Federal Reserve Bank of Minneapolis
Research Department

The Career Decisions of Young Men

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Working Paper 559

October 1995

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This paper presents a dynamic structural model of schooling, work and occupational choice decisions over the life cycle, estimated on data for young men from the 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (NLSY). A key innovation of our work is that we treat decisions on school attendance, work and occupational choice as being made jointly. Previous research has generally treated these decisions in isolation. Yet, it is clearly important to consider them jointly because, for example, optimal school decisions depend on the probabilities individuals assign to future occupational choices, and optimal occupational choices depend on the degree of transferability of human capital across occupations. Another important aspect of our work is that we take human capital investment theory seriously as a potential vehicle for explaining observed patterns of school attendance, work, occupational choice and wages. Thus, we adopt a structural estimation framework in which the restrictions of the theory are fully imposed in estimation, and then investigate if such a theoretically restricted model can succeed in "explaining" observed data patterns.

We find that a 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. Our structural model also produces very reasonable forecasts of the future work decisions and wage patterns for the youth cohort. Given such a structural approach to modelling joint educational and occupational choices, we can perform policy experiments to predict how interventions such as college tuition subsidies would affect not only college attendance rates, but also subsequent occupational choice decisions and lifetime wealth realizations. Arguably it is these later outcomes, rather than college attendance per se, that are actually of interest when considering impacts of tuition subsidies. Yet previous research that separates school from work decisions is limited in its ability to address such questions. Furthermore, we can also examine how exogenous events, such as a shock that causes one to not attend school at age 16, affect later life cycle outcomes, such as subsequent school attendance, future occupational choices and lifetime utility.

In order to understand the contribution of the present work it is useful to set it within the context of the existing literature on human capital investment. There exists a large literature in which the general theory of human capital accumulation has been used to interpret earnings functions and life cycle earnings profiles.[1] From its first statements and formalizations (Mincer (1958), Becker (1964), Ben-Porath (1969)), the theory has been related to observable measures of human capital investments such as schooling, work experience, and occupational choice. The novelty of treating skill acquisition as an investment in which there is a trade-off between current and future income led early on to considerable empirical research on quantifying the return to the investment. In the early "rate of return" literature, schooling was treated as if it were exogenously assigned to individuals in the population. Then, internal rate of return calculations were based on a straightforward comparison of deterministic earnings streams among school completion groups.

This early literature ignored the implications of the fact that school attendance 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 and/or financing constraints 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)).[2]

The treatment of work experience, i.e., 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, preferences, 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.[3]

For simplicity, much of the literature has assumed human capital to be homogeneous. This allows one to focus specifically on the work vs. not work decision. However, there has been a parallel and complementary literature in which the multi-dimensional nature of skills is prominent.[4] In Willis (1986), skills are occupation-specific and are perfect substitutes over workers within occupations. Worker's self-select into occupations based on the quantities of occupation-specific skills they have (their endowments) and on skill rental prices, which together determine potential earnings in each occupation. As in the case of schooling and general work experience an important selection bias problem arises. Comparing earnings of individuals in different occupations will not provide an accurate assessment of the differential productivity of human capital investments among occupations due to the self-selection mechanism.

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 of the 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 in which the environment is uncertain. We also allow for non-pecuniary aspects of occupations, for entry costs into occupations that depend on prior work experience, for post high school tuition costs and school re-entry costs, for home production, and for endowment heterogeneity. The estimation of the model involves the repeated numerical solution of a discrete choice finite horizon optimization problem, formulated as a dynamic programming (DP) problem.[5] Although the computational problem is substantial, it is made feasible by an approximate solution method for DP problems recently developed in Keane and Wolpin (forthcoming).

To implement the model we use the first 11 rounds of the NLSY. We follow approximately 1400 white males in the sample 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, and thus affecting 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 which are unknown prior to the current period. Thus, individuals take divergent schooling and occupation career paths because of the cumulative effects of the shocks and because they have heterogeneous endowments.

The outline of the paper is as follows: In section 1 we describe the structure of our model in detail and the approximate solution method we employ. Section 2 describes the NLSY data on which we estimate the model. Section 3 contains our empirical results. In section 4 we discuss the implications of our model in three important areas: 1) the importance of unobserved skill heterogeneity in determining life cycle outcomes, 2) the long term impact of not attending school at age 16, and 3) the impact of college tuition subsidies on life cycle outcomes. Section 4 concludes.

I. Model

a. Structure

Each individual has a potential working life of A periods, beginning at age a=0. At any age an individual can choose among M + 3 mutually exclusive and exhaustive alternatives: work in any of M civilian occupations, work in the military (M+1), attend school (M+2), or engage in home production (M+3).[6] Let $d_m(a) = 1$ if alternative m is chosen, m=1,...,M+3, at age a, and equal zero otherwise. Per period utility at any age a is given by

$$(1) \quad U(a) = \sum_{m=1}^{M+3} R_m(a) d_m(a)$$

where $R_m(a)$ is the per-period reward associated with the mth alternative. These rewards contain all of the benefits and costs, pecuniary and psychic, associated with each alternative. In particular, the rewards include, where applicable, direct wage payments, entry or job-finding costs, non-pecuniary valuations of occupations or fixed costs of work, tuition costs for schooling, psychic and pecuniary diploma effects, skill depreciation, and school re-entry costs. Current period rewards are specified as follows:

$$R_m(a) = w_m(a) - c_{m1}\cdot I(d_m(a-1)=0) - c_{m2}\cdot I(x_m(a)=0) + \alpha_m + \beta(a)\ , \quad m=1,\ldots,M$$

$$R_{M+1}(a) = \exp(\alpha_{M+1}(a))w_{M+1}(a) - c_{M+1,2}\cdot I(x_{M+1}(a)=0) + \beta'(a)\ ,$$

$$(2) \quad R_{M+2}(a) = -tc_1\cdot I(12 \leq g(a)) - tc_2\cdot I(g(a) \geq 16) + \alpha_{M+2}(a) - rc_1\cdot I(d_{M+2}(a-1)=0, g(a) \leq 11)$$
$$- rc_2\cdot I(d_{M+2}(a-1)=0, g(a) \geq 12) + \beta(a)\ ,$$

$$R_{M+3}(a) = \alpha_{M+3}(a) + \beta(a)\ ,$$

where I is an indicator function equal to one if the enclosed expression is true and equal to zero otherwise.[7] As seen in (2) there are both alternative-specific components (subscripted by m) and common components to the rewards. We consider first the alternative-specific components, then the common rewards, and finally we extend the model to allow for endowment heterogeneity.

I. Working in a Civilian Occupation ($d_m(a)=1$; $m=1,\ldots,M$):

(1) Pecuniary rewards:

(a) Direct compensation: The current period pecuniary return to working in a civilian occupation 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.[8] The latter will depend on the technology of skill production. It is assumed that the level of skill accumulated up to any age depends on the individual's current age, schooling history (sh) and job history (jh) at that age, on the individual's skill endowment in that occupation, and on an age-varying skill technology shock. Letting $e_m(a)$ be the number of skill units possessed at age a, $e_m(0)$ the skill endowment, and $\epsilon_m(a)$ a skill technology shock, the wage offer for occupation m is

$$(3) \quad w_m(a) = r_m e_m(jh(a),\ sh(a),\ e_m(0),\ a)\ \exp(\epsilon_m(a)), \quad m=1,\ldots,M.$$

The randomness in the wage arises from purely idiosyncratic shocks that are independent of calendar time.[9]

The state variables for schooling that affect skill acquisition are assumed to be given by the total number of years of schooling (successfully) completed, $g(a)$, by whether a high school diploma was earned, $I(g(a) \geq 12)$, and by whether a college diploma was earned, $I(g(a) \geq 16)$. Job histories are summarized by the total number of periods worked in each occupation, $x_m(a)$, (occupation-specific experience), by an indicator variable denoting whether or not the individual worked in the same occupation in the previous period (skill depreciation effect), $d_m(a-1)$, and ever, $I(x_m > 0)$, a first-year experience effect. The technology of skill production in the three civilian occupations are thus:

$$
\begin{aligned}
e_m(a) = \exp\{ & e_m(0) + e_{m11} g(a) + e_{m12} I(g(a) \geq 12) + e_{m13} I(g(a) \geq 16) \\
& + e_{m2} x_m(a) - e_{m3} x_m^2(a) + e_{m4} I(x_m > 0) + e_{m5}(a) + e_{m6} I(a < 18) \\
& + e_{m7} d_m(a-1) + \sum_{n(\neq m)=1}^{M} e_{m,n+7} x_n(a) \}, \qquad m = 1,..M.
\end{aligned} \tag{4}
$$

Note that the specification allows accumulated experience in one occupation to affect the skill levels in other occupations, although to conserve on parameters, unlike "own" experience which has a quadratic effect, the cross experience effects are only linear. In addition, we allow for a linear age effect and for an age less than 18 effect.

(b) Mobility and job search costs: Obtaining a job in a particular occupation is assumed to carry a cost. The cost of finding a job in occupation m if the person has worked in that occupation previously, but is not currently working in occupation m, is c_{m1}. If the person has no prior work experience in that occupation, there is an additional cost of c_{m2}.

(2) Non-pecuniary rewards: We allow for non-pecuniary aspects of employment in the M civilian occupations. Specifically, the current period reward for each civilian occupation is

augmented by α_m , m=1,...,M, the net (positive or negative) monetary-equivalent value of working conditions and/or indirect compensation associated with the mth occupation. Alternatively, these parameters can be interpreted as occupation-specific fixed costs of work.

II. Working in the Military Occupation ($d_{M+1}(a)=1$):

(1) Pecuniary rewards: The pecuniary reward, the wage, associated with working in the military occupation is treated symmetrically to that of civilian sector occupations. The current reward is a restricted version of equation (4). In particular, there are no diploma effects, no white- or blue-collar cross-experience effects, and no skill depreciation effect. Unlike civilian occupations, there is a cost of entering the military only if one has no prior military experince, (i.e we set $c_{M+1,1}=0$).[10]

(2) Non-pecuniary rewards: The non-pecuniary 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, non-pecuniary aspects of military employment must be fully compensated in its rental price (wage) and, in equilibrium, their existence cannot affect an individual's choice. To accommodate this assumption, the military reward is written as the wage multiplied by the exponential of $\alpha_{M+1}(a)$, i.e., the total reward, inclusive of the non-pecuniary component, is proportionate to the wage.[11]

III. Attending School ($d_{M+2}(a)=1$):

(1) Direct tuition costs of schooling: Direct schooling costs are assumed to be zero through high school. College and graduate school tuition costs are denoted by tc_1 and tc_2, and are subtracted from the gross reward associated with school attendance.

