INTERNATIONAL ECONOMIC REVIEW
Vol. 42, No. 4, November 2001

THE EFFECT OF PARENTAL TRANSFERS AND BORROWING CONSTRAINTS ON EDUCATIONAL ATTAINMENT*

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1. INTRODUCTION

A strong positive association between one's school attainment and that of one's parents has been consistently documented in numerous empirical studies.[2] The underlying cause of this intergenerational correlation has been the subject of contentious debate in the social sciences for many years. Two competing types of explanations are prominent. The first is based on the heritability of traits, that is, that children of more educated parents may inherit the abilities, personalities, and preferences that led to the higher educational achievement of their parents. The second type of explanation is based on human capital production, namely that more educated parents, due to their own preferences for more educated children and/or due to their higher wealth, may invest more heavily in their children's human capital.

Human capital investments in children take many forms, such as parental time (e.g., reading to young children), the purchase of market goods that are complementary to learning (e.g., books), or direct financial subsidies (e.g., in the form of college tuition payments). In this article, we focus on the decision process of young adults (beginning at age 16) for whom parental subsidies (monetary and in-kind transfers) to postsecondary education are likely to be the most salient of parental human capital investments. A central question we ask is: To what extent and through what mechanisms do differences in parental transfer behavior account for the positive intergenerational correlation in educational attainment?

The importance of parental transfers in the postsecondary educational decisions of their children may be affected by the degree to which young adults have access to capital markets as a means of financing postsecondary educational expenditures. Thus, a second key question we address concerns the extent to which borrowing constraints, i.e., restrictions on the availability of uncollateralized loans, affect educational attainment. Clearly, if borrowing constraints are binding, then youths from families with

* Manuscript received June 1998; revised December 1999.

[1] Support for this research from the Bureau of Labor Statistics is gratefully acknowledged. The views expressed are our own. We are also grateful for support from the Minnesota Supercomputer Institute. The comments of three referees and the editor improved the article significantly.

[2] See Haveman and Wolfe (1995) for a recent survey.

less financial resources (those with less educated parents) will face a higher implicit schooling cost.

To understand how parental transfers and borrowing constraints affect educational attainment, we construct and structurally estimate a dynamic optimization model of the joint schooling, work, and savings decisions of young men. The model is estimated using data from the 1979 youth cohort of the National Longitudinal Surveys of Labor Market Experience (NLSY). This data provide us with 11 years of longitudinal information on a representative sample of youths beginning at age 16. The model is fit using data for white males on wages, assets, school, work, marriage, parental co-residence, and parental education.

The model contains a number of mechanisms that can account for the intergenerational correlation in school attainment. First, the model allows for heterogeneity among youths when they reach age 16 in market skills and preferences for schooling and leisure. The model is, however, agnostic as to the source of these differences, be they innate or a result of prior parental (and youth) investment behavior or both. The joint distribution of these age 16 "endowments" is permitted to depend on parental schooling, which may account for all or part of the positive correlation between parent and child schooling.

Second, parents are assumed to provide transfers to their young adult children according to a parental transfer rule that is taken as given by the youth. The transfer rule includes a component that is independent of the youth's behavior as well as a component that depends on whether the youth attends college. Transfer amounts also depend on the level of parental schooling. Larger transfers from more educated parents that are conditioned on school attendance will obviously lead to increased schooling among their children. But, in addition, larger unconditional transfers from more educated parents will increase the schooling of their children if attending school is a normal good.

Third, the model assumes that net assets must exceed a lower bound (that may be negative). This lower bound varies over time in a way that depends on the youth's current characteristics, determined in part by the youth's prior decisions. The closer this lower bound is to zero, the more binding is the borrowing constraint and the potentially more important are parental transfers in affecting the schooling of their children. Fourth, the borrowing rate of interest is allowed to differ from, and presumably exceeds, the lending rate of interest, again imparting a potentially important role to parental transfers.

Finally, school attendance and market work are not mutually exclusive. Youths can work (part or full time) while attending school (part or full time) to augment their consumption and/or to help finance tuition costs. Thus, the possibility of working while attending school serves to mitigate the advantage that larger parental transfers provides for financing tuition costs of college attendance.

Our estimate of the parental transfer function indicates that more educated parents do indeed make larger transfers to their children and that transfers are greater while attending college. We also find that the maximum net debt amount is quite small, regardless of the youth's current characteristics; borrowing constraints exist and are tight. Indeed, it is impossible to finance even one year of college using uncollateralized loans.

The estimates of the model are used to perform counterfactual experiments that address the two questions posed above. In one experiment, to determine the extent to which larger parental transfers are responsible for the higher completed schooling levels observed for the children of more educated parents, we modify the parental transfer function to be independent of parental schooling (keeping the overall mean level of transfers constant). We find indeed that equalizing parental transfers in that way would significantly reduce the completed schooling levels of children whose parents are college graduates. However, such an equalization would increase by only a small amount the completed schooling of children of less educated parents.

To assess the importance of borrowing constraints in the determination of school attainment, we perform the experiment of allowing youths to borrow up to the full amount of the tuition cost. We do this experiment both for the case where parental transfers are maintained at their estimated levels and where parental transfers are set to zero. Although, as noted, borrowing constraints are estimated to be severe, in neither of these experiments does relaxing the borrowing constraint have a significant effect on completed schooling. The implication of these findings is that while some of the intergenerational correlation in schooling can be attributed to the larger college attendance contingent transfers made by more educated parents, essentially none of the correlation can be attributed to capital market constraints.

The finding that borrowing constraints are tight yet have little effect on school attendance decisions may be surprising. Certainly, both the economics and public policy literatures on college financing have taken it for granted that if borrowing constraints exist they would have substantial effects on enrollment for low income youth. In contrast, we find borrowing constraints have their primary effects on other choices made by youths. Specifically, the relaxation of borrowing constraints induces students to work less and consume more while in college, but it does little to affect attendance decisions. As we describe below, an external validation of the predictions from the estimates of our model is provided by Leslie (1984), who found that the when government sponsored grants and guaranteed student loans were made more generous in the 1970s, earnings of college students did in fact decline substantially.

This article is related to work on sequential models of school attendance by Cameron and Heckman (1998, 1999). They find a strong positive association between current family income and the probability of college attendance conditional on high school graduation, even after controlling for the effects of dynamic selection on unobservables. But, after an additional control for AFQT scores measured at either age 16 or 17 (which they interpret as a proxy for a youth's skill endowment at that age), the relationship between current family income and college attendance becomes small and statistically insignificant.[3] They interpret this as evidence that short term liquidity constraints (as proxied by current family income) play no significant role in college attendance decisions.[4] Our results, which show that borrowing

[3] The AFQT test, a composite of several tests in the Armed Services Vocational Aptitude Battery, may largely measure investments in children made prior to the age at which the test is taken, rather than any heritable endowment. As Cameron and Heckman argue, their interpretation does not rest on AFQT measuring an innate endowment, but it also holds if AFQT measures acquired skills.

[4] This result does not preclude an interpretation that borrowing constraints are related to permanent income. Precisely because it may measure household investments in children over an extended

constraints affect consumption and work decisions of college students but have little impact on the college attendance decision itself, appear to reconcile the view that liquidity constraints play no important role in school attendance decisions with the view that important liquidity constraints do exist for youths.

It should be stressed that our results rest on strong identifying assumptions. Most importantly, data limitations require us to make strong assumptions in order to identify the parental transfer function that is central to our model. In fact, the NLSY does not contain direct observations on parental transfers. Rather, our model in effect infers the amounts of parental transfers, and how they differ across parents with different education levels, from the behavior of assets, as well as the other decisions of youths (i.e., work and school attendance).

A key assumption in identifying the transfer function is that only young men who are "co-resident" with their parents receive transfers. Because the large majority of youths who are away at college full time report they are co-resident, we interpret the responses to this question as likely indicating whether the youth is a dependent receiving substantial financial support from parents (rather than whether the youth physically lives with the parents). We further assume that parental co-residence is not a choice made by youths, but rather by their parents. Co-residence is treated as probabilistic from the youth's perspective and dependent on the youth's characteristics. As long as youths cannot directly choose their co-residence status (although they can influence the parental decision through their prior saving, school, and work decisions), it is possible to identify the level of parental transfers they receive by comparing the saving, work, and school decisions of youths who do to those who do not live with their parents. In other words, because parental transfers provide additional exogenous income, observing the different decisions made by youths who co-reside and those who do not allows one to infer the amount of additional income the parents must have provided in order to rationalize the different choices.[5]

The estimated model fits the data reasonably well with parameter values that appear sensible. In addition, we present evidence that provides external validations of the model, which is particularly important because data on transfers, student loans, grants, and tuition costs either do not exist or are available only periodically in the NLSY. Our estimates, for example, of the way in which parental transfer amounts vary across parental education levels accords with that reported by respondents from

period of time, AFQT may proxy for the household's permanent income even given the other household level characteristics included in their analysis. Furthermore, if children and/or parents are forward looking, then anticipating that borrowing constraints will limit college attendance would reduce investments in children, thus leading to lower AFQT scores. In that case, part of any effect of alleviating borrowing constraints on college attendance would occur through the indirect channel of increasing AFQT scores. Indeed, Keane and Wolpin (1997, 1999), who structurally estimate a dynamic model of schooling, find that college tuition subsidies increase high school attendance rates at ages 16 and 17, implying that such financial incentives would improve the age 17 skill endowment. On a related point, note that it would be incorrect to use AFQT as a proxy for age 17 endowments in a decision model that begins at an earlier age, because AFQT will not be invariant to policy experiments such as introducing tuition subsidies, relaxing borrowing constraints, etc. Hence, we treat the initial skill endowments as unobserved latent variables as in our earlier work.

[5] In this regard, however, it is important to note that we allow for classification error in the youths' reports of co-residence status.

the NLS young women's cohort (NLSYW) who have children attending college. Also, when the model is used to simulate the effect of relaxing borrowing constraints, it predicts changes in college enrollment and work while in school that are comparable to changes that were observed historically. And, our model predicts effects of tuition on enrollment that are comparable to estimates in the literature.

Finally, the article also makes a methodological contribution in the area of estimation of dynamic discrete choice models. As has been well known since Heckman (1981), unobserved initial conditions, and unobserved state variables more generally, can pose formidable computational problems for consistent estimation of such models. In this article we present a simple approach to estimation of dynamic discrete choice models when there are unobserved state variables. Our approach relies on the assumption that all observed choices and other outcome variables that enter the likelihood function are measured with error. Then, it is possible to simulate the likelihood function value using simple unconditional simulations of agents' choice and outcome histories. An estimate of the likelihood contribution for an agent is then simply the joint density of measurement errors necessary to reconcile the simulated and observed outcome history for the agent.[6]

The rest of the article is organized as follows. Section 2 presents a background discussion of the literature on borrowing constraints and education, as well as a discussion of prior literature on education finance and determinants of life cycle consumption paths to which our article is related. Section 3 presents the model, its basic structure, solution method, estimation method, and parameterization. The data are described in Section 4. Section 5 presents estimation results, including a brief discussion of specific parameter values and fit. Section 6 interprets the results and presents the counterfactual experiments that we use to address the questions of how parental transfers and borrowing constraints affect educational attainment. Section 7 presents conclusions.

2. BACKGROUND AND RELEVANT LITERATURE

2.1. *Borrowing Constraints and Educational Attainment*. The notion that borrowing constraints and other capital market "imperfections" lead to underinvestment in human capital has been widely accepted among economists (see, e.g., Becker, 1960; Schultz, 1961; Friedman, 1962).[7] Friedman (1962; p. 103) noted that with physical capital the solution to the analogous problem takes the form of equity investment

[6] In contrast, in the standard approach to forming the likelihood for sequential models, the likelihood is built up by forming the likelihood contribution of each period's choices and other outcomes conditional on the agent's state at the start of the period. If state variables are unobserved, it is necessary to integrate over their distribution, which is often intractably complex in models like ours. By assuming all choices and outcomes are measured with error, we can avoid the need fot conditional simulations. Hence, this method does not utilize any information on state variables (observed or not).

[7] There are two main arguments for this position. First, because education is not tangible, being embodied in a human being, it cannot itself serve as collateral. The second, and related, point is that, because the expected future earnings stream of an individual is the only possible security for a loan, the riskiness of this stream and the inherent moral hazard associated with it creates the potential of default.

with limited liability on the part of the shareholders. He argued that "the counterpart for education would be to 'buy' a share in an individual's earning prospects; to advance him the funds needed to finance his training on condition that he agree to pay the lender a specified fraction of his future earnings." Friedman further argued that the obstacle to the creation of such loan contracts by private lenders is the ease with which individuals could avoid repayment by moving from one place to another and/or by concealing earnings. He went on to advocate "equity investment in human beings" by the federal government and private financial institutions, with the federal role arising from the relative ease with which the IRS can verify income of individuals from tax returns (provided they do not exit the country).

In fact, Friedman's proposal has never been implemented on any significant scale. What has instead emerged is a system of government subsidy and loan programs. The passage of Title IV of the Higher Education Act of 1965 created the Guaranteed Student Loan (GSL) Program, later renamed the Stafford Loan Program. The GSL program provides government guarantees for student loans made by private lenders and subsidizes the interest rate on the loans. In addition, the Higher Education Act of 1965 also initiated a system of means tested federal grants to subsidize college costs for low income youth. These were originally called Educational Opportunity Grants (EOG), later renamed Basic Educational Opportunity Grants (BEOG), and finally renamed the Pell grant.

It might be argued that borrowing constraints cannot have any important influence on college attendance decisions, given the existing system of GSLs and Pell grants.[8] However, although the maximum Pell grant has varied widely in real terms over time (it was $3000 in 1998), it has generally been well below half of most estimates of tuition, room, and board costs at four year institutions (see, e.g., Kane, 1994: Figure 2). Further, an individual's grant cannot exceed a certain fraction of college expenses (set at 50% during most of our sample period). The maximum annual GSL amount is $2500, as compared to a Digest of Educational Statistics estimate of $9536 for the average undergraduate tuition, room, and board expense across both two and four year institutions in 1997–98. Thus, GSLs and Pell grants alone will not cover the cost of a college education.

Evidence on this point is provided by Leslie (1984), who examined the Cooperative Institutional Research Program (CIPR) data on college expense financing by first-time full-time freshman. He reports (p. 333) that in 1979–80, for youths from families in (roughly) the bottom income quintile, 59.4% of college expenses were financed with scholarships, grants, and loans. But 19.8% came from the youth's own saving and earnings, and 19.3% came from parental transfers. Thus, even among the bottom income quintile, parental transfers and self-finance are important.[9] In the second income quintile, the percentage of expenses that are self-financed or financed by parental transfers rise to 21.7% and 33.0%, respectively. And, in the top three-fifths of the income distribution, these percentages are 18.0% and 58.5%, respectively. In

[8] For instance, Heckman (1999: p. 16) argues that "[i]n the current environment, with the institution of the community college in place, and with generous loan and grant programs available, the arguments that tuition costs and commuting are major barriers to college attendance by the poor are implausible."

