275
Some college	.023	.021	.043	.058	.294	.166	.263	.133	152	328,856
College graduate	.007	.005	.049	.023	.388	.151	.222	.154	142	339,593
Household structure at age 14:										
Live with mother only	.001	.062	.133	.119	.123	.137	.297	.128	178	296,019
Live with father only	.026	.037	.088	.120	.062	.180	.378	.106	44	291,746
Live with both parents	.011	.049	.097	.082	.169	.184	.284	.124	1,123	310,573
Live with neither parent	.0001	.090	.154	.184	.037	.175	.275	.085	28	290,469
Number of siblings:										
0	.002	.041	.086	.092	.142	.227	.285	.126	50	310,833
1	.002	.029	.064	.051	.236	.199	.287	.133	261	320,697
2	.016	.048	.104	.063	.191	.157	.275	.146	364	311,053
3	.013	.056	.119	.090	.147	.182	.288	.104	320	306,395
4+	.009	.067	.117	.141	.081	.171	.303	.111	378	296,089
Parental income in 1978:										
$Y \leq \frac{1}{2}$ median*	.002	.078	.155	.181	.071	.132	.221	.161	214	292,565
$\frac{1}{2}$ median $< Y \leq$ median	.007	.053	.120	.103	.103	.173	.328	.113	382	296,372
Median $\leq Y \leq 2 \cdot$ median	.015	.044	.071	.051	.177	.204	.304	.134	446	314,748
$Y \geq 2 \cdot$ median	.014	.025	.024	.021	.479	.167	.182	.087	83	358,404

* Median income in the sample is $20,000.

human capital investments that were made in offspring up to age 16 (including family inputs as well as those related to schools and neighborhoods) and to biologically heritable endowments. The fact that the family background characteristics we used account for less than 10 percent of the total variation in expected lifetime utility implies that these characteristics are only crude proxies for endowments measured at age 16. We also added an ''ability'' score, the Armed Forces Qualification Test (AFQT) administered in 1980, as an additional regressor. The point estimates implied that a one-standard-deviation increase in the AFQT score is related to a \$14,000 increase in the expected present value. Of course, AFQT may itself be the outcome of child investments, possibly confounding rather than clarifying the interpretation of the family background variables.[39]

B. *The Impact of a College Tuition Subsidy on School Attainment and Inequality*

School attainment varies considerably among endowment types as already seen in table 11. Table 14 explores these differences further and also considers the quantitative effect on school attainment of a direct college tuition subsidy of \$2,000 per year of college attendance (a reduction in tc_1 by about 50 percent). While the subsidy is limited to the college level, the value of attending high school will also increase because individuals are forward-looking and graduating from high school provides the only path to attending college. Overall, the college tuition subsidy increases the percentage of high school graduates (12 or more years of schooling) from 74.8 to 78.3. College graduation rates (16 or more years of schooling) increase from 24.2 to 31.3 percent. Because college graduation is so prevalent among type 1's regardless of the subsidy, the increases in college graduation rates are much larger for the other three types: graduation rates approximately double for types 2 and 3. Overall, the population average completed schooling level would increase by one-half year because of the subsidy, from 13.0 to 13.5 years.

Private gains from the subsidy are small. As table 15 shows, a universal subsidy would help type 1's the most in expected present value terms. Type 1's attend college regardless of the subsidy. If the cost of the program was shared strictly on a per capita basis, only type 1's would have a positive net utility gain.[40] Type 4's would lose \$406,

[39] The R^2 of the regression including AFQT is .14.