(2) Psychic rewards: The psychic value of attending school, $\alpha_{M+2}(a)$, the direct consumption value net of the "cost" of effort, is allowed to depend on age.[12] There are also

psychic costs of re-entry into school following a school interruption, denoted by rc_1 in the case of high school and by rc_2 in the case of college and graduate school.[13]

IV. Remaining at Home $(d_{M+3})=1)$:

The payoff to remaining home depends on the parameter $\alpha_{M+3}(a)$. This m... be interpreted either as the value of home production or the psychic value of leisure during a period. It is allowed to be age-dependent.

V. Common Returns

$\beta'=\beta_1 I(g(a)\geq 12)+\beta_2 I(g(a)\geq 16)$ and $\beta=\beta'+\beta_3 I(x_{M+1}=1)$ are common rewards. The first term (β_1), the psychic value of having earned a high school diploma and the second (β_2), the additional psychic value of a college diploma, enter all alternatives. However, (β_3) the cost of leaving the military prematurely, that is, without having remained there for at least two years enters the rewards of all alternatives except the military.[14] That is, choosing any alternative other than the military given that the individual has exactly one year of military experience leads to a loss in the reward associated with the alternative.

VI. Endowment Heterogeneity

Individuals may not have identical endowments. Specifically, define a type k individual, $k=1,..,K$, by an endowment vector $(e_{mk}(0){:}m=1,..M+1;\ \alpha_{mk}(0){:}m=M+2,M+3)$. Thus, individuals may have comparative advantages in different alternatives, including schooling and home production. Types are common knowledge.

Both α_{M+2} and α_{M+3} are assumed to be subject to additive shocks, namely $\alpha_{M+j}(a)=\bar{\alpha}_{M+j}(a)+\epsilon_{M+j}(a)$ for $j=2,3$. The M+3 random shocks, that is, the M+1 shocks to the number of skill units supplied to the M civilian occupations and to the military, the shock to the psychic value of attending school, and the shock to home production, are assumed to be mutually serially independent.[15] They may, however, be contemporaneously correlated. We assume that the five stochastic elements of the model are joint normal. The joint density of these shocks is denoted as $f(\epsilon_m(a))$.

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

$$(5)\quad V(S(a),a) = \max_{d_m(a)_{m\in M}} E\,[\sum_{\tau=a}^{A} \delta^{\tau-a} \sum_{m=1}^{M} R_m(\tau)d_m(a)\,|\,S(a)]\ .$$

The state space consists of all factors, known to the individual, that affect current rewards or the probability distribution of future rewards. Thus, 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 $m=1,\ldots,M+3$.[16] 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 distributions of shocks and endowments). The maximization in (5) is achieved by choice of the optimal sequence of control variables $\{d_m(a):m=1,..,M+3\}$ for $a=0,\ldots,A$.

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

$$(6)\quad V(S(a),\ a) = \max_{m\in M} \{V_m(S(a),\ a)\}\ ,$$

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

$$
\begin{aligned}
V_m(S(a),a) &= R_m(S(a),a) \\
&\quad + \delta\, E\,[V(S(a+1),a+1)\,|\,S(a);d_m(a)=1], \quad a<A, \qquad (7)\\
V_m(S(A),A) &= R_m(S(A),A) \quad .
\end{aligned}
$$

The expectation in (7) is taken over the distribution of the random components of $S(a+1)$ conditional on the random components of $S(a)$. In this case, because the shocks are serially independent, the expectation is taken over the joint density of the shocks at a, $f(\epsilon_1(a),\ldots,\epsilon_{M+3}(a))$. The other state variables, the schooling and job histories, evolve in a Markovian manner that is (conditionally) independent of the shocks, for example, $x_m(a+1)=x_m(a)+d_m(a)$ in the case of occupation-specific work experience. In addition, all state variables have given initial conditions at $a=0$. Notice that the dependence of the current period reward on the state space, or a subset of it, is made explicit in (7). The Bellman optimality principle, as seen in (7), implies that future choices are made optimally.

b. Solution Method

The standard method for solving the individual's finite horizon optimization problem is by backwards recursion. Consider an individual entering the last decision period, $a=A$, with a particular schooling and job history. At A the individual draws $M+3$ random shocks from the joint $\epsilon_m(A)$ distribution, uses them to calculate the $M+3$ rewards, and chooses the alternative with the highest realized reward. The optimal decision is given by the rule

$$(8) \quad d^*(S(A),\, A) = \underset{m\in M}{\arg\max}\ \{R_m(S(A),\, A)\}\,.$$

Thus, the mth alternative is chosen, $d_m(S(A),A)=1$, if and only if $d^*(S(A),A)=m$.

To outline the solution method, it is convenient to denote the predetermined elements of the state space, the schooling and job histories, and an individual's endowment type, as $\bar{S}(a)$. At age A-1, for any given predetermined state $(\bar{S}(A-1))$, it is necessary to calculate the alternative-specific value functions (7). To do so requires that an M+3 multivariate integration be performed for each of the m=1,...,M+3 alternatives at A-1, namely

$$
\begin{aligned}
&E[\max(R_1(S(A),A),\ldots,R_{M+3}(S(A),A)) \mid \bar{S}(A-1),\ d_m(A-1)] \\
(9) \qquad &= \int\int \cdots \int \max(R_1(S(A),A),\ldots,R_{M+3}(S(A),A) \mid \bar{S}(A-1), d_m(A-1)) \\
&\qquad f(\epsilon_1(A),\ldots,\epsilon_{M+3}(A))\ d\epsilon_1(A)\ldots d\epsilon_{M+3}(A) \quad .
\end{aligned}
$$

It is important to notice two characteristics of (9): (i) It is in general a multivariate integral even when the shocks are stochastically independent, and (ii) It must be calculated at all of the feasible state space points that can evolve at A given $\bar{S}(A-1)$ and $d_m(A-1)$. Having calculated (9), the value functions (7) at A-1 are known 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

$$(10) \quad d^*(S(A-1),\ A-1) = \underset{m \in M}{\operatorname{argmax}} \{V_m(S(A-1),\ A-1)\}.$$

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

Moving backwards, the individual must compute, analogously to (9), the expected maximum of the alternative-specific value functions at every age, a=0,...,A. These expressions take the form

$$(11) \quad E[\max(V_1(S(a+1),a+1),\ldots\ldots,V_{M+3}(S(a+1),a+1)) \mid \bar{S}(a), d_m(a)] \quad .$$

As in (9), (11) is an M+3-variate integration over the joint $\epsilon_m(a+1)$ distribution. Moreover, in order to calculate (11), the alternative-specific value functions at a+1 must have been calculated for all of the possible predetermined state space values at a+1, $\bar{S}(a+1)$, that may arise given $\bar{S}(a)$ and $d_m(a)$. This implies that at a+2,a+3,...,A, the alternative-specific value functions must have been calculated at all of the feasible state space points that could have arisen at those ages given $\bar{S}(a)$ 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 (9) for every combination of $\bar{S}(A-1)$ and $d_m(A\text{-}1)$, i.e., for every possible point in $\bar{S}(A)$. Depending on how schooling and job histories are modeled, the state space at A may be extremely large.

"Exact" numerical solution of (11) is not feasible in the context of estimation (discussed below) 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 in Keane and Wolpin (forthcoming). The approximation is based on simulating (11), which we denote by EMAX, at a subset of the state points and interpolating the non-simulated 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+3 choices is calculated, 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

$$\text{(12)}\quad EMAX(S(a),a) \approx MAXE(S(a),a) + g(MAXE(S(a),a) - \bar{V}_m(S(a),a)),$$

where $\bar{V}_m(S(a),a)$ is the expected value of V(S(a),a) and MAXE(S(a),a) is their maximum (over m), i.e., $\max_m(\bar{V}_m(S(a),a)$, and where the g function takes the explicit form

$$(13) \quad \pi_0 + \sum_{m=1}^{M+3} \pi_{1m}(MAXE - \bar{V}_m) + \sum_{m=1}^{M+3} \pi_{2m}(MAXE - \bar{V}_m)^{\frac{1}{2}}.$$

In (13), the π's are freely age-varying and are estimated by ordinary least squares. Keane and Wolpin (forthcoming) find that this approximation method performs extremely well in exactly the type of occupational choice model described above.

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. Consider 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, say in the age range $[0,\bar{a}]$. [17] In addition, assume, as is commonly the case, that the rewards (more precisely, the wage component of the rewards) are observed only in the periods in which market work is chosen and only for the occupation that is chosen. Thus, for each individual, n=1,...,N, the data consist of the set of choices and rewards $\{d_{nm}(a), w_{nm}(a)d_{nm}(a): m=1,..,M+1\}$ and $\{d_{nm}(a): m=M+2,M+3\}$ for all ages in the given range. Let c(a) denote the choice-reward combination at age a. Serial independence of the shocks implies that the probability of any sequence of choices and rewards for a given endowment type k can be written as follows:

$$(15) \quad \begin{aligned} &Pr(c(0),c(1),\ldots\ldots,c(\bar{a}) \mid sh(0),jh(0),type=k) \\ &\qquad = \prod_{a=0}^{\bar{a}} Pr(c(a) \mid sh(a),jh(a),type=k). \end{aligned}$$

If we observed an individual's type, the sample likelihood would be the product of the probabilities in (14) over the N individuals. Assume that endowment heterogeneity is unobserved by us, but that we know there to be K types. Denote π_k as the proportion of the kth type in the population. In this case, the likelihood function is a mixture of the type-specific likelihoods, i.e., $\prod_{n=1}^{N}\{\sum_{k=1}^{K}\pi_k L_{nk}\}$, where L_{nk} is the likelihood of person n's observed choice sequence and rewards if person n is of endowment type k, and where the parameter vector is augmented to include the endowment vectors for the K types and the type probabilities.[18] The solution to the dynamic program provides the elements of the right hand side of (15).[19]

II. Data

The data are from the 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (NLSY). The NLSY consists of 12686 individuals, approximately half of them men, who were 14 to 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 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 each individual in the subsample defined above from the first year they reach age 16 as of October 1 of that year through September 30, 1988.

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 enrollment in each calendar month, 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 was collected back to January 1, 1978.