[9] The average amount financed by the youth and parents was $943 ($1994 in 1998 dollars).

terms of absolute amounts, for youths from families in the bottom quintile of the income distribution, the average parental contribution was \$465 (roughly \$978 in 1998 dollars), while for families in the top three-fifths of the income distribution the figure was \$2089 (roughly \$4393 in 1998 dollars).[10] As these figures demonstrate, not only are transfers from parents and self-finance important even for low income youths, but the share and amount of parental transfers rises rapidly with income.

2.2. *Borrowing Constraints and Life Cycle Consumption*. In addition to contributing to the empirical literature on borrowing constraints and educational attainment, the present article also contributes to the large literature on explaining life-cycle consumption profiles (see the recent extensive review by Browning and Lusardi, 1996). A major focus of that literature has been to test for the existence of borrowing constraints. In order to implement such tests, investigators have estimated versions of the Euler equation for intertemporal consumption allocation implied by what Browning and Lusardi (1996) refer to as "the standard additive" life cycle model, that is, a model with intertemporally additive utility, a constant discount factor, and perfect capital markets, and in which agents have rational expectations and maximize the expected present value of lifetime utility.

In the standard model with perfect capital markets, changes in consumption are unrelated to predictable changes in income. Thus, the test for liquidity constraints typically takes the form of estimating the Euler equation for the change in consumption from t to $t+1$, but including in the equation either income at t or the change in income from t to $t+1$. If this equation is estimated by instrumental variables, using as instruments variables that were elements of the agents' information sets at time t, then identification of the coefficients on the income variables comes off of the predictable part of the level of income or change in income. Since these predictable parts of income should be unrelated to consumption growth, their significance is taken as evidence of liquidity constraints.

In an influential paper, Zeldes (1989) found that lagged income was significant and negative in the consumption Euler equation estimated on a sample of low asset households in the PSID. This implies that consumption tends to decline following a period of predictably high income, which he takes as evidence of liquidity constraints. However, Keane and Runkle (1992) pointed out that the fixed effects estimator used by Zeldes' is inconsistent because it violates the orthogonality conditions implied by rational expectations. Using a consistent estimator on the same data set, both Keane and Runkle (1992) and Runkle (1991) find no evidence for liquidity constraints.

A problem with the PSID data used in these studies is that they contain only data on food consumption. Attanasio and Weber (1993) use synthetic cohort data from the British Family Expenditure Survey (FES), which contains more complete consumption data, to estimate an Euler equation including income growth. They find this variable is significant but argue it may be because leisure and consumption are

[10] Leslie reports an even stronger positive association between parental transfers and a measure of socioeconomic status (SES) that is closely related to parental education. Further, for the average family he finds an upward trend in the fraction of college expenses financed by parental transfers, from roughly 40 percent in 1973 to roughly 50 percent in 1980 (the last year he examined).

nonseparable. When they include information on employment status of households (which they interpret as taste shifters) to the Euler equation, they find that the income growth variable becomes insignificant. Meghir and Weber (1996) use U.S. Consumer Expenditure Survey data and model expenditures for food, transport, and services. They find little evidence of liquidity constraints, but like Attanasio and Weber (1993) they find that allowing for nonseparability of goods and leisure is crucial in fitting the data.[11] While these studies appear to support the standard model, the fact that changes in leisure may be so closely related to changes in income suggests that tests which control for leisure may have little power to identify liquidity constraints.

Attanasio and Browning (1995) note that consumption paths over the life cycle closely match income paths, but they point out that one can easily find reasonable equivalence scales to adjust consumption for household demographics such that life cycle consumption paths are rendered quite flat for the typical individual. Since equivalence scales are fundamentally arbitrary (due to their reliance on interpersonal utility comparisons), this means the standard model can always be reconciled fairly well with observed consumption data by allowing for enough interactions between consumption and household demographics in the utility function. Browning and Lusardi (1996) argue that this result should be interpreted not as favorable to the standard model but rather as showing how difficult it is to find convincing tests for liquidity constraints using the consumption Euler equation alone.[12]

In light of this, Browning and Lusardi (1996) argue that "what gives the standard life cycle framework real bite is that we must account for a whole range of behavior (short- and long-run saving, schooling, and occupational choice, fertility choice, portfolio decisions, retirement decisions, etc.) with the same set of parameters" and that "this is an ambitious undertaking which we have hardly yet begun." They note that Hubbard et al. (1995) take a step in this direction, in that they calibrate an additive life cycle model to fit not only data on short run consumption changes, but also distributions of wealth conditional on age and education. They modify the standard model by assuming agents cannot borrow, and they incorporate social security and pension payments and medical costs. Most importantly, they incorporate a government transfer program that guarantees a minimum consumption level after taxing income and assets at a 100% rate. They find that if the guaranteed minimum is set sufficiently high it can explain the existence of a large segment of households with low education levels who have very little saving over the whole life cycle.

As Hubbard et al. (1995) note, a major failing of their model is that it predicts asset levels for young college graduates that are far too high.[13] They speculate that this may be due to the failure to account for parental transfers, which may be relatively large

[11] Meghir and Weber use a direct translog utility function that allows for nonseparability in the demand for each good. They also find no evidence for nonseparability.

[12] Even if one argues that this literature has provided convincing tests for the existence of borrowing constraints, the Euler equation approach cannot shed much light on the quantitative importance of borrowing constraints for life cycle decisions such as school attendance, labor supply, and saving. To accomplish that requires a full solution and estimation of the dynamic optimization problem.

[13] In a standard life cycle model, college graduates would be expected to borrow substantially when they are young because they will have high income later in life. Given a non-negative asset constraint as Hubbard et al. (1995), they should stay close to the asset floor.

for this group. Our estimates are able to provide a much better fit to distributions of wealth conditional on age and education than in Hubbard et al. (1995)—at least at young ages—and imply that large parental transfers from college educated parents do indeed play a major role in accounting for the high asset levels observed for college graduates at young ages.

Our work goes well beyond Hubbard et al. (1995) in that, following the program advocated by Browning and Lusardi (1996), we use the life cycle framework to fit data also on schooling and work decisions. Further, we fit asset distributions conditional not only on age and education but also on marital status, parental co-residence status, and parental background. And we fit our model by simulated maximum likelihood, rather than simply by calibration, and we provide estimates of the importance of borrowing constraints rather than simply assuming they exist.

3. MODEL

In this section, we present the basic structure of the model, the solution, and estimation methods necessary for empirical implementation and specific parameterizations. The model corresponds to the decision problem of a single individual.[14]

3.1. *Basic Structure*

3.1.1. *Decision period*. The decision horizon begins at the start of the Fall school semester at which the individual first reaches age 16. A year is divided into three distinct decision periods corresponding to the Fall, Spring, and Summer semesters. The Fall and Spring semesters are each of equal length (4.8 months), with the Summer semester half as long (2.4 months).

3.1.2. *Choice set*. The elements of the choice set in each period consist of school attendance, work participation, and asset (or saving, and thus consumption) combinations. Attending school full time during Fall or Spring semesters advances schooling by 0.5 years (one-half of a grade level), attending part time by 0.25 years (one-quarter of a grade level). Attendance during a Summer semester is equivalent to part-time attendance during the other semesters and similarly increases schooling by 0.25 years. Part-time attendance is only an option in college; high school requires full-time attendance.[15] We denote $s_t = \{0, 0.5, 1\}$ as indicating nonattendance, part-time attendance, or full-time attendance at decision age t. There are three alternative work intensities: no work, part-time work, and full-time work. We denote $h_t = \{0, 20, 40\}$ as the possible choices of hours of work per week at decision age t. Finally, the individual can choose (given feasibility) at each decision age t among a fixed number of discrete levels of saving in excess of interest income,

[14] However, in implementing the model we introduce unobserved population heterogeneity in preferences and abilities and observed heterogeneity in resource constraints.

[15] There is no uncertainty regarding school progress given attendance. Failure is equivalent to a choice of nonattendance. We do not allow for Summer school attendance in high school.

$\Delta a_{t+1} = a_{t+1} - (1+r)a_t = \{\underline{\Delta a}, \ldots, \overline{\Delta a}\}$, where a_t is the level of assets at t.[16] Thus, although the amount of (excess) saving in a period is constrained to lie within this range, the range of feasible asset levels grows with age. Net borrowing is not ruled out; that is, Δa may be less than zero.

3.1.3. *Preferences*. The individual has preferences over the choice variables, i.e., consumption, c_t, school attendance, and hours of work, conditional on marital status, $m_t(m_t = 1$ if married at age t and zero otherwise), on parental co-residence, $p_t(p_t = 1$ if co-residing with parents at age t and zero otherwise), and on preference shocks to work (ϵ_t^h) and to school attendance (ϵ_t^s); i.e., $u_t = u(c_t, s_t, h_t; m_t, p_t, \epsilon_t^h, \epsilon_t^s)$.

3.1.4. *Constraints*. A part-time and a full-time hourly wage offer (w_t^p and w_t^f) is received at each age t. Wage offers are given by the product of the rental price of human capital, which may differ for part- and full-time jobs (r^p and r^f), and the level of human capital (Ψ_t), which depends on the amount of schooling obtained by age $t(S_t = S_{t-1} + s_{t-1})$, on work experience at age t as measured by cumulative hours worked over part- and full-time jobs $(H_t = H_{t-1} + 20 \cdot I(h_t = 20) + 40 \cdot I(h_t = 40))$ where $I(\cdot)$ is an indicator function equal to one if the term inside the parentheses is true and equal to zero otherwise), and by work status in the previous period (h_{t-1}), on age and on idiosyncratic shocks to productivity (ϵ_t^w). We adopt a multiplicative form for the human capital function, $\Psi_t^j = \Psi_t^{0j}(\cdot)\exp(\epsilon_t^w)$, which leads to a Mincer-type wage function. If the individual chooses to engage in market work, the accepted wage is $w_t = w_t^p I(h_t = 20) + w_t^f I(h_t = 40)$.

The full-time cost of college (graduate school) is tc (tg), inclusive of tuition, room and board, etc.; the part-time cost is assumed to be half of the full-time cost. Parents are assumed to provide positive net transfers when co-resident, tr_t^p, while spousal transfers, tr_t^m, may be positive or negative.[17] The amount of parental transfers is assumed to depend on some aspects of the youth's behavior, namely whether the youth is attending college and on the level of the youth's assets, and on the parents' schooling, S^P.[18] The parental transfer rule is taken by the youth as given. We assume that transfer amounts within marriage are independent of behavior.[19] Co-residence with parents and marriage are taken as (weakly) exogenous and probabilistic. We denote π_t^p and π_t^m as the probability of co-residence and of being married at age t. Their determinants are discussed below.

[16] We discretize hours worked and saving in order that the agent's choice set be entirely discrete, which increases the tractability of the problem.

[17] Transfers are assumed to be half as large during the Summer as in the Fall of Spring.

[18] The majority of college students identify themselves as members of their parental household. Based on the data we use for our analysis, 76 percent of (unmarried) white male high school graduates less than age 24 report living in the same household as at least one of their parents during semesters of full-time college attendance. The similar figure for those attending part time is 71 percent and for those not attending 63 percent.

[19] This assumption is at best only a first approximation. Ideally, one would prefer to model the intrahousehold allocation decision from which the transfer rule would be derived as a function of the decisions and/or characteristics of both spouses.

Letting y_t denote earned income, i.e., $y_t = 20[w_t \cdot h_t]$ in the Fall and Spring semesters in which there are assumed to be 20 work weeks and $y_t = 10[w_t \cdot h_t]$ in the Summer semester, the budget constraint is given by

$$(1) \quad c_t + a_{t+1} = (1+r^l)a_t I(a_t > 0) + (1+r^b)a_t I(a_t < 0) + y_t - tc \cdot s_t^c - tg \cdot s_t^g + \mathrm{tr}_t^p \cdot p_t + \mathrm{tr}_t^m \cdot m_t$$

where r^l is the fixed lending rate and r^b is the fixed borrowing rate of interest, s_t^c is equal to s_t if attending college, and s_t^g is equal to s_t if attending graduate school. We assume the existence of a consumption floor, $\underline{c}$, such that a choice (an $s_{t,}$, h_t, Δa_{t+1} combination) is feasible only if $c_t \geq \underline{c}$. However, if by working full time, borrowing the maximum permissible amount, and not attending college, consumption is below the minimum given the level of net family transfers, minimum consumption is provided. In addition, there is a lower bound asset level ($\underline{a}_t$) that can vary with age and the level of human capital and that is, as noted, not necessarily constrained to be non-negative; i.e., the individual is allowed to hold some amount of uncollateralized debt.[20]

3.1.5. *Objective function*. The individual is assumed to maximize the present discounted value of lifetime utility from age 16 ($t = 1$) to a known terminal age, $t = T$. The choice set in each period consists of the discrete alternatives given by the Cartesian product, $s \times h \times \Delta a$. Denoting the choice of the kth element of this set as $d_t^k = 1$ (and the choice of any other element as $d_t^k = 0$), $k = 1, \ldots, K$, and the utility associated with that choice as u_t^k, the maximized objective function at any age $t \geq 16$, $V_t(\Omega_t)$, is given by

$$(2) \quad V_t(\Omega_t) = \max_{(d_t^k)} E\left[\sum_{\tau=t}^{T}\sum_{k=1}^{K} \delta^{\tau-t} u_\tau^k d_\tau^k \mid \Omega_t\right]$$

where E is the expectations operator, Ω_t is the state space at t (the relevant information set with which the individual enters decision age t), and δ is the subjective discount factor, which we allow to depend on marital status to capture the potentially increased importance of the future when there are or will be offspring.[21] As the model is specified, the state variables include the level of human capital (net of the productivity shock), Ψ^0, accumulated assets, a_t, parental co-residence status, p_t, marital status, m_t, age, parental schooling, S^P, and the contemporaneous shocks, the ϵ_t's. We assume that the ϵ_t's are jointly serially independent. Initial conditions include the age 16 values of the state variables, $\{S_{16}, H_{16}, a_{16}, S^P\}$, respectively, the level of schooling completed by the beginning of the decision horizon, the number of hours worked up to age 16 (assumed to be zero), the level of assets accumulated up

[20] It is possible that the amount of permissible uncollateralized debt may fall between periods. If paying off the debt necessary to satisfy the maximum debt constraint would force the individual to the minimum consumption level, the debt repayment is set at a minimum level ($ 500).

[21] We do not explicitly account for the number of children which would have expanded the state space. The cost of this omission is that the discount rate falls to its level in the unmarried state if the individual divorces, regardless of whether there are children.

to age 16 (assumed to be zero), and parental schooling.[22] The maximization of (2) is achieved by choice of the optimal sequence of feasible control variables $\{d_t^k\}$ given current realizations of the stochastic components of preferences and wage offers.