[40] Because the optimization model contains no explicit constraints on financing college, i.e., individuals can always pay the direct tuition costs (regardless of its magnitude) out of current consumption, the gross gain for any individual cannot exceed the discounted sum of the subsidies received (about \$6,000 discounted to

TABLE 14

Effect of a $2,000 College Tuition Subsidy on Selected Characteristics by Type

	All Types	Type 1	Type 2	Type 3	Type 4
Percentage high school graduates:					
No subsidy	74.8	100.0	68.6	70.2	67.0
Subsidy	78.3	100.0	73.2	74.0	72.2
Percentage college graduates:					
No subsidy	28.3	98.7	11.1	8.6	19.5
Subsidy	36.7	99.5	21.0	17.1	32.9
Mean schooling:					
No subsidy	13.0	17.0	12.1	12.0	12.4
Subsidy	13.5	17.0	12.7	12.5	13.0
Mean years in college:					
No subsidy	1.34	3.97	.69	.59	1.05
Subsidy	1.71	3.99	1.14	1.00	1.58

Note.—Subsidy of $2,000 each year of attendance. Based on a simulation of 5,000 persons.

TABLE 15

Distributional Effects of a $2,000 College Tuition Subsidy

	Type 1	Type 2	Type 3	Type 4
Mean expected present value of lifetime utility at age 16:				
No subsidy	413,911	391,162	225,026	286,311
Subsidy	419,628	392,372	226,313	288,109
Gross gain	5,717	1,210	1,287	1,798
Net gain:				
Subsidy to all types*	3,513	−994	−917	−406
Subsidy to types 2, 3, and 4†	−1,134	76	153	664
Subsidy to types 3 and 4‡	−862	−862	425	936

* The per capita cost of the subsidy program is $2,204.
† The per capita cost of the subsidy program is $1,134.
‡ The per capita cost of the subsidy program is $862.

type 3's $917, and type 2's $994. If types were observable, the subsidy could be targeted. If type 1's were not subsidized at all, the per capita cost of the program would drop from $3,513 to $1,134. In this case, type 1's would lose their share of the cost, $1,134, and type 2's would gain $76, type 3's $153, and type 4's $664. A subsidy only to the least "endowed," only types 3 and 4, would cost $862 per capita and if shared equally would imply a net gain of $425 to type 3's and $936 to type 4's. All these amounts are quite small relative to lifetime util-

age 16). Providing a subsidy in a model with explicit borrowing constraints might yield a larger private gain.

ity. The root cause of inequality, differential age 16 endowments, is offset only slightly by increased school attainment induced by the college subsidy program.

If types are unobservable to the government, family background characteristics could serve as imperfect proxies. For example, a program that provided subsidies only for those with parental incomes below the median income (see table 13) would include 60 percent of the type 3's and 4's, but would exclude only about 69 percent of the type 1's and 49 percent of the type 2's. Or, restricting subsidies only to those whose mothers did not attend college would include 82 percent of type 3's and 4's, but would exclude only 47 percent of type 1's and 17 percent of type 2's. One could reduce coverage of type 1's significantly by restricting the subsidy to those with non–high school graduate mothers. In that case, 94 percent of type 1's would be excluded. However, coverage of type 3's and 4's would fall to only 30 percent.[41]

VII. Conclusion

In this paper we have structurally estimated a dynamic model of educational and occupational choices over the life cycle using 11 years of data from the NLSY. Our framework combines earlier work by Willis and Rosen (1979), Heckman and Sedlacek (1985), and Willis (1986) that treated educational and occupational choices separately, and extends it to a dynamic setting. The estimation of this model has been made feasible by recent advances in solution and estimation methods for discrete-choice dynamic programming models (see Keane and Wolpin 1994).

We find that an augmented human capital investment model does a good job of fitting the data on the educational and occupational choices of this cohort. The model, however, is a considerable extension beyond a ''bare-bones'' human capital investment model. Of particular importance for fitting the data was the inclusion of skill depreciation during periods of nonwork, of mobility or job-finding costs, of school reentry costs, and of nonpecuniary components of occupational payoffs. A more parsimonious model, which allowed only for occupation-specific human capital accumulation (occupation-specific work experience), general human capital accumulation (schooling), and unobserved endowment heterogeneity, but did not contain these additional elements, could not explain either the degree of persistence in occupational choices or the rapid decline in schooling with age.