The behavioral model is implemented on annual aggregates of the discrete alternatives beginning as of the first time the individual was age 16 on October 1 of any particular year.[20] The sample consists of 1373 individuals who are first observed according to the above criterion in the years 1977-1981, with 98.4 percent of the first year observations between 1977 and 1980. Definitional arbitrariness in assigning observations to alternatives is unavoidable given that the assumed decision period is longer (annual) than the weekly observation period. The assignments were made as follows:

(1) Enrolled in school: To simplify the determination of school enrollment, we looked at an individual's activity in the 40th week of each year (October 1), the first week of each year (January 1), and the 14th week of each year (April 1), beginning with January 1, 1978. An individual is considered to be enrolled in school during the year if the individual was enrolled in any of the three weeks <u>and</u> the individual reported completing one grade level by October 1 of the next year.[21,22]

(2) Worked: The work assignment used data on work status in nine weeks, again to simplify the classification, between October 1 and June 30.[23] An individual is considered to have worked during the year if the individual was not enrolled in school and was employed in at least two-thirds of the weeks for at least 20 hours per week on average.[24]

(a) Occupation Classification: A working individual is assigned to any one of three occupations, blue-collar (BC), white collar (WC) and the military (ML). 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).[25] Aggregating occupations into just two categories implies that the disaggregated occupations within each category utilize the same type of skill units. Although a finer disaggregation would probably be desirable, a non-trivial number of year-to-year transitions between finer occupational categories (even between one-digit codes) appears to be spurious.[26] 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 fifty weeks. The wage is, therefore, a "full-time" equivalent.[27]

(3) Home: An individual is classified as being at home during the year if the individual was neither enrolled in school nor worked during the year, according to the above definitions. 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 criterion.

Table one shows the choice distribution by the ages that span the eleven years of data (from October 1, 1977 through September 30, 1988), namely ages 16 through 26. There are 1373 individuals in the sample at age 16; the number declines slightly over the first eight years primarily due to sample attrition.[28] Over the last three years the sample size falls because of the right censoring that arises 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, approximately 86 per cent of the sample is in school at age 16. There is an 11 percent drop by age 17, and by age 18, only 42 percent of the sample is enrolled. Enrollment declines steadily from there, reaching only 8.5 percent by age 23. Less than five percent of individuals are still in school at age 25. The propensity to work increases monotonically from less than four per cent at age 16 to almost 37 percent at age 18, 77 percent at age 23 and 86 percent at age 25. However, the pattern differs considerably by occupation.

Participation in both white- and blue-collar occupations increase monotonically, but at different rates. At age 18 there are four times as many individuals working in the blue-collar occupation than in the white-collar occupation, by age 22 there are twice as many, but by age 15 there are only 25 percent more. Moreover, participation in the blue-collar occupation is essentially unchanged after age 22, while 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 the movement into white-collar employment. Participation in the military increases to a peak of 8.5 percent at age 20, and then declines to about 4 percent at age 25.[29] Perhaps somewhat surprisingly, more than one-fifth of the sample is at "home" at each of the ages from 18 to 21, rising from 10 per cent at age 16. The proportion at home falls steadily after age 21, reaching ten percent at age 25.

The one-period transition matrix is reported in Table 2. The first figure shows the percent of transitions from origin to destination (the row percent) and the second the reverse, that is, the percentage in a particular destination who started from each origin (column percent). 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 percent), while of those in school in any year 91 percent came from school the previous year (column percent). Leaving school and returning is a reasonably rare event.[30] 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 sixty percent of the remaining transitions are into the blue-collar occupation and about 20 percent return to school.

Table 2 also reveals substantial state dependence in occupation-specific employment.

Over two-thirds of the current white-collar observations remain in white-collar employment in the next period, with the comparable figure being around three-fourths for blue-collar employment and four-fifths for military employment. In addition, the transition 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 inter-occupational 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), while 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 is 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 level nine through 17. Note that because the unit of observation is the person-period and thus an individual appears several times even at the same schooling level, the figures in the second row do not correspond to usual continuation rates. The pattern is for continuation rates to 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 obtaining 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 emplovment 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 increases beyond the first year, at least until the individual has five years of military experience. It is this decline between the first two years of experience that accounts for the inclusion of the military exit cost parameter, β_3, in the reward structure (2).

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.

III. Estimation Results

1. Parameter Estimates

Tables 5-7 provide the estimated parameters and their associated standard errors[31]. The occupation-specific parameters, shown in Table 5, are divided into four categories, those corresponding to skill functions, to non-pecuniary 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 seven percent, blue collar skill by 2.4 percent and military skill by 5.8 percent. (2) Graduating from high school, that is completing the twelfth grade, has substantively no additional impact on skills in either the white- or blue-collar occupation. Graduating from college also has a negligible impact on either white- or blue-collar skills over and above the completion of the additional year of schooling.[32] (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*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*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*x_3 percent after the first year. Military earnings peak at 45 years. An additional year of military experience increases skills in white-collar occupations by 1.3 percent and in blue-collar occupations by 1.7 percent. (7) White-collar skills depreciate much more rapidly than do 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, while blue-collar skill is only 9.6 percent lower under a similar circumstance. Non-continuous employment in an occupation is costly in terms of skill acquisition. (8) Age effects are similar among the occupations, skill in each being augmented by about one percent per year. Skill levels are considerably lower for those less than eighteen years of age (given schooling, experience, etc.). (9) Skill variance is approximately the same for the civilian occupations, but considerably lower for the military. Shocks to white-collar skills are essentially uncorrelated with those to either blue-collar or military skill, while shocks to blue-collar skill and military skill have a simple correlation of .473. (10) Military wages are reported with the most error; measurement error accounts for 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 2543 dollars due to its non-pecuniary aspects or to fixed (yearly) costs of working. In the case of blue-collar employment, the reward is reduced by 3157 dollars. 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. With respect to the military, the estimates indicate that the total reward is 9 percent less than the wage at age 16 and decreases by an additional 3.1 percent of the wage for each additional year of age.[35] The cost of finding a white-collar job is 3941 dollars if the individual has no previous white-collar experience and 1181 dollars if the individual has white-collar experience but did not work in a white-collar occupation in the previous period. These entry costs do not differ substantially on the basis of experience in the case of blue-collar occupations, being 2141 and 1647 dollars respectively. The cost of entering the military is 560 dollars if one has no previous military experince. Finally, the cost of exiting the military prematurely is 1525 dollars per year.

The estimated school and home parameters are shown in Table 6. The per period reward associated with attending school has the following selected features: (1) The net consumption value of attending schooling (net, for example, of the cost of effort) for a 16 year old ranges from as low as the monetary equivalent of 5763 dollars (11031-8900+3632) of the consumption good for a person of type 3 to as high as 14663 dollars for a person of type 1. The consumption value of schooling declines for each type by 1502 dollars between the ages of 16 and 17, by an additional 5134 (3632+1502) dollars between the ages of 17 and 18 and by a further 1502 dollars for each additional year of age thereafter. (2) The consumption value of all alternatives is augmented by 804 dollars upon receiving a high school diploma and by 2005 dollars upon receiving a college diploma. (3) The net tuition cost, net of the psychic differential consumption value of attending college, is 4168 dollars, while the net cost of attending graduate school is 11197 (4168+7030) dollars. (4) The psychic or effort cost of attending high school (college) in a period followed by non-attendance is higher by 23283 (10700) dollars.

With respect to the home alternative, the value of being home is roughly constant with age, ranging from as low as 5564 for type 3 persons to as much as 20242 for type 1 persons. As also seen in the table, the discount factor is estimated to be .936.

Table 7 shows the proportion of individuals that are of each of the four endowment types. In estimation, we allowed for the distribution of types to differ by the level of schooling that had been attained by age 16 (initial schooling). Sixty-seven percent of the individuals had attained grade ten by age 16, with an additional 7.5 percent attaining grade eleven. 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 of any given year. Approximately 60 per cent of the individuals are either of type 2 or type 3 regardless of whether they had completed at least ten years of schooling by age 16. However, only five percent of those with less than 10 years of schooling are of type 1, while almost a quarter of those with ten years or more of schooling are of that type, with the appropriate remainders in each group being of type 4. The table also shows relative endowment rankings: type 3's, the largest group in the population, have the lowest endowments in all of 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.

2. Model Fit

Figures 1.1-1.5 graphically depict the fit of the model to the actual choice distribution. For comparison purposes we also report the fit of a static model, which is identical to our model in terms of the specifications of the payoff functions, but in which the discount factor is set to zero. In addition, we report the fit of a model based on a linear-in-parameters approximation to the alternative-specific value functions in terms of their relevant state variables. This takes the form of a five-alternative panel probit model with unobserved heterogeneity introduced by allowing the intercept vector to have four possible values.[34] The figures also show the forecasts of each model through age 65, well beyond the actual data. From the graphs, it is difficult to distinguish the within-sample fit of the three models. However, out-of-sample forecasts diverge considerably. The static model predicts rapid changes in the choice constellation with age, culminating in almost everyone opting for white-collar employment by age 50. Although neither the approximation model nor the dynamic programming model forecast such extreme outcomes, they nevertheless differ in important ways. In general, the approximation model tends to more closely extrapolate trends in within-sample age profiles. This is most apparent in the forecasts for the military and home alternatives. The dynamic programming model forecasts less white-collar employment and more blue-collar employment over the life cycle than does the approximation model.

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 164261 dollars, while the blue-collar wage forecast is 93390. The corresponding forecasts for the dynamic programming model are 48497 and 42222. The static model's forecasts are clearly unreasonable.

Table 8 presents within-sample chi-square 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.[35] However, the dynamic programming model has the most difficulty with the fit at normal college leaving ages (21 to 23), while the approximation model fits worst at the extremes (ages 16, 23-26). It should be recognized that while the dynamic programming model contains eight more parameters than does the approximation model, it is fitting the wage data as well as the choice data. Although there are some "free" parameters (in the sense that some parameters appear in only the wage (skill) function or in the non-wage components of the rewards, but not in both) the dynamic programming model is still restricted in terms of how it can fit the choice data alone.

To assess the impact of the decision process on estimated wage functions, we ran within-occupation OLS regressions of actual wages on the same set of regressors as in the dynamic programming model. The schooling coefficients in those regressions were .07 for white collar wages, .04 for blue-collar wages, and .03 for military wages. While these appear to be relatively close to the estimates in table 5, the OLS estimates of high school and college degree effects differ greatly. Having a college degree is estimated to augment white collar wages by 30 percent and blue collar wages by 18 percent. Even more striking are the experience effects estimated from the regressions. After the first year of white-collar experience, each additional year increases wages at low levels of experience by 13 percent, as opposed to the 2.7 percent estimate in table 5. The former figure is also roughly the blue-collar experience effect in the blue-collar wage regression. Moreover, depreciation effects are estimated to be significantly smaller from the regressions than from the dynamic programming model.

IV. Discussion

1. The Importance of Unobserved Skill Heterogeneity

As seen in Tables 5-7, there is considerable variation in type-specific endowments of civilian occupation skills, and in school and home productivities. Table 9 presents selected characteristics at age 24, based on a simulation of our estimated model. By age 24, types differ substantially in their completed schooling levels, work experience, and in their current choices, holding constant their schooling at age 16. 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 higher 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 the 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 in the military, and type 4's 31 percent of their post-schooling 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 given by the expectation of (5), as well as the expected alternative-specific value functions given by the expectation of (6), can be calculated at any feasible age-state combination.[36] At age 16, the only relevant state is initial schooling and type. Table 10 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 expected present discounted value of lifetime utility at age 16 is 307673 dollars, 321921 dollars for those with ten or more years of initial schooling and 275634 dollars for those with nine years or less.