3.2. *Solution Method*. The maximization problem can be recast in a dynamic programming framework. In particular, the value function, V_t, can be written as the maximum over alternative-specific value functions, denoted as V_t^k for $k = 1, \ldots, K$, that satisfy the Bellman (1957) equation; namely

$$\begin{aligned} V_t(\Omega_t) &= \max[V_t^1(\Omega_t), \ldots, V_t^K(\Omega_t)] \\ V_t^k(\Omega_t) &= u_t^k + \delta E(V_{t+1}(\Omega_{t+1}) \mid d_t^k = 1, \Omega_t) \end{aligned} \tag{3}$$

The expectation in (3) is taken over the joint distribution of the stochastic shocks ϵ_{t+1}^h, ϵ_{t+1}^s, and ϵ_{t+1}^w, and over the $t+1$ marriage and parental co-residence states. The terminal-period alternative-specific value functions V_t^k consist only of the contemporaneous utilities.

The solution of the model is in general not analytic. In developing the numerical solution algorithm, it is convenient to regard the solution of the model as consisting of the set of all values of $EV_{t+1}(\Omega_{t+1})$, i.e., for all values of t, d_t^k, and Ω_t. We refer to this function as $E\max_t$ for convenience. As seen in (3), treating these functions as a known scalar for each value of the state space transforms the dynamic optimization problem into the more familiar static multinomial choice structure. Given the finite horizon, the solution method proceeds by backward recursion. The difficulty with this procedure is that for high dimensional problems, where the state space and/or the choice set is large, computing the solution can be burdensome in terms of computation time and memory. The "curse of dimensionality" problem is particularly severe in the context of estimation because then the optimization problem must be solved repeatedly.

To maintain computational tractability, we adopt an approximation method developed and implemented in our previous papers (Keane and Wolpin, 1994, 1997). Specifically, we write the $E\max$ functions as general functions of the state space elements.[23] In the current application, we restrict these functions to be polynomials. In each step above, i.e., at each t, we calculate the $E\max_t$ function for a subset of the state space and estimate a regression function as a polynomial in those state space elements.[24] We substitute these estimated polynomials into the alternative-specific value functions given by (3), using the predicted values from the regression to substitute for the $E\max$ values.

One reason the state space is large in this model is because the lifetime horizon encompasses many decision periods (three per year). The terminal date T should

[22] We do not have information on assets at age 16. Differential wealth at age 16 is captured by allowing for differential levels of parental transfers related to parental schooling.

[23] We also follow our previous work in using Monte Carlo integration to calculate the multivariate integrals necessary to compute the Emax functions.

[24] In Keane and Wolpin (1994), this form of the Emax approximation was found to work well in approximating the full solution of the dynamic programming problem, although not quite as well as other more computationally burdensome approximations.

correspond to the last period in which the $E\max$ function is dependent on state variables. To avoid the computational burden of having to solve the model over an arbitrarily long horizon, say to age 65, we instead begin the backward recursion at a computationally convenient age, say T^*, using the polynomial form of the $E\max$ function at that age as the terminal condition. The parameters of this quasi-terminal value function are estimated along with the structural parameters of the model, subject to identification limitations discussed below; i.e., the restrictions that are embedded in the parameters are ignored.

3.3. *Estimation Method*. The (approximate) solution to the agents' maximization problem provides (polynomial approximations to) the $E\max$ functions that appear on the right hand side of (3). At this point, the only unknowns in the alternative-specific value functions V_t^k for $k = 1, \dots, K$ are the current period payoff functions u_t^k. These, in turn, are known up to the random shocks ϵ_t^h, ϵ_t^s, and ϵ_t^w. Thus, conditional on the deterministic part of the state space, Ω_t, the probability that an agent is observed to choose option k takes the form of an integral over the region of the space of the three errors ϵ_t^h, ϵ_t^s, and ϵ_t^w such that k is the preferred option. If option k corresponds to a work option, then ϵ_t^w is observed, and the choice probability is an integral over the two remaining error terms. In that case, the likelihood contribution for the observation also includes the density of the wage error.

In our application the choice set contains 135 elements ($s \times h \times \Delta a$). It is well known that evaluation of choice probabilities is computationally burdensome when the number of alternatives is large. But in recent years, highly efficient smooth unbiased probability simulators, such as the GHK method (see, e.g., Keane, 1993, 1994), have been developed for these situations. Unfortunately, the GHK method, as well as other smooth unbiased simulators, relies on a structure in which there is a separate additive error associated with each alternative. Further, as discussed in Keane and Moffitt (1998), in structural models such as ours, where the number of choices exceeds the number of error terms, the boundaries of the region of integration needed to evaluate a particular choice probability are generally intractably complex. Thus, given Ω_t, the most practical method to simulate the probability for an agents' observed choice in our model would be to use a kernel smoothed frequency simulator. These were proposed in McFadden (1987) and successfully applied to estimate a structural model with a large choice set in Keane and Moffitt (1998). Kernel smoothed frequency simulators are, of course, biased for positive values of the smoothing parameter, and consistency requires letting the smoothing parameter approach zero as sample size increases.

But in the present context, this approach is not feasible because of severe problems created by unobserved state variables. Most importantly, the NLSY does not contain asset information for 1979–1983 and 1989. Further, hours worked (h) and school attendance (s) are sometimes unobserved, in which case the state variables for experience and schooling level cannot be constructed. The parental co-residence (p) and marital status (m) outcomes, which are elements of Ω_t, are sometimes also unobserved, as in some cases are the youth's initial schooling level (S_{16}) and his parents' schooling level (S^P). It has been well known since Heckman (1981) that unobserved initial conditions, and unobserved state variables more generally, pose formidable computational problems for estimation of dynamic discrete choice models. If some or all elements of Ω_t are unobserved, then to construct conditional choice probabilites one must integrate over the distribution of the unobserved elements. Even in much simplier dynamic models than ours, such distributions are typically intractably complex.

We have developed an estimation algorithm that deals in a practical way with the problem of unobserved state variables. The algorithm is based on simulation of complete (age 16 to age T^*) outcome histories for a set of artificial agents. An outcome history consists of the parents' schooling (S^P) and initial school level of the youth (S_{16}), along with simulated choices in all subsequent periods for the six outcome variables in the model (co-residence, marriage, the wage, hours of work, school attendance, savings). The construction of an outcome history can be described compactly as follows.

At the current trial parameter value:

(1) Draw parents' initial school and the youth's initial school, S^p, S_{16}.
(2) Draw co-residence and marriage status at $t = 1$.
(3) Draw $(\epsilon_1^w, \epsilon_1^s, \epsilon_1^h)$. Construct $V_1^k(\epsilon_1^w, \epsilon_1^s, \epsilon_1^h)$ for $k = 1, \ldots, K$ and choose the optimal $(h_1, s_1, \Delta a_1)$.
(4) Update the state variables.
(5) Go to $t = 2$. Repeat steps (2)–(4).
(6) Go to $t = 3$. Repeat steps (2)–(4), etc., until terminal period T^* is reached.

Do this N times to obtain simulated outcome histories for N artificial persons. Denote by $\widetilde{O}^n$ the simulated outcome history for the nth such person, $\widetilde{O}^n = (\widetilde{S}^n, \widetilde{O}^n_{t=1}, \ldots, \widetilde{O}^n_{t=T^*})$, for $n = 1, \ldots, N$, where $\widetilde{S}^n = (S^{P,n}, S^n_{16})$ and where $\widetilde{O}^n_t = (p^n_t, m^n_t, w^n_t, h^n_t, s^n_t, a^n_t)$ for $t = 1, \ldots, T^*$. We specify the specific functional forms that are assumed for the distributions of parents' school, youths' initial school, co-residence, marriage, and the errors ϵ^h_{t+1}, ϵ^s_{t+1}, and ϵ^w_{t+1} in the next section.

In order to motivate the estimation algorithm, it is useful to ignore for now the complication that wages are continuous. Let O^i denote the observed outcome history for person i, which may include missing elements. Then, an unbiased frequency simulator of the probability of the observed outcome history for person i, $P(O^i)$, is just the fraction of the N simulated histories that are consistent with O^i. In this construction, missing elements of O^i are counted as consistent with any entry in the corresponding element of $\widetilde{O}^n$. Note that the construction of this simulator relies only on unconditional simulations. It does not require evaluation of choice probabilities conditional on state variables. Thus, unobserved state variables do not create a problem for this procedure.

Unfortunately, this algorithm is not practical. Since the number of possible outcome histories is huge, consistency of a simulated history with an actual history is an extremely low probability event. Hence, simulated probabilities will typically be 0, as thus will the likelihood, unless an impractically large simulation size is used (see Lerman and Manski, 1981). In addition, the method breaks down if any outcome is continuous, e.g., w_t, regardless of simulation size, because agreement of observed with simulated wages is a measure zero event.

We solve this problem by assuming, as is apt, that all observed quantities are measured with error. With measurement error there is a nonzero probability that any observed outcome history might be generated by any simulated outcome history. Denote by $P(O^i \mid \widetilde{O}^n)$ the probability that observed outcome history O^i is generated by simulated outcome history $\widetilde{O}^n$. Then $P(O^i \mid \widetilde{O}^n)$ is the product of classification error rates on discrete outcomes and measurement error densities for wages and assets that are needed to make O^i and $\widetilde{O}^n$ consistent. Observe that $P(O^i \mid \widetilde{O}^n) > 0$ for any $\widetilde{O}^n$, given suitable choice of error processes. The specific measurement error processes that we assume are described below. The key point here is that $P(O^i \mid \widetilde{O}^n)$ does not depend on the state variables at any time t. It only depends on the outcomes, i.e., $(S^p, S_{16}, p_t, m_t, w_t, h_t, s_t, a_t)$.[25]

Using N simulated outcome histories we obtain the unbiased simulator

$$\widehat{P}_N(O^i) = \frac{1}{N}\sum_{n=1}^{N} P(O^i|\widetilde{O}^n) \tag{4}$$

Note that this simulator is analogous to a kernel-smoothed frequency simulator, in that $I(O^i = \widetilde{O}^n)$ is replaced with an object that is strictly positive, but that is greater if $\widetilde{O}^n$ is "closer" to O^i. However, the simulator in (4) is unbiased because the measurement error is assumed to be present in the true model.

To handle unobserved heterogeneity (i.e., types) in this framework, define $\pi_{k|S_{16},S^p}$ as the probability a person is type k given his initial school (at age 16), and parents' education, for $k = 1, \ldots, K$, where K is the number of types. In this case, simulate N/K vectors $\widetilde{O}^n_k$ for each type. Then,

$$\widehat{P}_N(O^i) = \frac{1}{N}\sum_{k=1}^{K}\sum_{n=1}^{N/K} P(O^i|\widetilde{O}^n)\frac{\pi_{k|S_{16},S^p}}{N/K} \tag{5}$$

Observe that in (5), the conditional probabilities $P(O^i|\widetilde{O}^n)$ are weighted by the ratio of the proportion of type k according to the model, $\pi_{k|S_{16},S^p}$, to the proportion of type k in the simulator, N/K.

Note that this simulator is smooth in the model parameters if simulated outcome histories are held fixed and reweighted as parameters are varied. Given an initial parameter vector θ and an updated vector θ', the appropriate weights are the ratio of the likelihood of the simulated history under θ' to that under θ. Such weights have the form of importance sampling weights (i.e., the ratios of densities under the target and source distributions) and are smooth functions of the model parameters. Further, it is straightforward to simulate the likelihood of an artificial history using conventional methods because the state vector is fully observed at all points along the history. Thus, $P(O^i|\widetilde{O}^n)$ can be simulated using a kernel smoothed frequence simulator, for example. We use a smoothing algorithm to construct standard errors using the BHHH algorithm. But, in searching for the SMLE, we did not use this

[25] As a simple example of this construction, assume a single discrete outcome variable with classification rates $P(1 \mid 1) = 0.9, P(1 \mid 0) = 0.1, P(0 \mid 1) = 0.1, P(0 \mid 0) = 0.9$. Suppose $T = 4$. Then $P(1\ 0\ 1\ 0 \mid 1\ 1\ 1\ 1) = (0.9)(0.1)(0.9)(0.1) = 0.0081$ and $P(-9\ 0\ -9\ 1 \mid 1\ 0\ 1\ 1) = (0.9)(0.9) = 0.81$, where -9 indicates that the observation is missing. In the first example O^i and $\widetilde{O}^n$ are inconsistent. In the second they are consistent.

algorithm but rather drew new outcome histories at each trial parameter vector. To accommodate the fact that the resultant simulated likelihood is not smooth, a Simplex algorithm was used.

Finally, it is necessary to describe the specific assumptions for the measurement error processes. First, we assume that discrete outcomes (i.e., hours worked (h), school attendance (s), parental co-residence (p), and marital status (m), as well as to the youth's initial schooling level and his parents' schooling level) are subject to classification error. The structure we adopt is simply that there is some probability that the reported response category is the truth and some probability that it is not.[26] Second, we assume that wages and assets, which are continuous variables, are also subject to measurement error. In particular, we assume that the wage error is multiplicative, i.e., $w_t^{\text{obs}} = w_t \exp(\eta_t^w)$, and the asset error is additive, i.e., $a_t^{\text{obs}} = a_t + \eta_t^a$.[27] Both of these measurement errors are assumed to be serially independent and independent of each other.

3.4. *Parameterizations*. The solution/estimation of the model requires the choice of explicit functional form and distributional assumptions. Because the solution of the model is numerical, functional forms need not be chosen for analytical convenience but rather can be chosen for their correspondence to existing literature, their ease of interpretation, and their ability to fit the data. Indeed, the exact specifications were not chosen *a priori* but rather reflect an iterative specification search based on assessing the fit of the model to elemental aspects of the data.[28] We were especially concerned about distinguishing between unobserved heterogeneity and other explanations for the age and transition patterns in the data and, therefore, liberally added age variables and lagged choice variables as estimation proceeded in order that the degree of heterogeneity not be overstated. The exact specifications are given in Appendix A. Here we present only the essential components of the specifications.

3.4.1. *Utility function*. The utility function is an augmented CRRA given by

$$u_t = \frac{\mu(m_t, s_t, t)}{\lambda} c^\lambda + g(h_t, s_t, s_{t-1}, t; m_t, p_t, \epsilon_t^h, \epsilon_t^s, \text{type}) \tag{6}$$

where $1 - \lambda > 0$ is the constant relative risk aversion parameter. Notice that the marginal utility of consumption is shifted by the elements in $\mu(\cdot)$. Including type in the utility function allows for permanent unobserved heterogeneity in preferences for work and school attendance.