We used the estimates to predict the impact of a $2,000 college

[41] To the extent that parents can share in the gain, restricting the program on the basis of parental characteristics creates a potential for moral hazard.

tuition subsidy on schooling decisions and other life cycle outcomes. Our results suggest that such a subsidy would increase high school graduation rates by 3.5 percentage points and increase college graduation rates by 8.4 percentage points. However, our results also indicate that such a subsidy would have a negligible impact on the expected present value of lifetime utility. Those who would benefit most are the types with high endowments of white-collar and school-related skills, that is, those who, for the most part, would have gone to college even without the subsidy. Those who are induced to attend college by the subsidy are primarily those with a comparative advantage in blue-collar occupations and poor endowments of school-related skills. Because most of the subsidy is needed simply to bring such people to the margin of indifference between college attendance and other options (in the model individuals are not financially constrained with respect to college tuition costs), it will tend to have little effect on their lifetime wealth. Tuition subsidies of this magnitude do little to compensate for utility differences arising from endowments.

The result that college tuition subsidies can have little effect on lifetime wealth follows, in part, from a more fundamental finding: that inequality in skill endowments ''explains'' the bulk of the variation in lifetime utility. According to our estimates, unobserved endowment heterogeneity, as measured at age 16, accounts for 90 percent of the variance in lifetime utility. Alternatively, time-varying exogenous shocks to skills account for only 10 percent of the variation.

It is important to consider carefully the exact meaning of this finding. First, it does not mean that lifetime utility is for the most part predestined regardless of one's behavior. For example, our estimates indicate that the type 1 agents (those with the greatest endowment of white-collar and school-related skills) have an expected present value of lifetime utility of roughly $416,000 at age 16, provided that they make optimal choices each period. However, if they stay home at age 16 (almost always a nonoptimal choice), making all choices optimally after that, their lifetime utility falls by about $35,000.

Second, it does not mean that most of the welfare variation is genetically determined through exogenous endowments, so that inequality is ''intractable'' and cannot be significantly altered by policy. The ''endowments'' in our model are measured as of age 16. Thus they may be partly or even mostly the outcome of the investment inputs that have been made in the child from conception to age 16. We find that parental schooling and parental income (prior to age 16) are particularly significant correlates of skill endowments, arguably reflecting both parental investment behavior and intergenerational endowment heritability. However, standard measures of family background account for less than 10 percent of the variation in expected lifetime utility that arises from endowment heterogeneity. Therefore, in order to understand the source of endowment heterogeneity, given its evident importance in the determination of lifetime well-being, obtaining measurements of investments in children before age 16, including prenatal care and maternal behaviors during pregnancy, child care, child nutrition, grade school experiences, and so forth, would seem to be a critical endeavor (see, e.g., Rosenzweig and Wolpin 1994).

Appendix A

Solution Method

The standard method for solving the individual's finite-horizon optimization problem is to use backward recursion. Consider an individual entering the last decision period, $a = A$, with a particular schooling and job history. At A the individual draws random shocks from the joint $\epsilon_m(a)$ distribution, uses them to calculate the rewards, and chooses the alternative with the highest realized reward. For generality, assume that there are M alternatives. The optimal decision is given by the rule

$$d^*(\mathbf{S}(A), A) = \underset{m \in M}{\operatorname{argmax}} \{R_m(\mathbf{S}(A), A)\}. \tag{A1}$$

Thus the mth alternative is chosen, $d_m(\mathbf{S}(A), A) = 1$, if and only if $d^*(\mathbf{S}(A), A) = m$. Recall that the predetermined elements of the state space, the schooling and job histories, and an individual's endowment type are denoted as $\bar{\mathbf{S}}$. At age $A - 1$, for any given predetermined state $\bar{\mathbf{S}}(A - 1)$, it is necessary to calculate the alternative-specific value functions as given in (6). To do so requires that an M-dimension multivariate integration be performed for each of the $m = 1, \ldots, M$ alternatives at $A - 1$, namely

$$\begin{aligned} &E[\max\{R_1(\mathbf{S}(A), A), \ldots, R_M(\mathbf{S}(A), A)\} | \bar{\mathbf{S}}(A - 1), d_m(A - 1)] \qquad \text{(A2)} \\ &= \int\int \cdots \int \max\{R_1(\mathbf{S}(A), A), \ldots, R_M(\mathbf{S}(A), A) | \bar{\mathbf{S}}(A - 1), d_m(A - 1)\} \\ &\qquad \times f(\epsilon_1(A), \ldots, \epsilon_M(A))\, d\epsilon_1(A) \ldots d\epsilon_M(A). \end{aligned}$$