The differences in lifetime utility due to variation in initial schooling are small relative to some of the differences due to endowment heterogeneity related to type. For instance, type 1's with ten years of initial schooling have a 28000 dollar larger expected lifetime utility than type 1's with nine or less, the largest difference for any type. On the other hand, holding initial schooling fixed, the greatest difference in expected lifetime utility among the types is about 185000 dollars (between type 1 and 3) for the higher level of initial schooling and 175000 for the lower level.

Interestingly, type 2 persons have much higher expected present values of lifetime utility than do type 3's, even though both are essentially blue-collar types (although type 3's have their careers interrupted by military service). Type 2's are well endowed with blue-collar skill, while 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, while 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, based on the simulated data, the between-type variance in expected lifetime utility is calculated to account for 90 percent of the total variance. Because of this result it is especially disturbing that unobserved heterogeneity is usually a black box. However, while we cannot determine each individual's actual type, Bayes' rule can be used to compute the probability of being an endowment type conditional on choices, wages, and initial schooling. Given these endowment-type probabilities for each individual, we can determine the extent to which observed family background characteristics are related to type.

The first row of Table 11 shows the baseline joint distribution of types and initial schooling in the sample. Compared to the baseline, those individual's whose mothers had completed less than twelve years of schooling are substantially more likely to have completed nine years or less schooling at age 16 and jointly to be of type 2, 3, or 4. They are significantly less likely to have completed 10 or more years of school at age 16 and jointly to be of type 1 or 2. Further, as the last column of the table indicates, having a mother who did not graduate from high school is associated with 21000 dollars lower expected lifetime utility than the average individual. The difference in expected lifetime utility between having a mother who is a college graduate and one who did not graduate from high school is 53000 dollars, or 18 percent.

Household structure seems to be quantitatively less strongly related to lifetime welfare than is maternal schooling. Lifetime utility for a person who was living with both parents at age 14 is between 14,000 and 20,000 dollars higher than other living arrangements, living at age 14 with either of the biological parents alone or with neither. Lifetime utility is also related to the number of siblings; individuals having only one other sibling have the highest lifetime utility, 10000 dollars more than either only children or those having two siblings. Persons from families with five or more children have expected lifetime utility of almost 25000 dollars less than those from two-child families.

Parental income in 1978, when the individuals in the sample were 14 to 17 years old, also seems to be significantly related to endowment type. Those whose parents' incomes were below the median income of the sample have an expected lifetime utility that is roughly 20000 dollars lower than those whose parents' incomes were above the median but less than twice the median, and over 60000 dollars lower than those whose parents' incomes were at least twice the median.

We also ran regressions of the expected present value of lifetime utility of each individual in the sample on family background characteristics. In terms of statistical and quantitative significance, father's schooling and parental income are the most important variables. But, a regression that included these variables along with mother's schooling, number of siblings and whether the person lived with both parents at age 14 explained only 10 percent of the variance in expected present value of lifetime wealth. Ideally, one would like to relate endowments at age 16 (summarized by the expected lifetime utility) to all of the 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 lifetime utility implies that these characteristics are only crude proxies for child investments or intergenerational heritability. We also added an ability score, the AFQT test 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 dollar increase in the expected present value, while, in contrast, a similar one standard deviation increase in family income is associated with an 11,500 dollar increase. Of course, AFQT may itself be the outcome of child investments, possibly confounding rather than clarifying the interpretation of the family background variables.[38]

2. The Long-Term Impact of Not Attending School at Age 16

At age 16 an individual decides to attend school depending on his type, his initial schooling, and on the set of random shocks to the alternative-specific rewards. Some individuals of a given type-initial schooling combination will receive a set of shocks that induce them to stay at home or to work. Upon making that decision, the individual chooses then to follow his optimal path from age 17 on. However, while the shock is temporary, the effects of not attending school at age 16 can be longlasting. Returning to school is costly and the first year of work experience has a high payoff in terms of future wages. Table 12 shows the consequences of staying home at 16 or of working at 16 for future schooling and for future wage offers, conditional on type and initial schooling. The table is based on a regression run on a simulated sample of 5000 individuals (heterogeneous in type and initial schooling), each of whom solves the dynamic programming model with the estimated parameters. As the table shows, there is clearly no catch-up in terms of completed schooling. Indeed, not only is the one year of schooling lost at age 16, but on average the individual will lose an additional three-quarters of a year of schooling as a consequence of not having attended at 16. Moreover, staying home at 16 leads to lower future wage offers, 4842 dollars lower in white-collar occupations and 1795 dollars lower in blue-collar occupations at age 40. Working at age 16 also leads to lower future wage offers, although the loss is somewhat smaller than when staying home due to the additional work experience.

The importance of controlling for unobserved heterogeneity in estimating the long-run effects of not attending school at age 16 is illustrated in Table 14. Controlling for neither initial schooling nor type would overstate the effect on additional schooling of staying home at age 16 by .74 years and of working at age 16 by 1.07 years. Controlling for initial schooling alone diminishes the bias by about .2 years in either case. Similarly, the white collar wage offer at age 30 would be estimated to be over 2.5 times lower without any controls and almost two times lower with only a control for initial schooling. And, with no controls or only the partial control for initial schooling, the blue collar wage offer actually would be estimated to be higher if the individual stayed home at age 16 rather than attending school.

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

School attainment varies considerably among the types as already seen in Table 9. Table 14 explores these differences further and also considers the quantitative effect of a direct college tuition subsidy of 2000 dollars per year of college attendance on school attainment. While the subsidy is limited to the college level, the value of attending high school will also increase because individuals are forward looking and attending high school provides the only path to attending college. Overall, the college tuition subsidy increases the percent of high school graduates from 74.8 to 78.3. Moreover, the increase is essentially only among types 2,3 and 4.

There is a larger effect of the subsidy on college graduation rates, inducing an increase from 24.2 to 31.3 percent. Again, because college graduation is so prevalent among type 1's regardless of the subsidy, increased college graduation rates are much larger for the other three types; graduation rates more than double for these types. It is estimated that the population average completed schooling level would increase by .5 years due to the subsidy, from 13.0 to 13.5 years.

As Table 15 shows, a universal subsidy would help type 1's the most in expected present value terms. Type 1's go to college the most and would go 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 gain.[39] Type 4's would lose 406 dollars, type 3's 917 dollars, and type 2's 994 dollars. 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 3513 dollars to 1134 dollars. In this case, type 1's would lose their share of the cost, 1134 dollars, while type 2's would gain 76 dollars, type 3's 153 dollars, and type 4's would gain 664 dollars. A subsidy only to the least "endowed", only types 3 and 4, would cost 862 dollars per-capita and if shared equally would imply a net gain of 425 dollars to type 3's and 936 dollars to type 4's. All of these amounts are quite small relative to lifetime utility. In fact, the present value of lifetime utility cannot increase by more than the present value of four years of a college tuition subsidy given the absence of liquidity constraints in the model.[40]

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 11) 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 to type 1's significantly by restricting the subsidy to those with non-high school graduate mothers. In that case, 94 per cent of type 1's would be excluded. However, coverage of type 3's and 4's would fall to only 30 per cent.

IV. Conclusion

In this paper we have estimated a dynamic structural model of educational and occupational choices over the life cycle, using eleven 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 methods for dynamic programming models (see Keane and Wolpin (forthcoming)).

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 were the inclusion of mobility or job finding costs, the allowance for skill depreciation during periods of non-work, the inclusion of diploma effects and of school re-entry costs, the existence of non-pecuniary components of occupational payoffs, and the existence of unobserved endowment heterogeneity. A more parsimonious model, which allowed for occupation-specific human capital accumulation (occupation-specific work experience) and general human capital accumulation (schooling), but which 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.

Our estimates reveal that schooling augments white-collar skill substantially more than blue-collar skill. Also, there is substantial asymmetry between white-collar and blue-collar occupations in the way that work experience augments skill. For example, skills depreciate more rapidly in white-collar than in blue-collar occupations. Our estimates show substantial transferability of skills across occupations, with blue-collar experience augmenting white-collar skill slightly more than white-collar experience augments blue-collar skill. We also find that there are larger non-pecuniary costs to working in blue-collar occupations than in white-collar occupations, and a larger cost of finding a white-collar job given no prior white-collar work experience than of finding a blue-collar job with no prior blue-collar experience.

Our estimated model of human capital investment decisions was used to perform a number of interesting policy experiments. For instance, we used the estimated model to determine the long run effect of not attending school at age 16. Controlling for skill endowment type, an exogenous shock that causes one to stay home rather than attend school at age 16 reduces completed lifetime schooling by 2.44 years, reduces the mean white-collar wage offer at age 40 by \$3287 per year, reduces the mean blue-collar wage offer at age 30 by \$328, and reduces the expected present value of lifetime utility by roughly seven percent. The model also indicates that failure to control for self selection on the basis of skill endowments would lead one to predict a 3.04 year reduction in completed schooling, a \$6446 reduction in the mean white collar wage offer, and a \$935 increase in the mean blue collar wage offer. Thus, failure to control for endowment heterogeneity would lead to severe bias in estimates of the effect of staying home at age 16 on subsequent career outcomes.

We also used our estimates to predict the impact of a \$2000 college tuition subsidy on schooling decisions and other life cycle outcomes. Our model implies that such a subsidy would increase the number of high school graduates from 74.8 percent to 78.3 percent and the number of college graduates from 28.3 percent to 36.7 percent of the cohort. However, our results also indicate that such a subsidy has a negligible impact on expected present value of lifetime wealth. Those who would benefit most are the types with high endowments of white collar and school related skills, i.e., those who for the most part would have gone to school even without the subsidy. Those who are induced to attend college by the subsidy are primarily those with a comparative advantage in blue-collar 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.

Our result that college tuition subsidies can have little effect on lifetime wealth follows, in part, from a more fundamental finding: that endowment type "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 pre-destined 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 non optimal choice), making all choices optimally after that, their lifetime utility falls by about $35000.

Second, it does not mean that most of the variation in lifetime wealth is somehow 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, etc., would seem to be a critical endeavor.[41]

FOOTNOTES

1. See the chapters by Willis and Weiss, respectively, in the Handbook of Labor Economics for a systematic treatment and survey of the literature.

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

3. Eckstein and Wolpin (1989), Shaw (1989), and Altug and Miller (1992) are some exceptions.

4. 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 (Rosen (1974), Tinbergen (1951), Welch (1969)). 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. The aggregation of task units enters as inputs into the output production function. Tasks may be sector-specific as in Heckman and Sedlacek (1985) or they may be occupation-specific as in Willis (1986). We adopt this second approach which is described in more detail below.

5. See Eckstein and Wolpin (1989) and Rust (1992) for recent surveys of solution and estimation methods for these models.