[26] To ensure that the measurement error is unbiased, the probability that the reported value is the true value must be a linear function of the predicted sample proportion (see Appendix A for details). Obviously, measurement error cannot be distinguished from the other model parameters in a nonparametric setting. As in the model without measurement error, identification relies on a combination of functional form and distributional assumptions, and exclusionary restrictions.

[27] Given an additive measurement error for assets, we assume that the measurement error variance depends on the level of assets.

[28] Although this method of iterating between model specification and model fit clearly contaminates statistical measures of model fit, it would seem that such a strategy is unavoidable given the complexity of the behaviors that we model.

3.4.2. *Wage functions*. The part- and full-time wage functions are log linear in human capital, which itself is assumed to depend on school attainment, accumulated hours worked, hours worked in the previous period, age, and type; namely

$$\ln w_t^j = r^j + \Psi^{0j}(S_t, H_t, h_{t-1}, t, \text{type}) + \epsilon_t^w \qquad j = p, f \tag{7}$$

The inclusion of type reflects differences in unobserved permanent skill "endowments" that existed at age 16.[29]

3.4.3. *Parental transfer and co-residence propensity functions*. The level of parental transfers is assumed to be a deterministic non-negative function of their schooling (S^P), the current school attendance status of the youth, and the amount of the youth's assets; namely

$$\ln \mathrm{tr}_t^p = \mathrm{tr}^p(s_t, S^p, a_t) \tag{8}$$

The parsimony of the specification reflects the fact that we do not actually observe parental transfers in our data. The probability of parental co-residence is specified as a (logistic) function of prior period co-residence, prior period marital status, prior period school attendance, human capital, and age[30]; thus,

$$\pi_t^p = \pi^p(p_{t-1}, m_{t-1}, s_{t-1}, \Psi^0, t) \tag{9}$$

3.4.4. *Marital transfer and marital status propensity functions*. The level of resource transfers to or from a spouse is assumed to depend only on age and type,

$$\mathrm{tr}_t^m = \mathrm{tr}^m(t, \text{type}) \tag{10}$$

As with parental transfers, it is outside of the scope of this article to provide a model of intrahousehold allocation that should motivate the specification of the transfer function.[31] The probability of being married is given by

$$\pi_t^m = \pi^m(p_{t-1}, m_{t-1}, s_{t-1}, a_t, t) \tag{11}$$

3.4.5. *Terminal value function and Emax approximations*. As discussed above, our solution method depends on an approximation of the Emax functions through the quasi-terminal period T^*. Their determinants must include all of the state variables to be consistent with the dynamic programming structure, although the functional form is not dictated by the optimization.[32] The Emax functions are specified as the following (polynomial) functions:

$$E\max_t = E\max_t(\Psi^0, a_t, p_t, m_t, s_{t-1}, h_{t-1}, S^p, \text{type}) \qquad t \leq T^* \tag{12}$$

[29] Note that a constant term in the human capital function would be confounded with the part-time and full-time skill rental price.

[30] The individual's type enters through their human capital stock.

[31] In order for the spouse to face a symmetric optimization problem, this specification implies that there is perfect marital sorting by type and age. As with the parental transfer function, it is likely that the marital transfer function would at least depend on the current state variables,but in this case including those of the spouse as well.

[32] An additional identification issue is raised by having to estimate the parameters of the terminal value function. Usually, the terminal value function is restricted. Either a terminal value function is imposed that is independent of state variables, for example, assuming that the finite horizon signifies

3.4.6. *Type, initial schooling, and parental schooling distribution functions*. The likelihood function includes the joint distribution of type, initial schooling, and parental schooling. Without loss of generality, we decompose the joint distribution into the conditional distribution of type given initial schooling and parental schooling times the joint distribution of initial schooling and parental schooling. The conditional type distribution is specified as a logit (with the conditioning variables as arguments). The joint initial schooling–parental schooling distribution is also factored as the conditional initial schooling density times the marginal parental schooling density. The former is estimated as a logit and the latter is estimated nonparametrically, both for a small number of discretized parent schooling categories. A fully nonparametric treatment of the trivariate joint distribution would unreasonably expand the parameter space.

3.4.7. *Capital market constraint*. The capital market constraint requires that assets not fall below some nonpositive lower bound. We allow the constraint to evolve as a function of the person's level of human capital and age. Specifically,

$$\underline{a}_t = \underline{a}_t(\Psi^0, t) \leq 0 \tag{13}$$

Recall that human capital is a combination of schooling and work experience and, as such, serves to forecast future earnings potential. We assume that lenders are not aware of (or do not think relevant) an individual's type, although they do know their human capital which is affected by their type.[33]

Notice that, unlike the parental transfer function, the borrowing constraint does not explicitly account for college attendance, e.g., special loan programs, nor does it vary with parental schooling. Lacking detailed data on semester by semester college loans and their characteristics, e.g., subsidized rates of interest, loan repayment schedules, etc., as well as on parental transfers, we felt it would be difficult to identify the effects of college attendance and parental schooling in both the borrowing constraint function and in the parental transfer function from data on net asset accumulation patterns alone.[34] But, as we demonstrate below, altering parental transfers has very different effects from altering borrowing constraints.

death or retirement (e.g., Keane and Wolpin, 1997) or the value function is assumed to be stationary, for example, assuming that agents live forever (e.g., Rust, 1987). It is perhaps intuitive that utility parameters in general may be confounded with parameters of the terminal value function. For example, it should make no difference if one obtains contemporaneous utility or future utility from some specific decision. In the present case, identification of utility parameters rests on restrictions we place on which state variables enter the terminal value function and the form in which they enter. Although identification of certain parameters may be somewhat arbitrary, it is important to recognize that the experiments we perform and the conclusions we draw do not depend on being able to separately identify those parameters.

[33] Individuals know their type as do employers.

[34] Note as well that we do not distinguish among assets by their liquidity; that is, we only consider a single asset. Indeed, if the borrowing rate of interest exceeds the lending rate, no individual would ever maintain an amount of gross debt greater than net debt. In order to accommodate college loans in a realistic fashion, we would have to treat them as distinct from other debt. Although we do not have the data to implement such a model, it would also be considerably more computationally demanding.

3.4.8. *Error distributions*. We assume that the within-period joint distribution of the ϵ's is $N(0, \Lambda)$ and the measurement error distributions of wages and assets, the η's, are independent $N(0, \sigma_{\eta^j})$, $j = w, a$.

4. DATA

The data are from the 1979 youth cohort of the NLSY. The NLSY consists of 12,686 individuals, approximately half of them male, who were 14 to 21 years of age as of January 1, 1979. The sample contains a core random sample and oversamples of blacks, Hispanics, "disadvantaged" whites, and members of 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, 1978. Interviews were first conducted in 1979 and have been conducted annually to the present. We follow each individual in the analysis sample from the first year they reach age 16 as of October 1 of that year through June 1992.

The NLSY collects schooling and employment data in event history form. Schooling data include highest grade attended and completed at each interview date, monthly enrollment in each calendar month (beginning with January 1980), school leaving dates, and the dates of diplomas and degrees. Employment data include the beginning and ending dates (to the calendar week) of all jobs (employers), all gaps in employment within jobs, usual hours worked per week on each job and the usual rate-of-pay on each job. In the 1979 interview, employment data were obtained back to January 1, 1978. Asset data were collected beginning with the 1984 interview and have been collected at each subsequent interview, except for 1989.[35]

Recall that the model divides a year according to a school calendar, into Fall, Spring, and Summer semesters. This characterization of the decision process implies that some of the data must be aggregated to match the model and that point-in-time data, such as assets, usually will exist for only one decision period per year. The details of the data construction follow.

4.1. *Schooling* (s_t). A male youth in our sample is defined to have attended school during a Fall semester if he reported having attended in the months of October, November, and December, during a Spring semester if he attended in February, March, and April, and during a Summer semester if he attended in July or August (college only). Attendance in high school was assigned full-time status and summer school attendance prior to high school graduation was ignored. If attending college at the interview date, the assignment for the semester in which the interview date falls was made on the basis of a question concerning whether the college considered the youth to be a full- or part-time student.

Unfortunately, assignments based on this information alone would have meant that no distinction between part- and full-time college attendance could be made for at least one of the two regular school semesters. Although our estimation procedure is designed to handle missing data, we decided to use auxiliary information about school attainment at each interview date to fill in missing data, i.e., because completed grade levels are reported at each interview date we were able to guess at the part- and

[35] That is the only year in which a telephone, as opposed to a personal, interview was conducted.

full-time enrollment status in each period that would be consistent with the grade accumulation pattern.[36]

4.2. *Employment* (h_t, w_t). The weekly hours worked assignment for the Fall semester is based on accumulating weekly hours worked over the months of September through January and dividing by the total number of weeks in the period. The summation is taken over the months of February through June for the Spring semester and over July and August for the Summer semester. To correspond to the model, hours worked per week (h_t) is set to zero if actual weekly hours from the above calculation is less than 10 hours, to 20 if actual hours is 10 or more but less than 30, and to 40 if actual hours is 30 or more. The hourly wage for a semester is calculated as the sum of usual weekly earnings over the semester divided by actual hours worked over the period.

4.3. *Assets* (a_t). Net asset values are obtained separately in the NLSY for (i) housing, (ii) savings and checking accounts, money market funds, retirement accounts, stocks, bonds, etc., (iii) farm operation, business or professional practice, other real estate, (iv) motor vehicles primarily for personal use, (v) other items worth individually more than \$500, (vi) other debts over \$500. The sum of these items, net worth, is used as the analog of the theoretical construct.

4.4. *Other Measurements*. Parental co-residence status is reported only at the interview date and therefore assignable only in the semester within which that date falls. Marital status is obtained from a dated (by the month) event history of all marriage events and is known in all semesters. Parental schooling (S^p) is measured as the maximum level of schooling achieved by either parent and is discretized into four levels: $S^p = \{0\text{–}11, 12, 13\text{–}15, 16\text{–}20)$.

4.5. *Descriptive Statistics*. Table 1 shows the marginal and joint distributions of school and work choices by age and semester.[37] With respect to school attendance, 86.6 percent of the sample is attending school in the Fall semester of their 16th birthday. All of these attendees are full-time students, almost universally because they are attending high school. Full-time attendance drops to 75.1 percent one year later and to 40.7 percent at age 18 (Fall semester), reflecting the normal high school graduation age. Attendance, full plus part time, continues to fall throughout the college-going ages (19–21), with again the largest one-year drop at age 22, reflecting the normal college graduation age. Over those ages, part-time attendance becomes relatively more common, increasing (based on Fall semesters) from only 12 percent of attendees at age 19 to 35 percent at age 21, 49 percent at age 22, and 54 percent at age 24. In absolute terms, part-time attendance peaks at 9.2 percent of the sample

[36] This task was complicated by the fact that the pattern of grade level completion is itself quite often not internally consistent; e.g, grade levels sometimes fall from one year to the next. In determining part- and full-time college attendance, we hand-edited every case to ensure consistency between the attendance record and the grade level completion record. Note that we do not make use of the grade completion record in the estimation.

[37] The sample consists of 1051 youths observed for 40,422 semesters.

TABLE 1
SCHOOL ATTENDANCE AND EMPLOYMENT BY AGE AND SCHOOL SEMESTER (PCT. DISTRIBUTION)*

	Attend School		Work		Att. School PT Work		Att. School FT Work	
Age: Semester (No. Obs.)	PT	FT	PT	FT	PT	FT	PT	FT
16: Fall (1051)	0.0	86.6	32.0	8.4	0.0	0.0	28.1	5.4
Spring	0.0	86.4	34.9	11.1	0.0	0.0	31.4	7.3
Summer	0.0	—	30.9	31.3	0.0	0.0	—	—
17: Fall (1047)	0.4	75.1	35.4	16.6	0.3	0.0	28.1	7.8
Spring	0.3	75.5	34.4	22.9	0.2	0.0	28.3	13.1
Summer	0.4	—	27.5	43.9	0.2	0.2	—	—
18: Fall (1037)	2.1	40.7	27.3	32.1	0.7	1.1	11.8	3.2
Spring	2.7	40.1	29.4	38.3	0.8	1.2	15.9	4.2
Summer	4.9	—	18.1	59.9	0.1	0.4	—	—
19: Fall (1030)	4.3	30.5	24.0	45.0	1.3	2.0	10.1	2.9
Spring	4.0	29.3	24.4	48.1	1.4	1.4	11.7	2.5
Summer	2.0	—	17.5	65.3	0.6	1.1	—	—
20: Fall (1024)	6.2	24.1	21.4	52.1	1.9	1.9	8.2	2.1
Spring	6.2	23.1	18.4	56.5	1.7	1.7	8.3	2.9
Summer	1.5	—	13.6	69.7	0.3	0.6	—	—
21: Fall (1015)	9.2	17.1	17.7	59.6	2.9	1.6	6.3	1.8
Spring	8.9	15.9	18.0	62.6	3.7	1.3	5.2	2.9
Summer	2.0	—	9.1	73.6	0.6	0.7	—	—
22: Fall (998)	9.0	9.3	14.0	67.9	3.0	2.4	2.5	1.6
Spring	7.3	7.9	13.7	72.1	2.6	2.1	2.8	1.7
Summer	1.4	—	8.0	76.9	0.1	0.1	—	—
23: Fall (984)	6.4	5.6	11.0	75.7	1.2	3.3	1.5	1.1
Spring	5.6	5.2	12.9	76.7	1.4	2.7	1.9	1.0
Summer	1.5	—	6.7	82.2	0.2	1.1	—	—
24: Fall (974)	4.5	3.8	8.4	81.7	0.9	2.7	1.0	1.0
Spring	4.5	3.4	10.2	82.9	1.0	2.6	0.8	0.8
Summer	1.3	—	7.4	84.8	0.1	1.0	—	—
25: All (959)	2.8	1.9	6.8	85.9	0.3	2.2	0.6	0.6
26: All (948)	2.7	1.2	6.8	86.5	0.3	2.1	0.2	0.4
27: All (932)	1.7	1.0	6.5	86.0	0.2	1.1	0.4	0.1
28: All (883)	1.7	0.8	6.1	85.2	0.2	1.2	0.3	0.0
29: All (589)	0.5	0.8	5.4	85.3	0.1	0.3	0.2	0.3
30: All (298)	0.3	1.3	4.9	86.8	0.3	0.0	0.2	0.7

* PT=part-time, FT=full-time.

at age 21 (Fall semester). Spring semester attendance, both full- and part-time, is with one exception always below Fall attendance in the same school year, but almost always by less than one percentage point. Summer semester attendance is always below 2 percent, except in the Summer semester in which they are 18 years old.