It is important to notice two characteristics of (A2): (i) it is in general a multivariate integral even when the shocks are stochastically independent, and (ii) it must be calculated at all the feasible state space points that can evolve at A given $\bar{\mathbf{S}}(A - 1)$ and $d_m(A - 1)$. Having calculated (A2), we know the value functions (6) at $A - 1$ up to the random draws of the $\epsilon_m(A - 1)$'s. The individual receives a set of such draws and chooses the alternative with the highest value. The decision rule at age $A - 1$ is given by

$$d^*(\mathbf{S}(A - 1), A - 1) = \underset{m \in M}{\operatorname{argmax}} \{V_m(\mathbf{S}(A - 1), A - 1)\}. \tag{A3}$$

At age $A - 1$ as at age A, the mth alternative is chosen, $d_m(\mathbf{S}(A-1), A-1) = 1$, if and only if $d^*(\mathbf{S}(A-1), A-1) = m$.

Moving backward, the individual must compute, analogously to (A2), the expected maximum of the alternative-specific value functions at every age, $a = 0, \ldots, A$. These expressions take the form

$$E[\max\{V_1(\mathbf{S}(a+1), a+1), \ldots, V_M(\mathbf{S}(a+1), a+1)\}|\bar{\mathbf{S}}(a), d_m(a)]. \quad \text{(A4)}$$

As in (A2), (A4) is an M-variate integration over the joint $\epsilon_m(a+1)$ distribution. Moreover, in order to calculate (A4), the alternative-specific value functions at $a+1$ must have been calculated for all the possible predetermined state space values at $a+1$, $\bar{\mathbf{S}}(a+1)$, that may arise given $\bar{\mathbf{S}}(a)$ and $d_m(a)$. This implies that at $a+2, a+3, \ldots, A$, the alternative-specific value functions must have been calculated at all the feasible state space points that could have arisen at those ages given $\bar{\mathbf{S}}(a)$ and $d_m(a)$. Thus, in order to solve for the $a = 0$ alternative-specific value functions, it is necessary to have calculated their counterparts at each future date at all feasible state space points. At age A, this means calculating (A2) for every combination of $\bar{\mathbf{S}}(A-1)$ and $d_m(A-1)$, that is, for every possible point in $\bar{\mathbf{S}}(A)$. Depending on how schooling and job histories are modeled, the state space at A may be extremely large.

''Exact'' numerical solution of (A4) is not feasible in the context of estimation for almost any reasonable specification of the way in which job and schooling histories matter. Therefore, we adopt an approximation method that we have previously developed (see Keane and Wolpin 1994). The approximation is based on simulating (A4), which we denote by EMAX, at a subset of the state points and interpolating the nonsimulated values using a regression function developed for that purpose. Specifically, EMAX is approximated for a randomly selected subset of the state points by Monte Carlo integration. That is, D draws are taken from the joint $\epsilon_m(a)$ distribution, the maximum of the value functions over the M choices is calculated for each draw, and these maxima are averaged over the draws to form a ''sample'' expectation. Then the EMAX values for the remaining state points are ''filled in'' with a regression function of the form

$$\begin{aligned} \text{EMAX}(\mathbf{S}(a), a) \approx\ & \text{MAXE}(\mathbf{S}(a), a) \\ & + g[\text{MAXE}(\mathbf{S}(a), a) - \overline{V_m}(\mathbf{S}(a), a)], \end{aligned} \quad \text{(A5)}$$

where $\overline{V_{\mathrm{m}}}(\mathbf{S}(a), a)$ is the expected value of $V(\mathbf{S}(a), a)$, $\text{MAXE}(\mathbf{S}(a), a)$ is their maximum (over m), that is, $\max_m\{\overline{V_{\mathrm{m}}}(\mathbf{S}(a), a)\}$, and the g function takes the explicit form

$$\pi_0 + \sum_{m=1}^{M} \pi_{1m}(\text{MAXE} - \overline{V_m}) + \sum_{m=1}^{M} \pi_{2m}(\text{MAXE} - \overline{V_m})^{1/2}. \quad \text{(A6)}$$