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

7. These alternative-specific reward functions can be interpreted as the respective utilities obtained after substituting appropriate budget constraints. We do not explicitly model the alternative-specific constraints. While this strategy is not unique in discrete choice problems, we view it as a shortcoming. One formulation with which the model is consistent is linear additive utility and the absence of lending and borrowing oppportunities.

8. As noted, 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.

9. The constancy of skill rental prices over time as in (3) implies stationarity at the aggregate level. While we could specify a time dependent process for rental prices, we do not do so for two reasons. First, because we use data essentially on only a single cohort, such a time-dependent process would be confounded with pure age effects (although identification could be achieved through functional form). Second, while an arbitrary process (beyond a simple time trend) can be motivated by shocks to the aggregate production technology or by time-varying cohort sizes, the translation of those shocks into rental price processes is far from clear. For example, given dynamic behavior, iid shocks to aggregate production will generally not result in iid shocks to equilibrium rental prices.

10. We omit the skill depreciation effect and the mobility cost ($c_{M+1,1}$) from the military reward function for computational reasons. Including these parameters, which depend on whether or not the individual worked in the military in the previous period ($d_{M+1}(a-1)$), would have expanded the state space by roughly 50 percent without, given our ability to fit the data, a significant payoff.

11. An increase in the non-pecuniary component reduces the wage payment proportionately, leaving the overall military reward unchanged.

12. The tuition cost parameters may also reflect a differential consumption value of college or graduate school attendance.

13. One possible reason for a re-entry cost is that due to 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.

14. The contractual obligation for military enlistment has been at least two years. This early exit cost can be thought of as a stigma effect associated with reneging on the contract.

15. Serial dependence in any of the shocks adds considerable computational complexity. See Keane and Wolpin (1994) for further discussion.

16. Past realizations of the shocks are also known, but do not enter the state space because of the assumption of serial independence.

17. Starting the observations at the first decision age ($a=0$) simplifies the presentation.

18. When there is no unobserved heterogeneity, it is necessary to solve the individual's optimization problem only back to the first period of the data, which may not be the first decision period. When unobserved heterogeneity exists, in order to condition the likelihood correctly on the state that occurs at the first observed period, regardless of whether that is the first decision period, the optimization problem must be solved over the entire decision period. It is then possible to correctly calculate the marginal probability for the observed state. Alternatively, one can treat the unobserved heterogeneity as an incidental parameters problem (Heckman (1982)).

19. In the full solution of the dynamic program, the presence of these K types would require that the dynamic program be solved K times, that is, for each type separately. Recognizing that the existence of differential skill endowments essentially multiplies the state space by the number of types, K, the approximation method simply treats this expansion in the state space like any other.

20. 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.

21. There are a considerable number of observations (as many as 20 percent) with longitudinally inconsistent enrollment and highest grade completed data. The records of all observations with inconsistent data were carefully scrutinized. In most cases we were able to reconstruct a reasonable school enrollment and grade completion history, or at least a partial history, based on the different

pieces of information that are reported in the NLSY, i.e., the monthly enrollment calendar; survey date enrollment, highest grade attended, 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 determining highest grade completed, an individual who obtained a GED was not considered to have completed 12 years of schooling; instead highest grade completed is the number of years that were actually attended and successfully completed. This treatment is consistent with recent work by Cameron and Heckman (1994).

22. The rule was a bit more complicated because of missing enrollment data. If two weeks or more of enrollment data was missing, then the only determinant of school enrollment 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.

23. 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.

24. If work status is missing for less than two-thirds of the weeks, then the work criterion is the same based on the non-missing weeks. An individual with missing data was assumed not to have worked if the sum of the weeks with missing data and the number of weeks worked was not greater than one-third of total weeks in the year.

25. Occupational categories are based on one-digit 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, (iii) farmers and farm managers, (iv) clerical and kindred.

26. With one-digit occupation codes, the transitions between the calendar quarters surrounding the interview date are significantly higher than 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.

27. The wage is deflated by the GNP deflator, with 1987 as the base year.

28. Given the sample restrictions, namely to respondents in the core component of the survey and to respondents who are male, white, and of a particular age group, there would have been at most 1401 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.

29. The fall to less than one per cent at age 26 would appear to be an aberration of the small sample size.

30. In terms of people instead of person-periods, approximately 20 per cent of those leaving school for at least one year return to complete at least one more grade level. The propensity to interrupt college is much greater than it is for high school. This figure may 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.

31. Standard errors are calculated using the outer product of numerical first derivatives. We found in Keane and Wolpin (forthcoming) based on Monte Carlo simulations that these standard errors seemed to be upward biased.

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

33. The assumption that military wages are fully compensating enables the identification of the non-pecuniary values for the civilian occupations. If the military had been treated symmetrically to the civilian occupations, a normalization would be required and only relative values would be estimable. The military parameters are identified because, by assumption, they have no effect on choices.

34. The approximation model is estimated using only the choice data, i.e., ignoring the wage data. The static model uses both choice and wage data.

35. These chi-square statistics have not been adjusted for the fact that the parameters of the model have been estimated. An appropriate degrees of freedom adjustment would increase the likelihood of model rejection.

36. The value functions, rather than their expected values, depend on the specific shocks that are drawn.

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.

38. The R-square of the regression including AFQT is .14.

39. Because the optimization model contains no explicit constraints on financing college, that is, 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. However, as we are dealing with numbers that are small relative to lifetime expected discounted values, our approximation of the dynamic programming solution did yield positive net gains in some instances. For this reason, we assumed that the subsidy cost to each type exactly equaled their gross gains, which overstates the subsidy cost and understates the net gains.

40. As noted, the model is silent as to the social return, that is, the efficiency aspects, of such a program.

41. See, for example, Rosenzweig and Wolpin (1994).

<u>References</u>

Altug, Sumru and Robert A. Miller. 1992. "Human Capital, Aggregate Shocks, and Panel Data Estimation." Institute for Empirical Macroeconomics Discussion Paper 47.

Becker, Gary S. 1964. <u>Human Capital</u>. New York: Columbia University Press.

Ben-Porath, Yoram. 1967. "The Production of Human Capital and the Life Cycle of Earnings." <u>Journal of Political Economy</u> 75:352-65.

Blinder, Alan and Yoram Weiss. 1976. "Human Capital and Labor Supply: A Synthesis." <u>Journal of Political Economy</u> 84:449-72.

Cameron, Steven and James J. Heckman. 1993. "The Nonequivalence of High School Equivalents." <u>Journal of Labor Economics</u> 11:1-47.

Eckstein, Zvi and Kenneth I. Wolpin. 1989a. "Dynamic Labour Force Participation of Married Women and Endogenous Wage Growth." <u>Review of Economic Studies</u> 56:375-90.

__________. 1989b. "The Specification and Estimation of Dynamic Stochastic Discrete Choice Models." <u>Journal of Human Resources</u> 24:562-98.

Heckman, James J. 1976. "A Life Cycle Model of Earnings, Learning, and Consumption." <u>Journal of Political Economy</u> 84(supplement):511-44.

__________ 1981. "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating Discrete Time Discrete Data Stochastic Processes and Some Monte Carlo Evidence." in C. Manski and D McFadden (eds.) <u>Structural Analysis of Discrete Data with Econometric Applications</u>. Cambridge: MIT Press.

Heckman, James J. and Guilherme Sedlacek. 1985. "Heterogeneity, Aggregation, and Market Wage Functions: An Empirical Model of Self-Selection in the Labor Market." Journal of Political Economy 93:1077-1125.

Keane, Michael P. and Kenneth I. Wolpin. Forthcoming. "The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence." Review of Economics and Statistics.

Manski, Charles F. and David A. Wise. 1983. College Choice in America. Cambridge: Harvard University Press.

Mincer, Jacob. 1958. "Investment in Human Capital and the Personal Income Distribution." Journal of Political Economy 66:281-302.

Rosen, Sherwin. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." Journal of Political Economy 82:34-55.

Rosen, Sherwin. 1977. "Human Capital: A Survey of Empirical Research." in R. Ehrenberg (ed.) Research in Labor Economics Greenwich: JAI Press, Vol. 1.

Rosenzweig, Mark R. and Kenneth I. Wolpin. "Are There Increasing Returns to the Intergenerational Production of Human Capital?" Journal of Human Resources 29: 670-693.

Roy, A.D. 1951. "Some Thoughts on the Distribution of Earnings." Oxford Economic Papers 3:135-46.

Rust, John. 1992. "Structural Estimation of Markov Decision Processes." forthcoming in R. Engle and D. McFadden (eds.) Handbook of Econometrics Vol. 4. Amsterdam: North Holland.

Shaw, Kathryn L. "Life-Cycle Labor Supply with Human Capital Accumulation." International Economic Review 30:431-456.

Tinbergen, Jan. 1951. "Some Remarks on the Distribution of Labor Incomes." International Economic Papers 1:195-207.

Welch, Finis. 1969. "Linear Synthesis of Skill Distribution." Journal of Human Resources 4: 311-27.

Weiss, Yoram 1986. "The Determinants of Life Cycle Earnings." in O. Ashenfelter and R. Layard (eds.) Handbook of Labor Economics Vol. 1: 603-40. Amsterdam: North Holland.

Weiss, Yoram and Reuben Gronau. 1981. "Expected Interruptions in Labor Force Participation and Sex Related Differences in Earnings Growth." Review of Economic Studies 48:607-19.

Willis, Robert J. 1986. "Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions." in O. Ashenfelter and R. Layard (eds.) Handbook of Labor Economics Vol. 1: 525-602. Amsterdam: North Holland.

Willis, Robert J. and Sherwin Rosen. 1979. "Education and Self-Selection." Journal of Political Economy 87(supplement): S7-S36.