As Table 1 also reveals, working during the high school and college ages is quite prevalent. Slightly over 40 percent of the 16 year olds were working in their Fall semester (part and full time), 52 percent were working a year later, and over 70 percent were working by the Spring semester of their 19th birthday. During those ages, part-time work declines between the Spring and following Summer semesters,

TABLE 2

NET ASSET DISTRIBUTION CHARACTERISTIC AGE*

Age (No. Obs.)	Mean	Median	Coef. of Var.	Minimum	Maximum	Percent Negative
20 (322)	4034	2118	1.71	−13,828	48,729	11.5
21 (607)	5386	2476	1.70	−12,500	59,855	11.0
22 (880)	6084	3002	1.72	−18,500	69,500	15.1
23 (819)	7624	3800	1.73	−30,200	77,399	16.1
24 (802)	9504	5293	1.55	−32,933	85,793	13.6
25 (719)	10,940	5166	1.57	−30,115	97,690	16.3
26 (657)	14,226	7472	1.46	−24,907	108,060	12.9
27 (563)	16,195	8487	1.43	−29,672	118,620	13.7
28 (466)	19,291	11,101	1.32	−35,711	126,021	11.2
29 (356)	21,243	11,210	1.25	−19,819	120,675	12.4
30 (154)	20,888	13,730	1.30	−25,685	149,671	9.1

* 1987 dollars.

although full-time work rises by substantially more and then falls in the following Fall semester. By age 23, shortly after the normal college-leaving age, over 90 percent of the sample is working.

A large percentage of youths who attend (postsecondary) school part time also work. At age 19 (Fall semester), 30 percent (100*1.3/4.3) of them work part time and 46.5 percent (100*2.0/4.3) work full time. However, while the percent of part-time attendees who work part- time remains roughly constant through age 22, the percent who also work full time falls to only 18 percent at age 20 and remains under 30 percent through age 22. A similarly large percentage of full-time students also work. At age 16 (Fall semester), 32 percent of full-time attendees work part time and 6 percent full time. By age 17, these figures increase to 37 percent and 10 percent and remain roughly the same through the college years.

Table 2 provides descriptive statistics for net assets. Recall that asset data were not collected until 1984 which, with the age restriction in the NLSY, implies that the earliest age at which we observe assets is essentially 20. Given the relatively small number of observations and the likely measurement error that accounts for some extremely large positive and negative reported net asset levels, outlier observations (in total, 18 asset observations from below and 95 from above) were deleted.[38] As the table indicates, mean net assets grow by a multiple of five between the ages of 20

[38] The upper and lower truncation points used to trim the asset data depended on age.

TABLE 3
COLLEGE LOANS AND NET WORTH *, †

Highest Grade Completed	Number of Youths	Percent With College Loans	Mean Loan Amount if Positive	Mean Net Worth for Youth with Zero Loans	Mean Net Worth for Youths with Positive Loans
≥13	255	53.7	5605	10,487	4850
≥14	211	59.2	5893	9940	4770
≥15	166	65.1	6227	9564	4672
≥16	128	68.0	6659	10,604	4706

* Youths age 22 or 23 in 1985 with reported net worth and college loan data in 1985.
† 1987 dollars.

($4034) and 30 ($20,888). At the same time, the coefficient of variation falls from 1.7 to 1.3.[39] The median is about one-half of the mean, reflecting the positive skewness that exists in the asset distribution. Table 2 also shows the prevalence of negative net worth. The proportion of the sample with negative net worth increases from 11.5 percent at age 20 to 16.3 percent at age 25 and then falls to 9.1 percent at age 30.[40] Average net debt (for those with net debt) is generally on the order of $5000. At age 25, 16 percent of the group with negative net worth held debt of more than $10,000 and 20 percent less than $1000.

The NLSY asset data presented in Table 2 are based on survey questions that do not explicitly mention college loans, which are presumably captured in the residual category "other debt." Although the asset questions remain the same each year, in a number of years the NLSY also collected separate data on college loans as part of the questions about school attendance. It is thus possible to provide some evidence on whether the asset data capture college loans. Table 3 presents evidence on the proportion of college attendees who had college loans, on the average amounts of those loans, and on the independently reported level of net assets for those with and for those without college loans. As the table shows, of the 255 youths who were ages 22 or 23 in 1985 and who had completed at least one year of college, 54 percent reported having received college loans totaling, on average, $5605 (in 1987 dollars). Similarly, of the subgroup of 128 youths who had already graduated from college, 68 percent reported receiving loans of, on average, $6659. The table also reports the net worth in 1985 of those with no college loans and those with positive loan amounts. As an aside, it is noteworthy that even those individuals who report having acquired college debt have positive net worth shortly after leaving college.

Now, as a purely accounting exercise, had the two groups had equal net worth save for college loans and had college loan amounts not been overlooked by respondents in reporting their residual liabilities, the difference in their net worth would be equal to the loan amount. This is, perhaps surprisingly, nearly the case; for the two examples given above, the net worth differences are $5637 and $5898. Of course, one cannot rule out the possibility that college loans had not been reported and that the existing

[39] Without trimming the data, the mean rises from $7635 to $27,068 and the coefficient of variation falls from 3.6 to 1.8, reflecting the greater importance of outliers at younger ages.

[40] These figures are almost identical for the untrimmed data.

TABLE 4
INITIAL CONDITIONS AND YOUTH OUTCOMES

	Parent's Highest Completed Schooling				
	High School Dropout	High School Graduate	Some College	College Graduate	All
All youths					
Percent	16.6	44.8	15.3	23.3	100
Mean highest grade completed*	10.9	12.7	13.6	15.2	13.1
Percent HS dropout	50.4	20.5	16.8	6.8	21.5
Percent HS graduate	36.2	44.4	32.1	15.0	34.3
Percent some college	9.9	17.2	18.2	17.4	16.2
Percent college graduate	3.5	17.9	32.9	60.8	28.0
Mean net assets†: ages 27–30	11,119	20,438	20,039	20,056	18,770
Mean earnings†‡: ages 27–30	5677	7266	8189	8861	7517
Mean hourly wage Rate†: ages 27–30	7.50	9.32	10.55	11.32	9.68
Youths completing less than 10 years of schooling by age 16					
Percent	45.8	23.9	16.4	10.7	23.4
Mean highest grade completed	9.6	11.2	11.9	12.7	10.9
Percent HS dropout	73.9	49.5	47.6	40.0	56.6
Percent HS graduate	24.6	32.6	23.8	15.0	27.3
Percent some college	1.5	12.6	14.3	10.0	8.8
Percent college graduate	0.0	53.0	14.3	35.0	7.3
Mean net assets: ages 27–30	8048	14,939	11,584	11,950	11,804
Mean earnings: ages 27–30	4905	5270	5351	5857	5207
Mean hourly wage rate†: Ages 27–30	6.61	6.97	7.02	7.83	6.93
Youths completing less than 10 years of schooling by age 16					
Percent	54.2	76.1	83.6	89.3	76.6
Mean highest grade completed	12.2	13.2	13.9	15.4	13.8

Continued...

difference in net worth merely represents the fact that those with fewer assets prior to entering college are more likely to rely on college loans. Nevertheless, the data is at least not inconsistent with the conclusion that college debt is not underreported to any significant degree in the NLSY asset data.

Table 4 illustrates the potential importance of family background, as measured by parental schooling, in determining school and employment outcomes. As the first

TABLE 4
CONTINUED

	Parent's Highest Completed Schooling				
	High School Dropout	High School Graduate	Some College	College Graduate	All
Percent HS dropout	27.8	11.3	11.2	3.2	10.8
Percent HS graduate	47.2	48.2	33.6	15.0	36.4
Percent some college	18.1	18.6	19.0	18.2	18.5
Percent college graduate	6.9	21.9	36.2	63.6	34.3
Mean net assets: ages 27–30	14,236	22,184	21,721	21,284	20,952
Mean earnings: ages 27–30	6397	7851	8750	9171	8204
Mean hourly wage rate: ages 27–30	8.33	10.01	11.25	11.68	10.49

*Youth completed schooling measured at age 28.
†1987 dollars.
‡Fall and Spring semesters only; conditional on positive earnings.

panel of the table shows, the difference in completed schooling between youths for whom neither parent completed high school (17 percent of the sample) and youths for whom at least one parent completed college (23 percent of the sample) is over 4 years. Of the former group of youths, about one-half themselves did not complete high school while about two-thirds of the latter completed college. As might be expected given the youths' schooling differences, labor market outcomes are also significantly related to parents' schooling. For example, the real hourly wage rate over the ages of 27 and 30 for those who are employed increases over the range of parents' schooling levels from $7.50 to $11.32.

Note that differences in school attainment actually have emerged by age 16, as about half of the youths from the lowest parents' schooling group, but only 10 percent of those from the highest group, have not completed 9th grade by that age. The second and third panels of the table show that school and employment outcome differences related to parents' schooling persist for youths even with the same level of completed schooling at age 16, although they are quantitatively smaller. On the other hand, it is also true that within parents' schooling groups, outcome differences by the level of age 16 completed schooling are of similar magnitude. Of course, interpreting these relationships as if they necessarily represented changes in youth outcomes achievable by manipulating either of the two initial conditions, parents' schooling or the youth's age 16 schooling, would be incorrect. We return to this point below.

5. ESTIMATION RESULTS

5.1. *Parameter Estimates*. The model's estimated parameters are reported in Appendix B together with standard errors. In total, there are 174 parameters.[41]

[41] To place this model in a more familiar perspective, in a nonstructural estimation framework one would need to specify equations for the eight mutually exclusive schooling–work combinations

TABLE 5

ESTIMATED PARENTAL TRANSFER AMOUNTS BY PARENTS' SCHOOLING AND YOUTHS' POSTSECONDARY SCHOOL ATTENDANCE*,†

	Parents' Completed Schooling				
	High School Dropout	High School Graduate	Some College	College Graduate	All
			Panel A		
Youth not attending post secondary school	1234	1526	2391	3801	1940
Youth attending postsecondary school	3271	4045	6338	10077	5610
Difference	2037	2519	3947	6276	3670
			Panel B		
Youth not attending post secondary school	1161	1431	2256	3285	1924
Youth attending postsecondary school	3074	3823	5961	8444	5945
Difference	1913	2392	3705	5159	4021

* Evaluated at zero youth assets.
† 1987 dollars.

However, the data consist of over 40,000 (person-semester) observations and the model is being fit to large choice set: the joint sequence of school attendance (part and full time), work hours (part and full time), levels of net saving (15 possible levels between $-\$7,500$ and $+\$15,000$), and accepted wages over as many as 44 periods.[42]

Our estimates of the parameters of the parental transfer function imply that parents increase their transfers significantly during periods when their co-resident children are attending postsecondary school, and that the amount of this parental educational subsidy depends importantly on parental education. The top panel of Table 5, derived directly from the estimated transfer function, shows that, on average, parents provide a \$1940 transfer (per full-time equivalent semester) when the co-resident child (who has not accumulated any net assets) is not in college. How-

together with an ordinally ordered level of net borrowing that takes on as many as 15 values, a wage function that differed for part- and full-time jobs, and functions that determine parental co-residence and marital status. In our specification, the latter three contain almost 50 parameters alone. Even a relatively parsimonious specification for the joint schooling–work–saving decisions would contain as many, and probably more, parameters as we have in the utility function, parental and marital transfer functions, and the joint error distribution. Moreover, an econometric specification that does not recover structural parameters would not be useful in assessing the impact on youth outcomes of parental transfers and borrowing constraints, for which there are no explicit measures in the data.

[42] The actual values are $\pm(7500, 5000, 3000, 2000, 1000, 500)$ and 0, +11,000, and +15,000.

TABLE 6

ESTIMATED MAXIMUM PERMISSABLE NET DEBT AT SELECTED AGES AND SCHOOL COMPLETION LEVELS BY YOUTH TYPE*

	Type 1	Type 2	Type 3	Type 4
Age, Completed Schooling				
18, 12	−1165	−1059	−849	−846
19, 13	−1120	−976	−764	−761
20, 14	−1062	−923	−696	−693
21, 15	−1047	−890	−642	−639

*Evaluated at zero hours of work experience.

ever, that transfer increases to $5610 when the child is in college. Although the average educational subsidy is thus $3670 per semester, the subsidy varies from a low of $2037 from parents in the lowest to $6276 from parents in the highest schooling group. It is important to note that the figures in panel A are not the same as is the model's predictions of parental transfers for the sample observations. The reason is that the parental co-residence, school attendance, and parental education are all subject to classification error and because assets would not be zero at all life cycle points. Panel B reports the model's predictions of parental transfers for the sample observations. The only sizable difference between the two panels is for college graduate parents, which is due mostly to the asset restriction in panel A.

The other relationship of particular interest is the borrowing constraint function (12), assumed to depend on age and human capital. Clearly, if assets were measured without error and if the model's implied restrictions were ignored, a consistent estimate of that function's parameters would be the smallest observed value of net assets (if negative) at each age and level of human capital. With measurement error and recognizing that the model might predict that no individual actually chooses to hold the maximum permissible debt at every age and level of human capital, the parameters of that function incorporate all of the assumptions of the model.

Now, as was shown in Table 2, only a relatively small proportion of these youths at any age are in a negative net asset position. Based on our estimate of the borrowing constraint function, Table 6 shows the maximum permissible level of net debt for youths who are progressing through college at the usual ages, i.e., enters the first year of college at age 18, the second year at age 19, etc. The debt limit ranges from about $600 to $1000, differing only slightly by an individual's type (due to their differential levels of human capital). More importantly, the level of permissible net debt does not rise as the youth progresses through college. Thus, a youth would clearly not be able to finance much of college costs (which we estimate to be $3673 per semester) with uncollateralized borrowing.[43] On the other hand, note from Table 5 that even

[43] However, recall that given our lack of data on the accumulation pattern of college loans as well as the computational difficulty in allowing for different forms of assets differing in their liquidity, we have chosen to allow for the subsidization of college costs only through the parental transfer function and not also through access to capital markets. While too extreme, it should be recalled from Table 3 that about 1/3 of those who had graduated from college by 1985 reported no college loans and among those that did, average annual loans amounted to only about $1650.

the least wealthy parents (as measured by their schooling) are willing to provide a subsidy that would finance over one-half of college costs and youths whose parents fall into the highest schooling group actually receive as a subsidy almost twice the cost of attending college.

The literature on the estimation of consumption Euler equations has, in addition to providing tests for the existence of borrowing constraints, also (to a lesser extent) focused on the estimation of the intertemporal elasticity of substitution (IES) of consumption, obtained from the interest rate coefficient in the Euler equation. With the CRRA form $u = c^\lambda/\lambda$, the coefficient of relative risk aversion is $1 - \lambda$, the IES is $(\lambda - 1)^{-1}$, and the coefficient of relative prudence (see Kimball, 1990) is $2 - \lambda$. Hubbard et al. (1994) survey the literature and conclude that the typical estimate of λ is about -2, which is the value used for the calibration in Hubbard et al. (1995). This implies an IES of $-1/3$ and a coefficient of relative prudence of 4. In sharp contrast, we estimate a λ of about 1/2, which corresponds to an IES of -2 and a coefficient of relative prudence of 1.5. Thus, our estimates imply a much greater willingness to substitute intertemporally, and a much lower degree of prudence, than most of the prior literature. This is presumably because we explicitly allow for an effect of borrowing constraints on life cycle consumption behavior. In models with income uncertainty and no borrowing constraints, a high degree of prudence is required to rationalize the failure of youth with steep age-earnings profiles to borrow heavily when they are young. Browning and Lusardi (1996) provide an excellent discussion of the difficulty of empirically distinguishing the effect of borrowing constraints from that of prudence using the consumption Euler equation alone and argue that this is an important reason for modeling consumption behavior jointly with other decisions.