In (A6), the π's are freely age-varying and are estimated by ordinary least squares. Keane and Wolpin find that this approximation method performs extremely well in exactly the type of occupational choice model described above.

Appendix B

TABLE B1

ESTIMATES OF THE BASIC MODEL

A. OCCUPATION-SPECIFIC PARAMETERS

	White-Collar	Blue-Collar	Military
Skill functions:			
Schooling	.0938 (.0014)	.0189 (.0014)	.0443 (.0027)
White-collar experience	.1170 (.0015)	.0674 (.0017)	...
Blue-collar experience	.0748 (.0017)	.1424 (.0011)	...
Military experience	.0077 (.0007)	.1021 (.0021)	.3391 (.0122)
"Own" experience squared/100	−.0461 (.0032)	−.1774 (.0041)	−2.9900 (.2156)
Constants:			
Type 1	8.8043 (.0124)	8.9156 (.0126)	8.4704 (.0234)
Deviation of type 2 from type 1	−.0668 (.0047)	.2996 (.0094)	...
Deviation of type 3 from type 1	−.4221 (.0100)	−.1223 (.0079)	...
Deviation of type 4 from type 1	−.4998 (.0176)	.0756 (.0058)	...
True error standard deviation	.3301 (.0077)	.3329 (.0070)	.3308 (.0156)
Measurement error standard deviation	.4133 (.0065)	.3089 (.0055)	.1259 (.0166)
Error correlation matrix:			
White-collar	1.0010 (...)		
Blue-collar	−.3806 (.0252)	1.0000 (...)	
Military	−.3688 (.0245)	.4120 (.0505)	1.0000 (...)

B. School and Home Parameters

	School		Home
Constants:			
Type 1	43,948 (850)		16,887 (413)
Deviation of type 2 from type 1	−26,352 (757)		215 (377)
Deviation of type 3 from type 1	−30,541 (754)		−16,966 (542)
Deviation of type 4 from type 1	226 (594)		−13,128 (1,000)
Net tuition costs:			
College	2,983 (156)		. . .
Graduate school	26,357 (737)		. . .
Error standard deviation	2,312 (105)		13,394 (460)
Discount factor		.7870 (.0048)	

C. Type Proportions by Initial School Level and Type-Specific Endowment Rankings

	Type 1	Type 2	Type 3	Type 4
Initial schooling:				
Nine years or less	.1751 (· · ·)	.2396 (.0172)	.5015 (.0199)	.0838 (.0125)
10 years or more	.0386 (· · ·)	.4409 (.0344)	.4876 (.0350)	.0329 (.0131)
Rank ordering:				
White-collar	1	2	3	4
Blue-collar	3	1	4	2
Schooling	2	3	4	1
Home	2	1	4	3

Note.—Standard errors are in parentheses.

Appendix C

A. Notation

Alternatives (m): employed in white-collar occupation ($m = 1$), employed in blue-collar occupation ($m = 2$), employed in military ($m = 3$), attending school ($m = 4$), and staying at home ($m = 5$).
$d_m(a)$: equals one if alternative m is chosen at age a, zero otherwise.
$R_m(a)$: utility of the mth alternative at age a, $m = 1, \ldots, 5$.
r_m: occupation-specific skill rental price.
$e_m(a)$: occupation-specific skill at age a, $m = 1, 2, 3$.
$w_m(a)$: occupation-specific wage offer received at age a, $m = 1, 2, 3$; equal to $r_m e_m(a)$.
$g(a)$: school attainment at age a: $g(a) = g(a-1) + d_4(a-1)$, $6 < g(a) < 21$.
$x_m(a)$: work experience in occupation m ($m = 1, 2, 3$); $x_m(a) = x_m(a-1) + d_m(a-1)$.
$I(\cdot)$: indicator function equal to one if term inside parentheses is true, zero otherwise.
k: endowment type: $k = 1, 2, 3, 4$.
$\epsilon_m(a)$: stochastic productivity shocks, $m = 1, \ldots, 5$.