Figure 1.1 Percent White Collar by Age

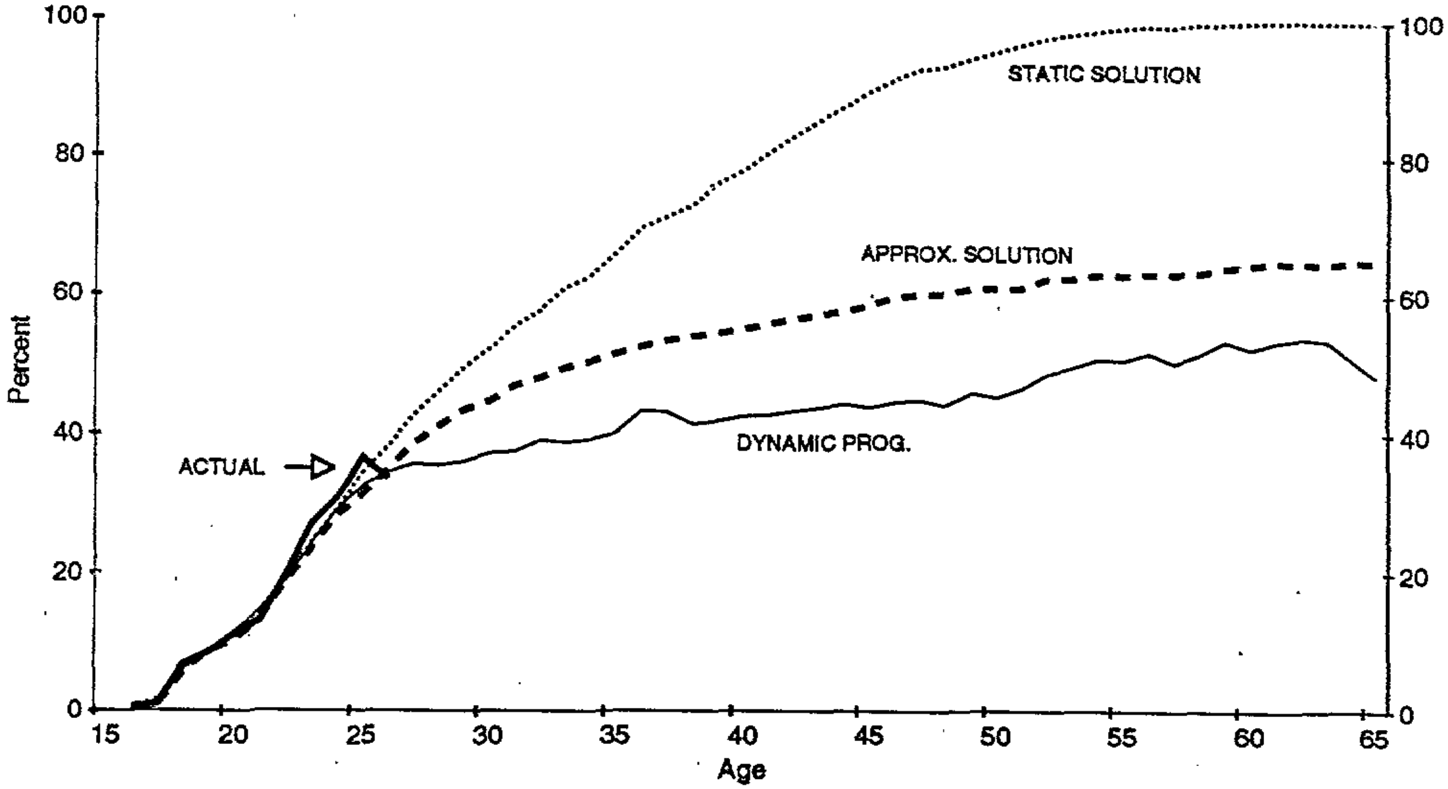

Figure 1.2 Percent Blue Collar by Age

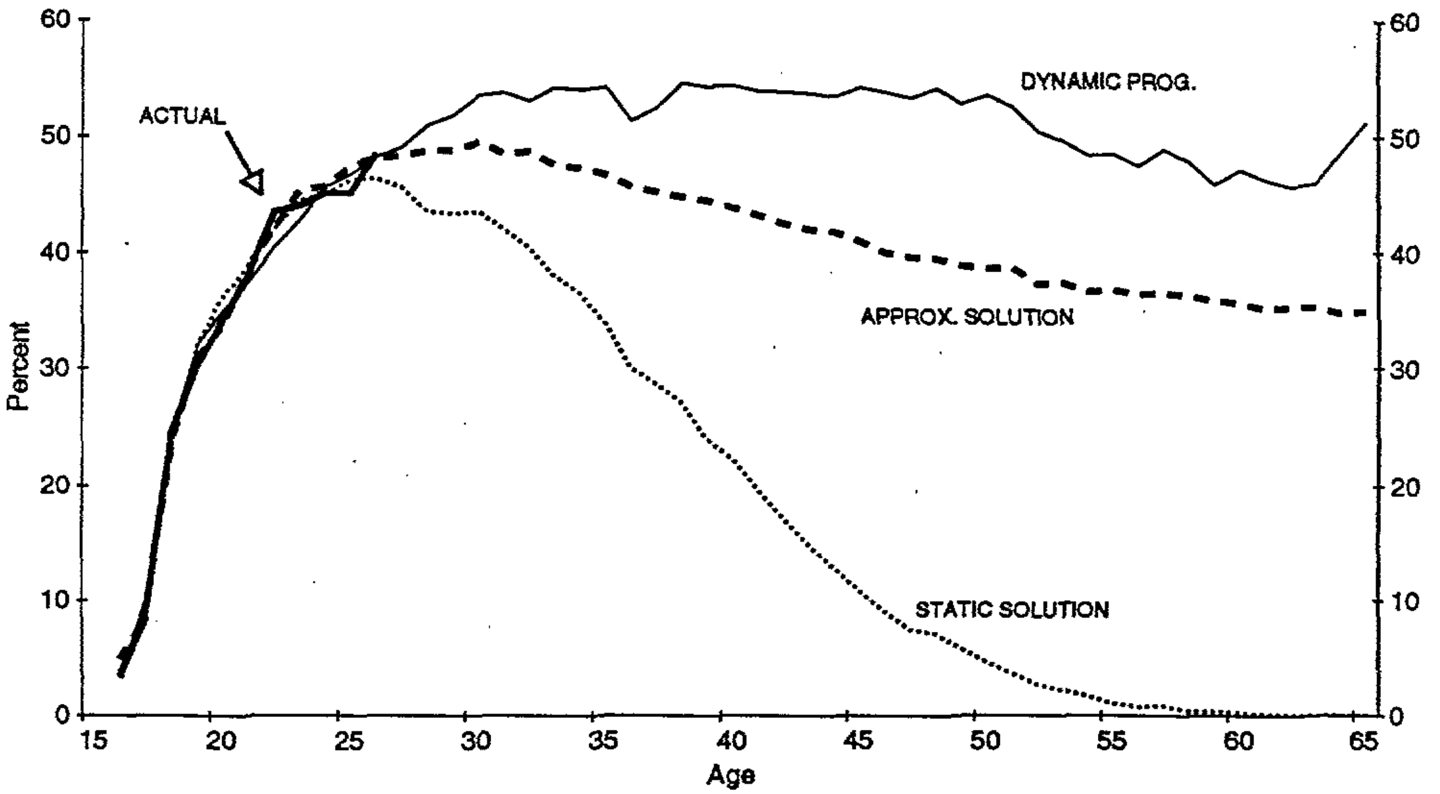

Figure 1.3 Percent in the Military by Age

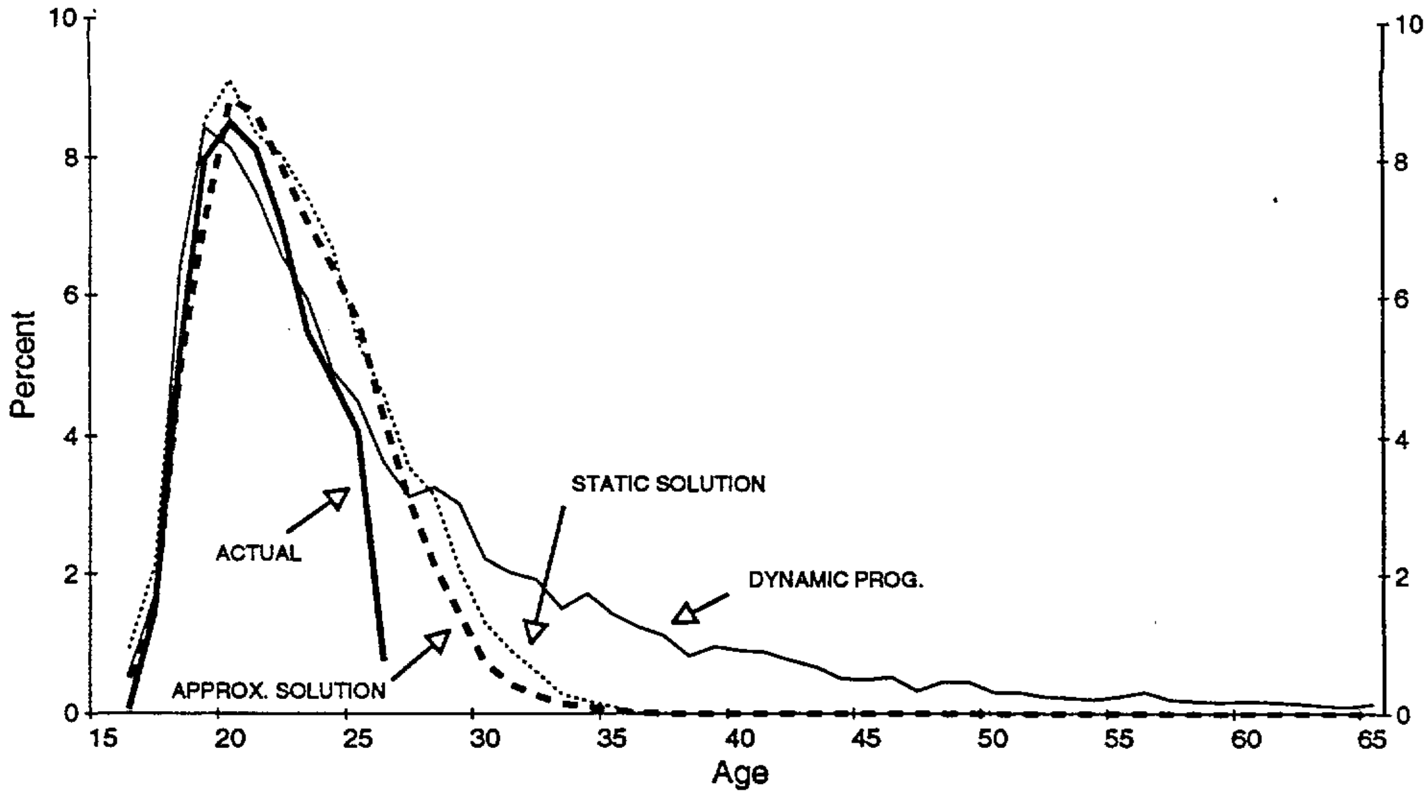

Figure 1.4 Percent in School by Age

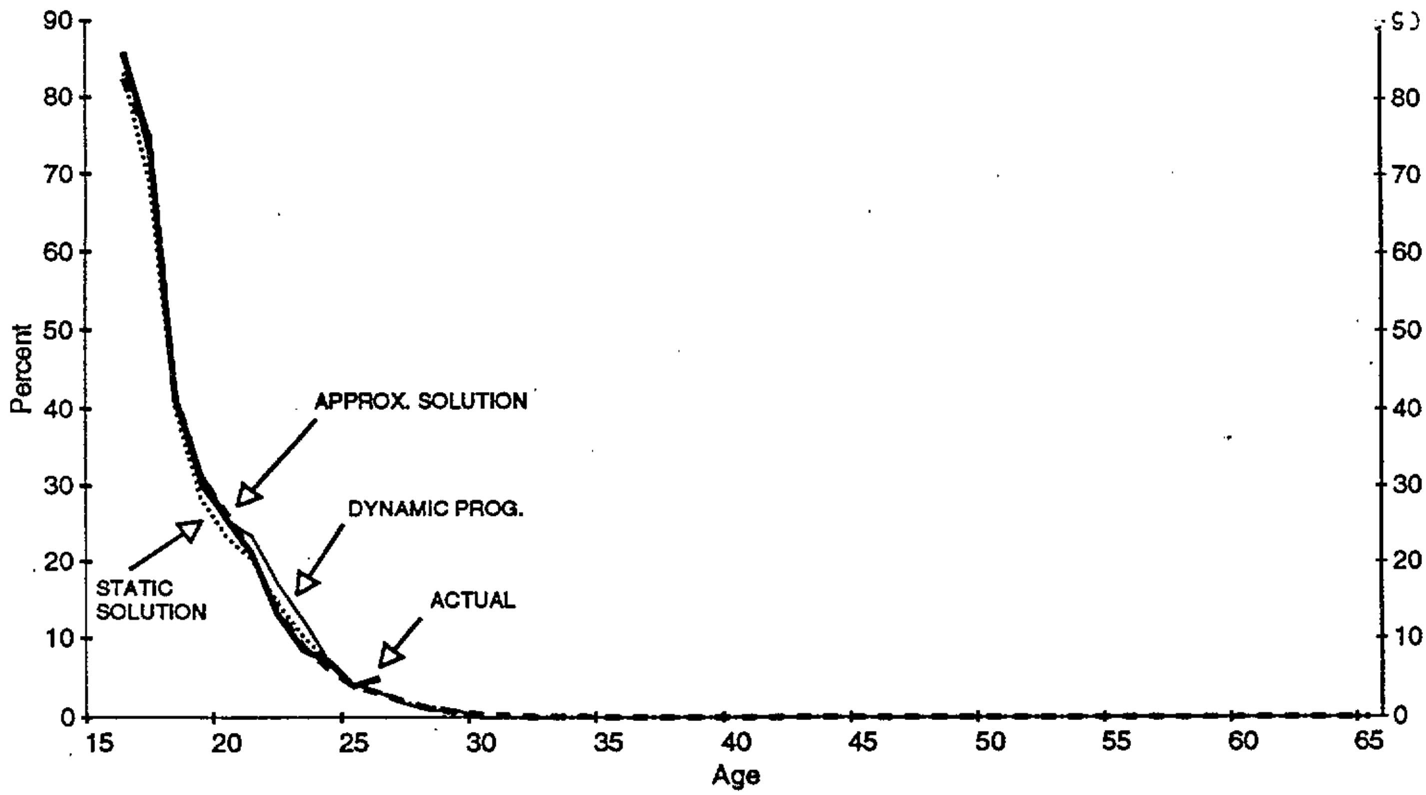

Figure 1.5 Percent at Home by Age

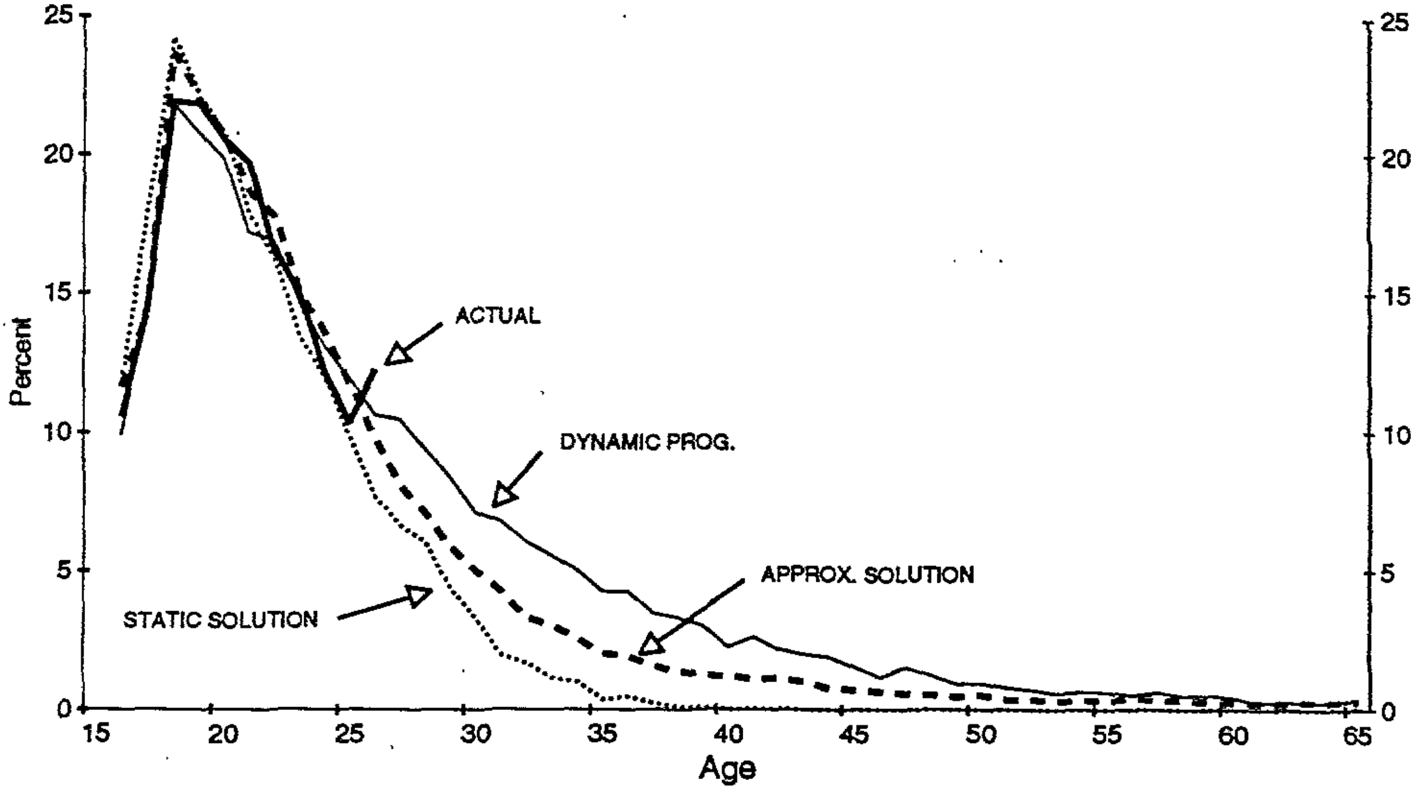

Table 1
Choice Distribution
White Males Age 16 to 26[a]

Choice	School	Home	White Collar	Blue Collar	Military	Total
Age						
16	1178	145	4	45	1	1373
	85.8	10.6	0.3	3.3	0.1	100.0
17	1014	197	15	113	20	1359
	74.6	14.5	1.1	8.3	1.5	100.0
18	561	296	92	331	70	1350
	41.6	21.9	6.8	24.5	5.2	100.0
19	420	293	115	406	107	1341
	31.3	21.9	8.6	30.3	8.0	100.0
20	341	273	149	454	113	1330
	25.6	20.5	11.2	34.1	8.5	100.0
21	275	257	170	498	106	1306
	21.1	19.7	13.0	38.1	8.1	100.0
22	169	212	256	559	90	1286
	13.1	16.5	19.9	43.5	7.0	100.0
23	105	185	336	546	68	1240
	8.5	14.9	27.1	44.0	5.5	100.0
24	65	112	2[illegible]	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	0.81	100.0
Total	4165	2063	1724	3762	645	12359
	33.7	16.7	14.0	30.4	5.2	100.0

[a] number of observations and percentages.

Table 2
Transition Matrix:
White Males Age 16 to 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	0.7
column %	1.8	4.0	51.4	7.0	1.4
Blue Collar					
row %	3.4	12.4	9.9	73.4	0.9
column %	2.6	19.0	18.2	61.7	4.3
Military					
row %	1.4	5.5	3.1	9.6	80.5
column %	0.2	1.6	1.0	1.5	72.4

Table 3
Selected Choice-State Combinations

Highest Grade Completed	9	10	11	12	13	14	15	16	17
Percent 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		
Percent 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	
Percent 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			