5.2. *Model Fit*. Before turning to substantive issues based on the results, we first present evidence on model fit. Table 7 compares actual and predicted values for selected state variables. As seen, the model overstates the mean level of completed schooling by 0.4 years.[44] A further disaggregation shows that although the model accurately predicts school completion levels dichotomized by whether or not the youth attended college (in the data 55.8 percent never attended college while the model predicts 54.8 percent), the model overstates the fraction of high school dropouts (by 1.6 percentage points) and also overstates the fraction of college graduates (by 5.6 percentage points). The model fits accumulated work experience at different ages quite accurately (generally less than a 5 percent error).[45] In fitting asset data, it is clear that the model captures the broad increasing age pattern (see also Figure 1). However, at age 20, essentially the first age in which asset data are reported in the NLSY, the model overstates mean assets by about 25 percent, converges at age 22, understates assets between ages 23 to 29 by as much as about 25 percent, and converges again by age 30.

Figure 2 displays the fit to the asset data by comparing the cumulative distributions of assets at each single year of age. At most ages the actual and predicted cumulative

[44] It should be recognized that the choice variable that is the basis for estimation is periods of attendance (full and part time), not completed schooling levels.

[45] As with completed schooling, the model does not directly fit work experience, but rather period by period decisions on employment status.

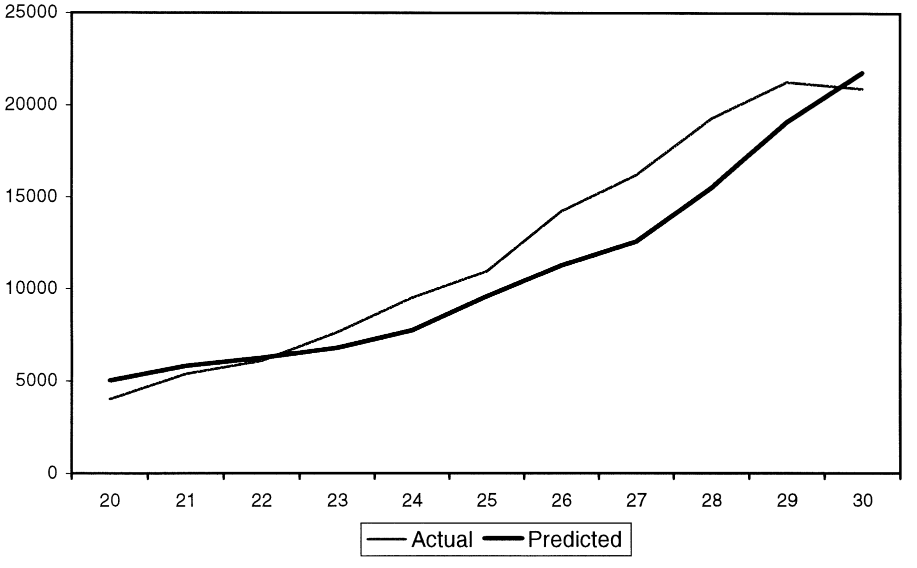

FIGURE 1

ACTUAL AND PREDICTED MEAN ASSETS BY AGE

distributions appear to be quite similar. The overall tendency is for the actual asset data to be more disperse, i.e., have a larger coefficient of variation, than the predicted data and to have considerably greater skewness as well. Moreover, the model generates skewness in large part because the measurement error variance is allowed

TABLE 7

ACTUAL AND PREDICTED SELECTED YOUTH OUTCOMES

	Actual	Predicted
Schooling*		
Mean highest grade completed	13.1	13.5
Percent high school dropout	21.5	23.1
Percent high school graduate	34.3	31.7
Percent some college	16.2	11.6
Percent college graduate	28.00	33.6
Employment: mean total hours worked by age		
20	3663	3487
23	7945	7798
26	13,092	12,983
29	18,510	18,423
Assets†: mean assets at age		
20	4034	5031
23	7624	6791
26	14,226	11,287
29	21,244	18,905

* At age 28.
† 1987 dollars.

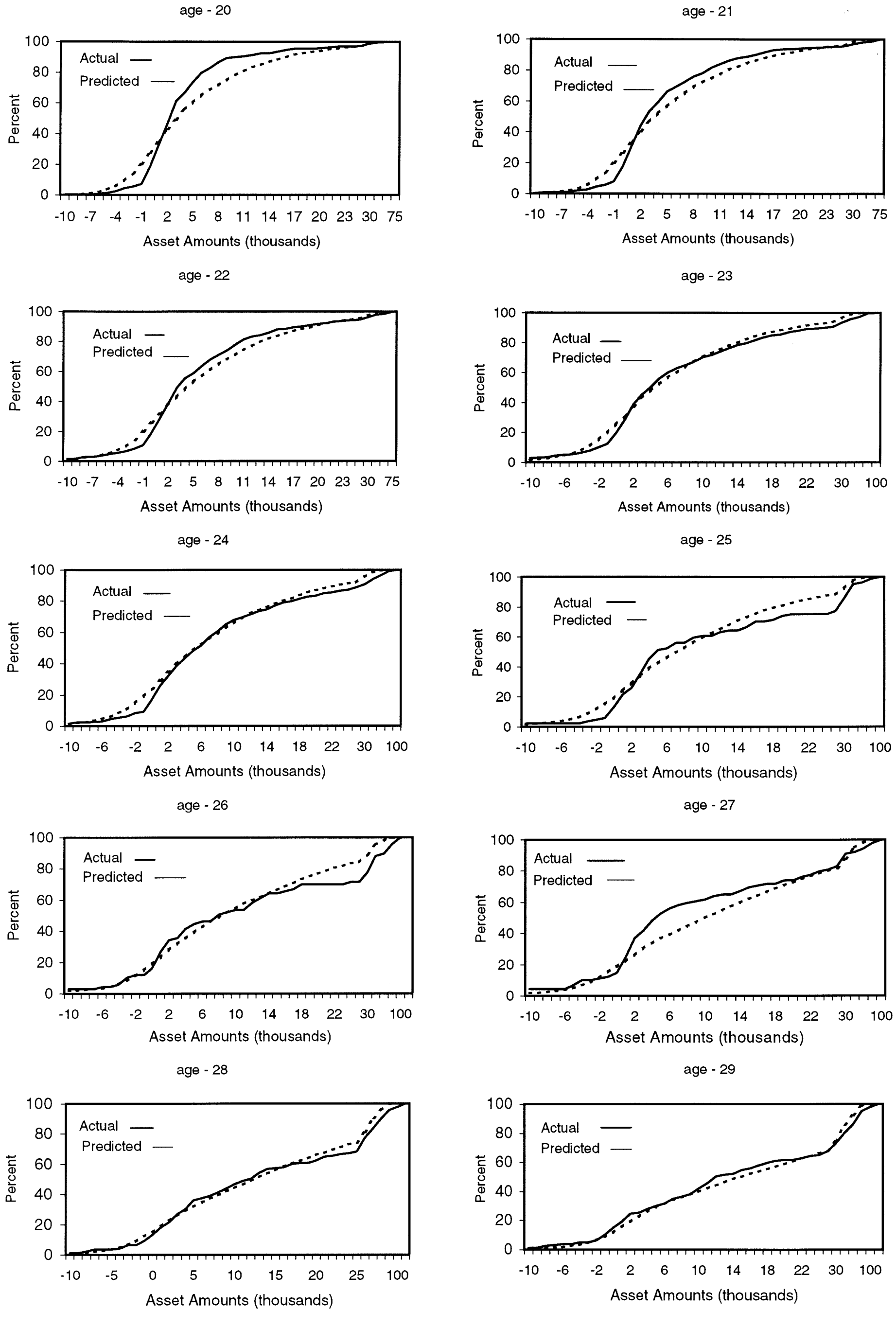

FIGURE 2

ACTUAL AND PREDICTED CUMULATIVE ASSET DISTRIBUTIONS to depend on the level of assets.[46] Finally, we contrast the serial dependence in assets by comparing a regression of assets on lagged assets and age in the simulated and actual data (standard errors below coefficients),

$$\text{Actual data}: \quad a_t = -14,093 + 0.722a_{t-1} + 756\text{age}_t$$
$$\qquad\qquad (1862) \qquad (0.022) \qquad (79.0)$$

$$\text{Simulated data}: \quad a_t = -14,581 + 0.547a_{t-1} + 815\text{age}_t$$
$$\qquad\qquad (565) \qquad (0.091) \qquad (25.8)$$

In the actual data, a \$1000 increase in assets at any age is associated with having \$722 more in assets the following period, while in the simulated data the increase in current assets is \$547. Thus, the model does not exhibit sufficient persistence in asset levels. Overall, the model seems to mimic the general qualitative features of the asset data well but is discordant with respect to some quantitative aspects.

Figures 3 and 4 compare the predicted and actual age patterns of school attendance and work decisions in each of the three semesters. Except in the summer semester, where school attendance is overstated during the prime college ages (note the different scale), the model fits the enrollment and employment data quite well. The age profiles of part- and full-time (accepted) wage rates for the actual and simulated data (Figure 5) also appear to be similar, although predicted and actual part-time wages diverge by over \$1.00 an hour at some ages.

The model fit comparisons conducted above provide a sense of the overall credibility of the model. The results appear mixed. Clearly, data simulated from the model do differ from the actual data, sometimes nontrivially. On the other hand, the model reasonably fits the overall patterns in the data. Whether the counterfactual and interpretative exercises that follow are credible given the fit of the model is an issue that we will leave to the individual reader to decide.

5.3. *An Out-of Sample Validation*. That the model reasonably fits the data used in estimation is a minimal requirement for validation. A stronger test is to compare results to data not used in estimation. Here we exploit information in the NLS's young women's survey (NLSYW) on parental subsidies to higher education. Those women were first surveyed in 1968 when they were 14–24 years of age and have been surveyed on a regular basis since that time. In the 1991 and 1993 surveys, when the women were mostly in their forties, they were asked to estimate the amount of support in the last 12 months they provided to each child who was in college. Of the slightly more than 900 white women with at least one child in college at either survey date, the average amount provided was \$4000 per child in 1993 dollars. Women with less than 12 years schooling provided roughly \$2000, those with exactly 12 years of schooling \$3100, those with 13–15 years of schooling \$3500, and those with 16 or more years of schooling \$6000.

[46] In asset data simulated from the model without measurement error the skewness parameter ranges from about 0.3 to 0.8, in the model with measurement error from 1.05 to 1.26, and in the data from 1.5 to 2.9.