*B. Extended Model Specification (*k *= 1, 2, 3, 4)*

1. Reward Functions

$$\begin{aligned}
R_{mk}(a) &= w_{mk}(a) - c_{m1} \cdot I[d_m(a-1) = 0] \\
&\quad - c_{m2} \cdot I[x_m(a) = 0] + \alpha_m \\
&\quad + \beta_1 I[g(a) \geq 12] + \beta_2 I[g(a) \geq 16] \\
&\quad + \beta_3 I[x_3(a) = 1], \quad m = 1, 2, \\
R_{3k}(a) &= \exp[\alpha_3(a)] w_3(a) - c_{32} \cdot I[x_3(a) = 0] \\
&\quad + \beta_1 I[g(a) \geq 12] + \beta_2 I[g(a) \geq 16], \\
R_{4k}(a) &= e_{4k}(16) - tc_1 \cdot I[12 \leq g(a)] - tc_2 \cdot I[g(a) \geq 16] \\
&\quad - rc_1 \cdot I[d_4(a-1) = 0, g(a) \leq 11] \\
&\quad - rc_2 \cdot I[d_4(a-1) = 0, g(a) \geq 12] \\
&\quad + \beta_1 I[g(a) \geq 12] + \beta_2 I[g(a) \geq 16] \\
&\quad + \beta_3 I[x_3(a) = 1] + \gamma_{41} a + \gamma_{42} I(16 \leq a \leq 17) + \epsilon_4(a), \\
R_{5k}(a) &= e_{5k}(16) + \beta_1 I[g(a) \geq 12] + \beta_2 I[g(a) \geq 16] \\
&\quad + \beta_3 I[x_3(a) = 1] + \gamma_{51} I(18 \leq a \leq 20) \\
&\quad + \gamma_{52} I(a \geq 21) + \epsilon_5(a).
\end{aligned} \tag{C1}$$

2. Skill Technology Functions

$$\begin{aligned}
e_{mk}(a) = \exp\{&e_{mk}(16) + e_{m11} g(a) + e_{m12} I[g(a) \geq 12] \\
&+ e_{m13} I[g(a) \geq 16] + e_{m2} x_m(a) - e_{m3} x_m^2(a)
\end{aligned}$$

$$+ e_{m4} I(x_m > 0) + e_{m5}(a) + e_{m6} I(a < 18) \quad \text{(C2)}$$
$$+ e_{m7} d_m(a-1) + e_{m8} x_{m' \neq m}(a) + e_{m9} x_3(a)\}$$
$$\times \exp[\epsilon_m(a)], \quad m, m' = 1, 2; a = 16, \ldots, 65.$$
$$e_3(a) = \exp[e_3(16) + e_{31} g(a) + e_{32} x_3(a) - e_{33} x_3^2(a) + e_{34} I(x_3 > 0) + e_{35}(a) + e_{36} I(a < 18)]. \quad \text{(C3)}$$

3. Initial Conditions ($S(16)$)

Skill endowments: $e_{1k}(16)$, $e_{2k}(16)$, $e_{3k}(16)$, $e_{4k}(16)$, and $e_{5k}(16)$.
School attainment: $g(16)$ given.
Work experience: $x_m(16) = 0$.
State space: $\mathbf{S}(a) = \{S(16), a, g(a), x_m(a): \{m = 1, 2, 3\}, d_m(a-1): \{m = 1, 2, 4\}, \epsilon_m(a): \{1, \ldots, 5\}\}$.

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