Percent 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 Age 16 to 26[a]

Age	Mean Wage All Occupations		Mean Wage White-Collar		Mean Wage Blue-Collar		Mean Wage Military	
16	10217	(28)	9320	(2)	10286	(26)	-	(0)
17	11036	(102)	10049	(14)	11572	(75)	9005	(13)
18	12060	(377)	11775	(71)	12603	(246)	10171	(60)
19	12246	(507)	12376	(97)	12949	(317)	9714	(93)
20	13635	(587)	13824	(128)	14363	(357)	10852	(102)
21	14977	(657)	15578	(142)	15313	(419)	12619	(96)
22	17561	(764)	20236	(214)	16947	(476)	13771	(74)
23	18719	(833)	20745	(299)	17884	(481)	14868	(53)
24	20942	(667)	24066	(259)	19245	(373)	15910	(35)
25	22754	(479)	24899	(207)	21473	(250)	17134	(22)
26	25390	(206)	32756	(79)	20738	(125)	25216	(2)

[a] number of observations in parentheses.

Table 5
Estimated Occupation-Specific Parameters

	White Collar		Blue Collar		Military	
1. <u>Skill Functions</u>						
Schooling	.0700	(.0018)[a]	.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[b]	.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 (.~~[illegible]~~)
Measurement Error Standard Deviation	.2415	(.0140)	.1942	(.0134)	.2063	(.~~[illegible]~~) .0207
Error Correlation						
White Collar	1.0000			-		-
Blue Collar	0.1226	(.0430)	1.0000			-
Military	0.0182	(.0997)	0.4727	(.0848)	1.0000	
2. <u>Non-Pecuniary Values</u>						
Constant	-2543	(272)	-3157	(253)	-.0900	(.0448)
Age	-		-		-.0313	(.0057)
3. <u>Entry Costs</u>						
If Positive Own Experience but not in occupation in previous period	1182	(285)	1647	(199)	-	
Additional entry cost if No Own Experience	2759	(764)	494	(698)	560	(509)
4. <u>Exit Costs</u>						
One Year Military Experience	-		-		1525	(151)

[a] Standard Errors are in parenthesis.
[b] Age is defined as age minus 16.