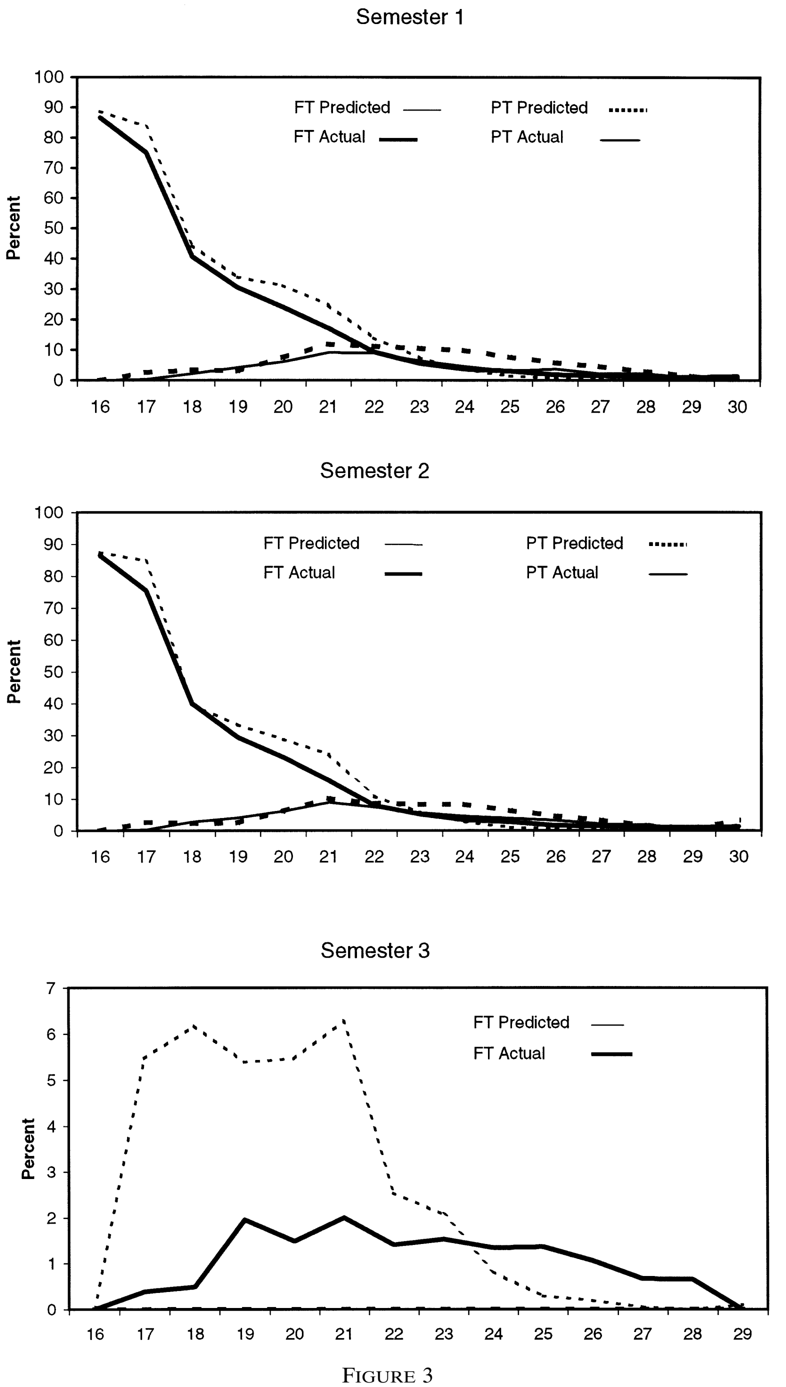

FIGURE 3

ACTUAL AND PREDICTED PART- AND FULL-TIME ENROLLMENT BY AGE

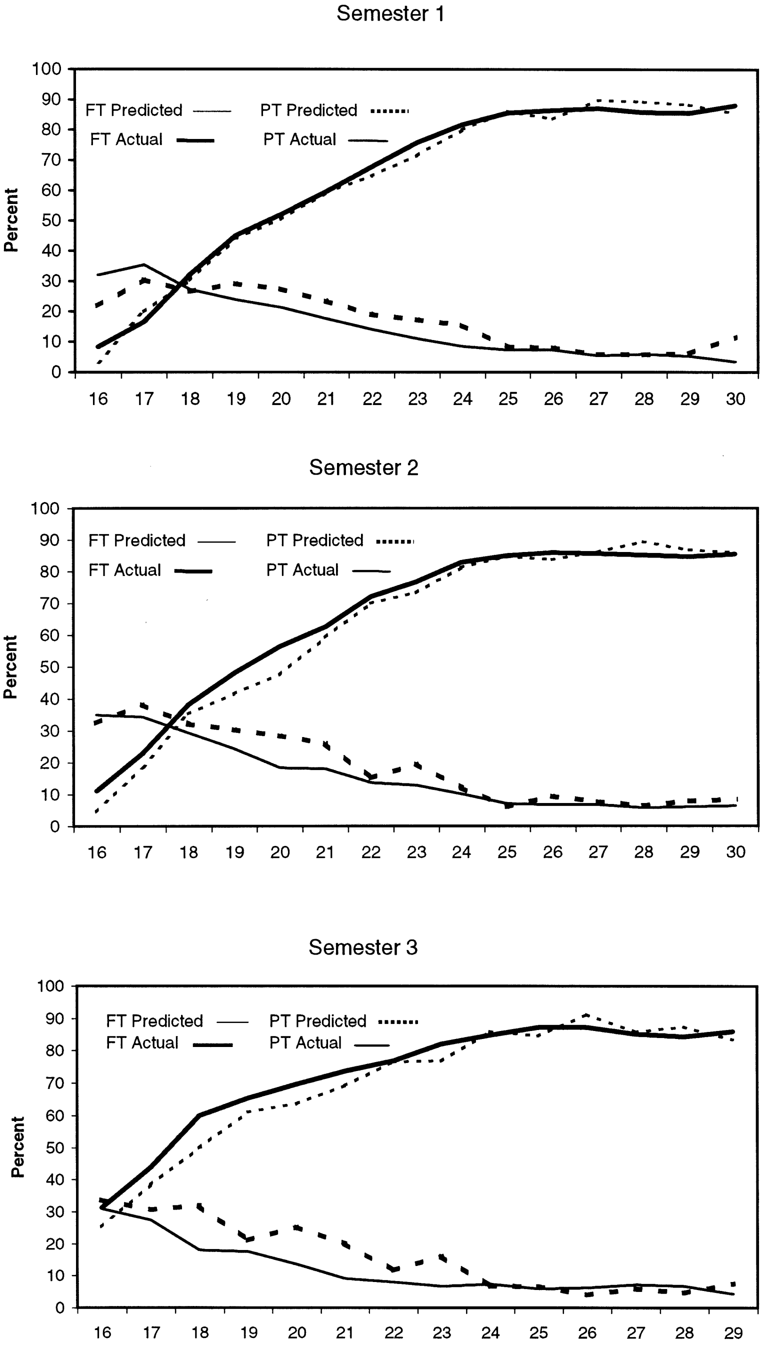

FIGURE 4

ACTUAL AND PREDICTED PART- AND FULL-TIME EMPLOYMENT BY AGE

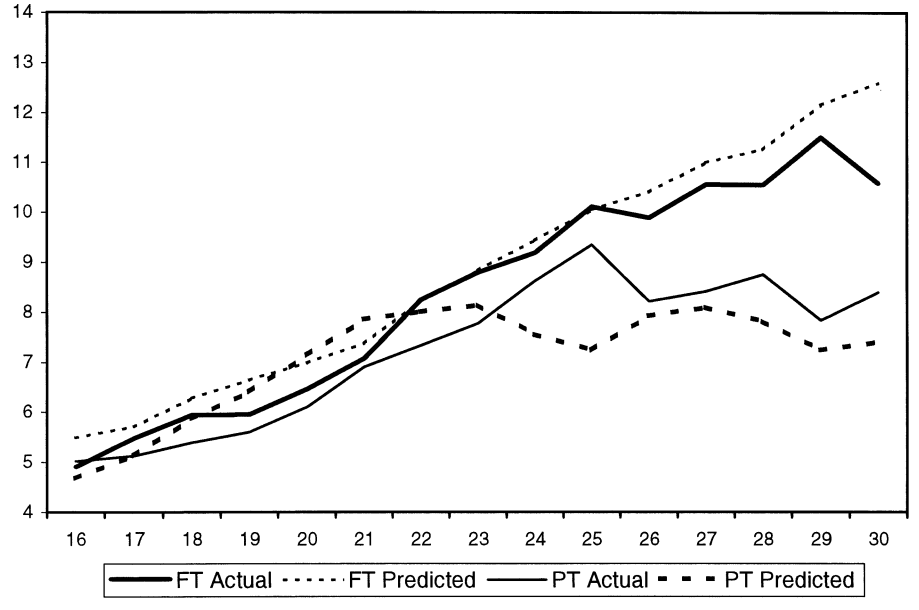

FIGURE 5

ACTUAL AND PREDICTED PART- AND FULL-TIME HOURLY WAGE RATE BY AGE

For several reasons, we cannot compare these absolute figures to our estimates of parental transfers in either panel A or B of Table 5. Panel A ignores classification error and assumes zero assets. Panel B is contingent on the measurement error process, type proportions, asset accumulation behavior, etc., of the NLSY sample which may differ from the children of the NLSYW sample. In addition, the format of the transfer question in the NLSYW does not conform to the conceptual definition of transfers that underlies the estimate of the transfer function.[47] Interestingly, although the magnitude of transfers differs between the two samples, the relationship of transfers to parents' schooling is quite close. In panel A of Table 5, relative to the high school dropout parents, total transfers from the high school graduate parents is 1.2 times as large, transfers from the some college group 1.9 times as large, and from the college graduate group 3.1 times as large. The comparable figures for the NLSYW

[47] First, the children of the NLSYW are from a different birth cohort, having been born about 10 years later than those youths in our NLSY estimation sample. Second, in order for the women in the NLSYW to have had children in college in 1991 or 1993, they must have been relatively young at the child's birth. The parents of the NLSY, on the other hand, would be cross-sectionally representative in terms of ages at birth. Third, our estimates are for full-time semesters, while the NLSYW expenditures cover both part-time and full-time students. Finally, our estimates of parental transfers include all expenses associated with the youth including, say, purchasing a car or paying for auto insurance, purchasing a computer, etc., while it is unlikely that the question wording in the NLSYW would have prompted respondent parents to include items beyond tuition and room and board. And room and board expenses for those living in their parental households while attending college would also have been excluded. Adjusting only for the price level, our estimates are about three times as large as the college expenses reported in the NLSYW.

respondents are 1,6, 1.8, and 3.0. Although our estimates are considerably higher in absolute dollars than those from the NLSYW, in our view their close correspondence to the parents' schooling pattern of transfers does provide a credible out-of-sample validation.

6. DISCUSSION

6.1. *Does Parents' Schooling Matter for Youth Outcomes*? In the data, as Table 4 illustrated, both the youth's completed schooling at age 16 and his parents' schooling were separately and significantly related to the youth's eventual school attainment. The behavioral model introduced an additional initial condition (at age 16) reflecting unobserved (to the researcher) heterogeneity in the youth's (age 16) skills and preferences. The model allows for the unobservable initial condition to be correlated with the other (observable) initial conditions but is silent about the fundamental structure governing these correlations. Depending on the structure that one imposes, the effect of a counterfactual experiment that altered parents' schooling for particular youths could be quantitatively quite different.

Table 8 presents the relationship between a youth's completed schooling and the initial conditions. Recall from Table 4 that the differential in completed schooling between the lowest and highest parents' schooling group was 4.3 years. The predicted differential using the model's estimates is of a similar magnitude, 3.8 years.[48] However, this differential is not uniform across unobserved types, either unconditionally or conditional on initial schooling. On average, youths of type one have at least 1 year of postgraduate education regardless of their parents' education, with the overall differential being 0.9 years from lowest to highest parents' schooling group. At the opposite extreme, type 4 youths on average obtain between 9.1 and 9.5 years of schooling depending on parents' schooling. Type 2 youths generally have some college, with completed schooling levels ranging from 13.2 to 15.6 over parents' schooling groups while type 3 youths on average obtain high school diplomas, with their completed schooling ranging from 11.7 to 12.7. As the table also shows, the predicted variation in completed schooling with parents' schooling is roughly the same whether or not one controls for the youth's initial schooling, although the level of completed schooling varies considerably with initial schooling.

The answer to the question of how a change in parents' schooling would affect youth outcomes clearly depends on whether altering parents' schooling also changes a youths's type and/or initial schooling. As the table shows, parents who have less schooling tend to have youths of the type whose preferences and skills (at age 16) would lead them to choose less schooling regardless of their parents' schooling. About 75 percent of the youths from the lowest parents' schooling group are types 3 or 4, but that falls to 57 percent for the next two parent's schooling groups and to 40 percent for the highest group. Similarly, type 1s, those who obtain the most schooling, comprise only 15 percent of youths from the lowest parents' schooling group, but almost 50 percent of youths from the highest group.

[48] These figures are based on a simulation of 5000 youths of each of the four types, weighted by their estimated population proportions. The model overstates the schooling level of youths from all parents' schooling groups by 0.8, 0.4, 0.2, and 0.3 years moving from the lowest to the highest group.

TABLE 8

PREDICTED PERCENT OF POPULATION AND COMPLETED SCHOOLING OF YOUTHS BY PARENTS' SCHOOLING, YOUTH'S INITIAL SCHOOLING, AND TYPE

	Parents' Highest Completed Schooling									
	High School Dropout		High School Graduate		Some College		College Graduate		All	
	%	Mean Schooling*	%	Mean Schooling	%	Mean Schooling	%	Mean Schooling	%	Mean Schooling
All Youths	100.0	11.7	100.0	13.1	100.0	13.8	100.0	15.5	100.0	13.5
Youth type										
1	14.5	17.0	25.9	17.0	27.8	17.3	47.9	17.9	29.3	17.4
2	11.4	13.2	16.7	13.4	14.5	15.2	12.4	15.6	14.5	14.1
3	34.1	11.8	46.9	11.7	53.0	12.0	37.2	12.7	43.4	12.0
4	40.6	9.2	10.5	9.1	4.7	9.5	2.5	9.4	12.8	9.2
Initial schooling less than 10										
Youth type										
1	1.6	16.4	5.8	16.2	5.8	16.3	17.9	17.3	6.2	16.6
2	3.8	12.4	14.9	12.6	11.8	14.1	14.1	14.4	11.9	13.0
3	20.0	10.9	52.0	10.8	66.6	10.9	55.3	11.0	46.1	10.9
4	74.7	8.7	27.3	8.8	15.9	8.8	12.7	8.9	35.8	8.7
Initial schooling 10 or more										
Youth type										
1	20.8	17.0	34.4	17.1	31.8	17.3	52.1	18.0	36.4	17.4
2	15.2	13.3	17.5	13.7	14.9	15.3	12.2	15.8	15.3	14.4
3	14.9	12.1	44.7	12.1	51.0	12.2	34.6	13.1	42.6	12.3
4	23.2	10.1	3.4	10.1	3.0	10.1	1.1	10.1	5.7	10.1

* At age 28.

The question of how much parents' schooling matters hinges on whether the youth's type and initial schooling (as measured at age 16) reflect investments by the parents and/or by the youth that respond to parents' schooling. At one extreme, if a youth's type and initial schooling are both invariant to changes in parents' schooling, then a change in parents' schooling reflects at most only a change in parental transfers (as in Table 5). Based on the figures in Table 8, increasing all youth's parents' schooling to that of highest group, holding the distribution of initial schooling and type fixed, would increase mean schooling in the population as a whole by two-thirds of a year.[49] Although that is not inconsequential, if youths' initial schooling and type were fully responsive to changes in parental schooling, completed schooling in the population would increase by two years under the same circumstance.

6.2. *Do Parental Transfers Matter for Youth Outcomes*? In the model, parents provide transfers to offspring while they co-reside. Recall that our estimates imply that the level of transfers differs substantially by parents' schooling and this difference is greater when the youth is attending college (Table 5). To assess the importance of parental transfers to youth outcomes, we simulated their impact on completed schooling and labor market success by varying the parameters of the parental transfer function.[50] Table 9 presents a number of these simulation exercises. In all of the simulation exercises, we hold endowment fixed, consistent with the simulated change in parental transfers being unanticipated by the youth.[51]

The first panel in Table 9 shows the baseline prediction for mean schooling, the proportion of youths with at least some college, and the (offered) hourly wage rate (at age 28) for each parents' schooling group. Strikingly, in the baseline, almost 80 percent of youths from the highest parents' schooling group have some college while that is true for less than half of youths from any other group and for only 20 percent for those from the lowest schooling group.[52] In terms of labor market outcomes, the hourly wage rate offered to youths from the lowest parent schooling group is \$3.75 less than that from the highest.

The second panel performs the counterfactual experiment of equalizing parental transfers at approximately the overall average (see Table 5, last column). As the figures in the last column indicate, the population averages of the three success measures are essentially unaffected. In fact, only the youths from the highest parents' schooling group, for whom the parental transfer is reduced by almost 50 percent, have noticeably different behavior; they obtain 1 year less schooling on average and 20 percent fewer of them have attended college. Youths from the lowest parents' schooling group, on the other hand, increase their schooling by only 0.2 years even

[49] The largest increase in completed schooling is 1.4 years for type 2s.

[50] If the same transfer function pertained to youths at earlier ages (prior to age 16), then, as in the case of varying parents' schooling, we would have to be concerned with the extent to which the other initial conditions would be altered.

[51] If the change were anticipated, the youth might alter his human capital investment prior to the college attendance decision, thus changing his "endowment." To estimate the impact of an anticipated change in transfers, similar to changes in parental schooling, would require modeling pre-age-16 investment decisions of youths and their parents.

[52] The comparable figures for the actual data, as shown in Table 4, are close.