Table 6
Estimated School and Home Parameters

	School		Home	
Constants:				
Type 1	11031	(626)[a]	20242	(608)
Deviation of Type 2 from Type 1	-5364	(1182)	-2135	(753)
Deviation of Type 3 from Type 1	-8900	(957)	-14678	(679)
Deviation of Type 4 from Type 1	-1469	(1011)	-2912	(768)
Has High School Diploma	804	(137)	-	
Has College Diploma	2005	(225)	-	
Net Tuition Costs: College	4168	(838)	-	
Additional Net Tuition Costs: Graduate School	7030	(1446)	-	
Cost to Re-Enter High School	23283	(1359)	-	
Cost to Re-Enter College	10700	(926)	-	
Age[b]	-1502	(111)	-	
Age 16 to 17	3632	(1103)	-	
Age 18 to 20	-		-1027	(538)
Age 21 and Above	-		-1807	(568)
Error Standard Deviation	12821	(735)	9350	(576)
Discount Factor	.9363 (.0014)			

[a] Standard errors are in parenthesis.
[b] Age is defined as age minus 16.

Table 7
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)[a]	.4066 (.0357)	.3456 (.0359)
Ten Years or More	.2343 (-)	.2335 (.0208)	.3734 (.0229)	.1588 (.0183)
Rank Ordering				
White Collar	1	2	4	3
Blue Collar	2	1	4	3
Schooling	1	3	4	2
Home	1	2	4	3

[a] Standard errors are in parenthesis.

Table 8
Chi-Square Goodness-of-Fit Tests of the Within-Sample Choice Distribution - Dynamic Programming Model and Multinomial Logit[a]

	School	Home	White Collar	Blue Collar	Military	Row
Age						
16						
DP	0.00	0.07	[b]	0.15	[b]	0.22
APP	2.00	0.19	[b]	7.05	[b]	9.24[c]
17						
DP	0.95	0.02	0.28	3.31	0.42	4.98
APP	0.02	0.00	1.78	0.03	0.00	1.84
18						
DP	0.03	0.00	0.93	0.01	3.09	4.06
APP	0.09	0.94	3.03	0.42	0.17	4.65
19						
DP	0.83	0.51	0.07	1.27	0.34	3.02
APP	0.00	0.02	0.01	0.17	1.53	1.73
20						
DP	0.16	0.25	0.24	0.22	0.22	0.94
APP	0.25	0.01	0.82	0.06	0.17	1.31
21						
DP	2.91	3.50	2.45	0.23	0.72	9.81[c]
APP	0.00	0.65	0.05	0.03	0.41	1.14
22						
DP	12.43[c]	0.11	0.61	3.04	0.38	16.60[c]
APP	0.12	1.49	0.72	0.64	1.21	4.19
23						
DP	14.66[c]	0.12	3.76	0.42	0.44	19.40[c]
APP	0.23	0.14	5.90	0.44	4.38	10.97[c]
24						
DP	0.18	0.99	0.81	0.04	0.04	1.89
APP	1.21	2.77	2.20	0.05	2.77	10.01[c]
25						
DP	0.14	3.45	2.71	0.29	0.23	6.82
APP	0.01	2.98	5.00	0.61	2.56	11.16[c]
26						
DP	2.61	2.14	0.45	0.00	[b]	5.20
APP	2.84	4.95	0.10	0.01	[b]	7.90[c]

[a] The dynamic programming (DP) model has 83 parameters and the approximate decision rule (APP) model has 75.
[b] Less than five observations.
[c] Statistically significant at the .05 level.

Table 9
Selected Characteristics at Age 24 by Type:
Nine or Ten Years Initial Schooling[a]

	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

[a] Based on a simulation of 5000 persons.

Table 10

Expected Present Value of Lifetime Utility for Alternative Choices at Age 16 and at Age 26 by Type ($)[a]

	All Types	Type 1	Type 2	Type 3	Type 4
			Initial Schooling 10 Years or More		
School					
Age 16	321008	415435	394712	228350	289683
Age 26	384352	499162	494107	272985	314708
Home					
Age 16	298684	380660	376945	207768	274901
Age 26	426837	611167	516547	291932	338653
White Collar					
Age 16	293683	372544	372733	207586	262370
Age 26	439970	637616	528107	303228	338967
Blue Collar					
Age 16	296736	373156	377618	210699	266206
Age 26	438240	617873	534578	305641	342195
Military					
Age 16	285686	350655	356202	210461	261944
Age 26	415374	581996	492531	298431	329938
Maximum Over Choices					
Age 16	321921	415503	396108	229265	291122
Age 26	445488	638820	537226	308259	346695
			Initial Schooling Nine Years or Less		
School					
Age 16	273186	387384	371369	211942	276040
Age 26	308808	564590	446163	243734	274979
Home					
Age 16	260668	352274	360495	197288	268047
Age 26	334643	578637	468465	268815	305262
White Collar					
Age 16	253764	342833	354261	196294	253686
Age 26	339093	602915	474796	277488	300917
Blue Collar					
Age 16	257720	343873	359370	199945	257697
Age 26	344179	583895	486456	282223	305520
Military					
Age 16	251710	322293	340126	199737	254386
Age 26	328916	550521	447443	275660	295996
Maximum Over Choices					
Age 16	275634	387384	374154	213823	286311
Age 26	347741	604549	487466	284073	310598

[a] Based on a simulation of 5000 persons.

Table 11
The Relationship of Initial Schooling and Type to
Selected Family Background Characteristics

	Initial Schooling Nine Years or Less and Person is of Type				Initial Schooling Ten Years or More and Person is of Type					
	1	2	3	4	1	2	3	4	No. Obs.	Expected PV Lifetime Utility at Age 16
All	.010	.051	.103	.090	.157	.177	.289	.123	1373	307673
Mother's Schooling										
Non-HS Grad	.004	.099	.177	.161	.038	.141	.276	.103	333	286642
HS Grad	.011	.043	.086	.071	.143	.210	.305	.131	685	309275
Some College	.023	.021	.043	.058	.294	.166	.263	.133	152	328856
College Grad	.007	.005	.049	.023	.388	.151	.222	.154	142	339593
Household Structural at Age 14										
Live with Mother Only	.001	.062	.133	.119	.123	.137	.297	.128	178	296019
Live with Father Only	.026	.037	.088	.120	.062	.180	.378	.106	44	291746
Live with Both Parents	.011	.049	.097	.082	.169	.184	.284	.124	1123	310573
Live with Neither Parent	.0001	.090	.154	.184	.037	.175	.275	.085	28	290469
Number of Siblings										
0	.002	.041	.086	.092	.142	.227	.285	.126	50	310833
1	.002	.029	.064	.051	.236	.199	.287	.133	261	320697
2	.016	048	.104	063	.191	.157	.275	.146	364	311053
3	.013	.056	.119	.090	.147	.182	.288	.104	320	306395
4+	.009	.067	.117	.141	.081	.171	.303	.111	378	296089
Parental Income in 1978										
$Y \leq 1/2$ Median*	.002	.078	.155	.181	.071	.132	.221	.161	214	292565
$1/2$ Median $< Y \leq$ Median	.007	.053	.120	.103	.103	.173	.328	.113	382	296372
Median $\leq Y < 2 \cdot$ Median	.015	.044	.071	.051	.177	.204	.304	.134	446	314748
$Y \geq 2 \cdot$ Median	.014	.025	.024	.021	.479	.167	.182	.087	83	358404

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

Table 12
Consequences at Selected Ages of Not Attending School at Age 16
(Regression Coefficients and Standard Errors)[a]

	Additional School Attainment			Wage Offers					
				White Collar			Blue Collar		
	Age 18	Age 22	Age 26	Age 20	Age 30	Age 40	Age 20	Age 30	Age 40
Home at Age 16	-1.66	-2.28	-2.44	-1155	-3287	-4842	-193	-328	-1795
	(.017)	(.047)	(.056)	(169)	(272)	(410)	(238)	(400)	(497)
Working at Age 16	-1.72	-2.22	-2.31	-1156	-2833	-3055	669	38	-608
	(.018)	(.054)	(.061)	(275)	(415)	(697)	(372)	(534)	(831)
Initial Schooling	.007	.090	.155	755	961	2347	387	538	333
	(.009)	(.027)	(.032)	(191)	(169)	(245)	(104)	(164)	(237)
Type:									
2	-.206	-2.71	-4.00	-1198	-15117	-17145	6242	3033	18425
	(.013)	(.049)	(.058)	(260)	(573)	(782)	(247)	(401)	(549)
3	-.209	-2.77	-4.09	-6681	-24190	-29857	-781	1234	1919
	(.011)	(.042)	(.050)	(211)	(506)	(686)	(167)	(251)	(365)
4	-.199	-2.30	-3.40	-6349	-23105	-28807	1338	2121	2880
	(.014)	(.057)	(.069)	(226)	(530)	(722)	(205)	(304)	(433)
Constant	1.92	4.36	5.18	6744	16970	24244	6012	8841	17259
	(.094)	(.278)	(.330)	(935)	(1760)	(2529)	(1048)	(2392)	(392)
R^2	.739	.596	.654	.332	.538	.418	.253	.291	.299

[a] Based on a simulation of 5000 persons.

Table 13
Effect of Heterogeneity on Consequences at Age 30 of Not Attending School at Age 16[a]

	Additional School Attainment			White Collar Wage Offer			Blue Collar Wage Offer		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Home at Age 16	-3.22	-3.04	-2.48	-8115	-6446	-3287	638	935	-328
	(.063)	(.065)	(.057)	(373)	(367)	(272)	(476)	(476)	(400)
Working at Age 16	-3.41	-3.22	-2.34	-7670	-5910	-2833	1551	1864	38
	(.071)	(.074)	(.063)	(510)	(506)	(415)	(664)	(666)	(534)
Controls:									
Initial Schooling	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Type	No	No	Yes	No	No	Yes	No	No	Yes

[a] Based on a simulation of 5000 persons.

Table 14
Effect of a $2000 College Tuition Subdsidy
on Selected Characteristics by Type[a]

	All Types	Type 1	Type 2	Type 3	Type 4
Percent 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
Percent 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	0.69	0.59	1.05
Subsidy	1.71	3.99	1.14	1.00	1.58

[a] Subsidy of $2000 each year of attendance. Based on a simulation of 5000 persons.

Table 15
Distributional Effects of a $2000 College Tuition Subdsidy

	Type 1	Type 2	Type 3	Type 4
Mean Expected PV of Lifetime Utility at Age 16				
No Subsidy	413911	391162	225026	286311
Subsidy	419628	392372	226313	288109
Gross Gain	5717	1210	1287	1798
Net Gain				
Subsidy To All Types[a]	3513	-994	-917	-406
Subsidy To Types 2,3,4[b]	-1134	76	153	664
Subsidy to Types 3,4[c]	-862	-862	425	936

[a] The per-capita cost of the subsidy program is 2204 dollars.
[b] The per-capita cost of the subsidy program is 1134 dollars.
[c] The per-capita cost of the subsidy program is 862 dollars.