TABLE 9

EFFECT OF PARENTAL TRANSFERS, BORROWING CONSTRAINTS, AND COLLEGE TUITION SUBSIDIES ON SCHOOL COMPLETION LEVELS AND WAGE RATES BY PARENTS' SCHOOLING

	Parents' Highest Completed Schooling				
	High School Dropout	High School Graduate	Some College	College Graduate	All
I. Baseline					
Mean highest grade completed*	11.7	13.1	13.8	15.5	13.5
Percent at least some college*	20.4	35.4	46.9	79.9	45.2
Mean hourly wage rate†	8.23	9.39	10.16	10.98	9.68
II. Equalized parental transfers					
Mean highest grade completed	11.9	13.3	13.6	14.5	13.4
Percent at least some college	24.8	41.3	43.0	59.5	42.9
Mean hourly wage rate	8.26	9.48	9.80	10.74	9.61
III. No additional parental transfer while attending postsecondary school					
Mean highest grade completed	11.3	12.4	12.9	13.8	12.6
Percent at least some college	12.9	22.8	28.1	48.1	27.6
Mean hourly wage rate	7.76	8.55	9.14	9.64	8.76
IV. Permitted to borrow up to $3000 if attending postsecondary school					
Mean highest grade completed	11.7	13.0	13.8	15.5	13.5
Percent at least some college	20.7	37.0	46.8	78.9	45.4
Mean hourly wage rate	8.24	9.06	10.10	10.83	9.48
V. College tuition subsidy of $3000 per semester‡					
Mean highest grade completed	12.6	14.3	15.3	16.4	14.6
Percent at least some college	48.9	71.7	87.1	93.3	75.1
Mean hourly wage rate	8.90	9.97	11.17	11.60	10.35
VI. III and IV					
Mean highest grade completed	11.4	12.6	13.0	13.8	12.7
Percent at least some college	15.2	26.5	29.9	48.4	29.8
Mean hourly wage rate	7.94	8.84	9.41	9.79	8.99
VII. III and V					
Mean highest grade completed	12.1	13.4	13.9	14.6	13.5
Percent at least some college	30.7	46.5	52.2	65.3	49.0
Mean hourly wage rate	8.52	9.61	10.17	10.34	9.68

* At age 28.

† 1987 dollars, ages 27–30.

‡ Subsidized college tuition cost during Fall and Spring semester is $3673 and one-half of that during Summer semester.

though their transfer is almost doubled. It is perhaps surprising that such a dramatic redistribution of parental transfers reduces the mean schooling differential only from 3.8 years to 2.6 years. Evidently, the other initial conditions are quite important, a point illustrated as well by the fact that the hourly wage rate hardly changes, even for the highest group for whom it falls by only $0.20.

As an alternative experiment for assessing the role of parental transfers, the third panel in Table 9 sets to zero the additional transfer youths receive while attending college. In part because this change impacts specifically on the payoff to college attendance and in part because the magnitude of the change is large for all groups, there is a substantial change in school completion levels. For the population as a whole, mean schooling falls by almost a year. The incentive effect created by the parent transfer rule evidently increases schooling of youths by 0.4, 0.7, 0.9, and 2.7 years moving from the lowest to the highest parents' schooling group and increases the proportion of youths with some college by 7.5, 12.6, 18.8, and 31.8 percentage points, respectively.

To assess the extent to which borrowing constraints affect postsecondary enrollment, suppose that the borrowing constraint were modified to allow all youths who attend college to borrow \$3000 per semester (at the market interest rate), almost enough to pay for the entire college cost. As the next panel in Table 9 shows, the effect on school completion levels is essentially zero. Thus, although, as the estimates in Table 6 indicated, youths cannot borrow enough even to finance one semester of college, relaxing that constraint does not affect their schooling decisions. This result might not appear surprising given the extent to which parents are already willing to subsidize college costs; however, as we shall see below that is not the explanation. On the other hand, as shown in panel V, providing a direct subsidy to attending college of \$3000 (over and above the parental transfer) has a large effect on school completion levels, as might have been anticipated given that such a subsidy is essentially the mirror image of the experiment in panel III in which the direct parental subsidy was eliminated.

The model takes the parental transfer as given to the youth. At the very least, the transfer rule would depend on market prices (interest rates, college costs) and governmental programs.[53] It is therefore possible that an increase in the government subsidy might reduce parental transfers to some extent.[54] Panels VI and VII in Table 9 combine the experiment of erasing the parental subsidy (as in panel 3) with relaxing the borrowing constraint (panel IV) and with providing the governmental subsidy (as in panel V). Comparing panel VI to panel III, we see that even when there is no parental subsidy to college attendance, relaxing the borrowing constraint has only a minor impact on schooling; the average schooling level increases from 12.6 to 12.7 and the percentage of the population with some college rises only from 27.6 to 29.8. Evidently, the borrowing rate of interest for loans used to finance college attendance (including consumption while attending college) is sufficiently high to make additional investment in college unprofitable.[55] In panel VII it is seen that the \$3000 governmental subsidy combined with a zero parental subsidy (a reduction of \$3533), on the other hand, is essentially offsetting on average. However, compared

[53] It would also obviously depend on parents' own preferences and constraints and in a more complete model would be derived from an explicit consideration of parent–offspring interactions.

[54] See Becker (1981) and Becker and Tomes (1979) for a theoretical development of parental responses to government compensatory programs and Goldberger (1989) for a critique. Also, see Rosenzweig and Wolpin (1994) for estimates of parent substitution in the context of welfare programs.

[55] Reducing the borrowing rate of interest to equal the lending rate of interest has no effect on this result.

to the baseline, the distribution of schooling becomes more equal as the reduction in the parental subsidy is considerably larger than the government subsidy for the youths with the highest schooling. Of course, without an explicit model incorporating parental behavior, we do not know how extensively parents will trade off government for own subsidies.

Table 10 shows financial flows of youths who were attending college, full and part time separately and for each parents' schooling group, in the baseline case and for the interventions given by panels IV and V in the previous table. Recall that those attending college full time must pay \$3673 per semester in college-related expenditures and those attending part time pay \$1837. In the baseline case, full-time attendees are net borrowers, on average, except for those youths from the highest parents' schooling group. Moving from the lowest to the highest parents' schooling group, consumption, savings, and parental transfers increase while labor market earnings decrease, with the differences becoming most distinct as between youths for whom at least one parent has some college (groups 3 and 4) and youths for whom neither parent has any college (groups 1 and 2). Differences among the four groups are much smaller for part-time attendees, who consume more, earn more, and receive less in parental transfers.

Relaxing the borrowing constraint, as shown above, provides virtually no additional inducement to college attendance. However, as seen in Table 10, allowing for additional borrowing opportunities does affect other decisions, at least for the two lowest parents' schooling groups. Among those youths who are attending college, borrowing is increased in order to augment consumption and to reduce labor market hours. Note that this response actually reduces parental transfers (due to the youth's having less assets).[56] In the case of the pure government subsidy to college attendance, regardless of whether the youth had attended college without the subsidy, those who attend college consume more and reduce their market hours. In contrast to the first intervention, however, youths use part of the subsidy to finance asset accumulation.

Regime changes that occurred in the 1970s can be used as a check on these predictions. Data reported in Leslie (1984: Table 2) show that between 1973–74 and 1975–76 there was a large increase in the use of grants to finance college education. This coincides with the introduction of the 1972 Amendments to the Higher Education Act, which created the BEOG grant program (now called Pell grants), which was more generous than the earlier EOG program (see Mumper and Vander Ark, 1991). Leslie shows that the real value of own earnings and savings used to finance college dropped substantially (about 20%) over that period. Then, in the late 1970s, rising interest rates raised the implicit subsidy in GSLs. At the same time, the Middle Income Student Assistance Act of 1978 removed the income cap on Stafford Loan eligibility (see Mumper and Vander Ark, 1991). Thus, there was about a 28 percent increase in the real value of loan financing between 1977–78 and 1979–80. Over that same period, the real value of own earnings and savings used to finance college again fell by about 20 percent. Over the whole period from 1973 to 1980, the increased generosity of grants and loans coincided with a drop of roughly 38 percent in the

[56] The effect of assets on parental transfers is concave.

TABLE 10

THE IMPORTANCE OF BORROWING CONSTRAINTS AND COLLEGE TUITION SUBSIDIES IF FINANCE COLLEGE EXPENDITURES*

	Baseline Parents' Schooling				Borrow up to $3000 per Semester Parents' Schooling				Tuition Subsidy of $3000/Semester Parents' Schooling			
	1	2	3	4	1	2	3	4	1	2	3	4
Attending college full-time												
Consumption	2461	2821	3811	4186	3042	3131	4052	4265	3749	3887	5122	5360
Saving	−483	−397	−24	1564	−2160	−1710	−494	1709	667	1060	1916	3310
Earnings	2569	2267	1493	630	1953	1699	1572	728	1627	1424	1351	702
Parental transfer	3122	3866	5995	8845	2632	3424	5678	8970	2834	3560	5712	8003
Attending college part-time†												
Consumption	3908	3815	4708	4157	4257	4082	5372	3930	4876	5091	6119	5784
Saving	475	487	1054	−517	60	155	676	−951	1549	1669	1470	1302
Earnings	5076	4739	5405	3765	4592	3140	5071	3205	4810	4856	5414	3909
Parental transfer	1353	1560	2330	1892	1666	1860	2950	1832	1737	2061	3035	3361

* 1987 dollars.

† Excludes Summer semester.

real value of own earnings and savings used to finance college.[57] These figures are broadly consistent with the patterns of response to loans and subsidies we observe in Table 10.

There is also a large literature on enrollment effects of college tuition changes to which the predictions of our model can be compared. These studies typically identify college cost effects on enrollment from time series and cross state variation in tuition rates and grant levels (see Kane, 1994). It has become standard in that literature to use the percentage change in the overall enrollment rate of 18–24 year olds in response to a fairly small tuition increase (i.e., $100 per year) as a common metric to compare studies. Leslie and Brinkman (1987) survey 25 empirical studies and report that the modal estimate is that a $100 tuition increase in 1982–83 dollars translates into a 1.8 percent decline in the enrollment rate for 18–24 year olds. When we simulate our model, we get a baseline enrollment rate of 29 percent for 18–24 year olds, which declines by 1.2 percent with a $100 per year tuition increase in 1982–83 dollars. Thus, our estimated tuition effect is somewhat smaller than the modal estimate.

Some studies also report effects of tuition changes on college enrollment decisions of 18–19 year old high school graduates. It has also been common to report effects of tuition increases separately by the income quantiles of the youth's parents. These studies typically find much larger tuition effects for low income youth. For instance, St. John (1990) estimates that a $100 tuition increase in 1982–83 dollars lowers this enrollment rate by roughly 0.85%. But for youth from families with income below $40,000 the figure is roughly 1.1%, compared to a much smaller effect of 0.4% for youth from families with higher income. Manski and Wise (1983) find that a $100 tuition increase in 1982–83 dollars leads to a large 3.6 percent decline in the enrollment rate among youth whose parents are in (roughly) the bottom income quintile, while they find much smaller effects for youth from higher income families. Based on more recent data, Kane (1994) estimates that a $1000 tuition increase in 1988 dollars leads to declines in the enrollment rate of 28.4, 16.7, 10.3, and 2.5 percent, respectively, for white males whose parents are in the first through fourth income quantiles. Converting to effects of a $100 increase in 1982–83 dollars, these figures are roughly 3.4, 2.0, 1.2, and 0.3 percent, respectively. Such statistics have often been interpreted as evidence for an important influence of borrowing constraints on college attendance (see, e.g., Kane, 1999: p. 63).

In comparison, we report enrollment effects based on parental education category, which should be fairly closely related to income. Our estimates imply that a $100 annual tuition increase in 1982–83 dollars leads to declines in the enrollment rate (for 18–19 year old high school graduates) of 2.2, 1.9, 1.5, and 0.8 percent, respectively, if the youth's parents are in each of our four education categories. Thus, our model generates a pattern of larger percentage declines in enrollment for youth whose parents have lower SES. But, as we have already reported, borrowing constraints have only a negligible effect on enrollment decisions. Thus, based on the estimates from our model, the earlier literature that has interpreted larger tuition effects for youth

[57] Over the same period, the real value of grants financing grew by 23 percent and the real value of loan financing grew by 5 percent.

with lower SES parents as evidence for the importance of borrowing constraints has been misguided.

7. CONCLUSIONS

In this article we have structurally estimated a dynamic model of the school, work, and savings decisions of young men. The model allows for parental transfers and borrowing constraints and includes parental co-residence and marriage as important additional factors that may influence decisions. We estimated the model on a cohort of young white males from the NLSY and used the estimated model to conduct counterfactual experiments with which we gauged the effects of parental transfers and borrowing constraints on school attendance and other decisions of youth.

Our estimates imply that parents provide substantial college attendance contingent transfers to their children, and that these transfers create important incentives for schooling attainment. We estimated that without these transfers, the cohort's mean educational attainment would have been about one year less, and the percent of persons in the cohort with a least some college would have fallen by about 17 percentage points. Our estimates also imply that college educated parents provide much larger college attendance contingent transfers than do parents with lower levels of education.

One key question addressed in the article is whether larger parental monetary transfers (from age 16 onward) by better educated parents can account for a substantial part of the observed intergenerational correlation of schooling. In a counterfactual experiment we found that an equalization of parental transfers at the mean level (regardless of education level of the parents) would lead to a modest equalization of the education distribution. But this only happens because children with college graduate parents, who provide very large college attendance contingent subsidies, would obtain substantially less education when transfers are equalized. Our model implies that children of less educated parents would obtain very little additional schooling if transfers were equalized.

The other key question is whether borrowing constraints have an important impact on college attendance decisions. Our estimates imply that borrowing constraints for youth are actually fairly tight, in that the youth cannot obtain enough in uncollateralized loans to finance even one year of college. But in a counterfactual experiment where we relax the borrowing constraint, we find that it has essentially no effect on college enrollment decisions. This is true even for youth whose parents have low education levels and who therefore only provide them with small subsidies to help finance college.

Putting our results on parental transfers and borrowing constraints together, we see that some of the intergenerational correlation of school attainment does arise because more educated parents make larger college attendance contingent financial transfers to their children. But the channel through which parental transfers affect the school attainment of their children does not rely on the existence of borrowing constraints to any significant extent.

While borrowing constraints have little effect on school attainment in our model, they do have an important impact on other decisions of youth. In our simulations, we found that relaxing borrowing constraints did lead to an increase in net borrowing by college students, but that these additional resources were used to reduce market work (and thus earnings) and increase consumption while in college. We noted that this pattern is consistent with historical data on educational financing in the 1970s by Leslie (1984). During that period, BEOGs and GSLs were made more generous and more easily available. And earnings by college students while in school did in fact decline substantially.

The notion that liquidity constraints could exist, but have almost no impact on college attendance decisions, is, to our knowledge, not a possibility that has been seriously considered in the literature on college financing. This literature has often found little effect of student loan programs on college attendance rates (see, e.g., Hansen, 1983) but has tended to attribute this lack of effect to lack of knowledge about aid programs (see, e.g., Orfield, 1992). In contrast, our model predicts essentially no effect of student loan programs on enrollment in an environment characterized by fully informed rational agents.

The model in this article can be viewed as an extension of our earlier work on human capital investment decisions of young men (Keane and Wolpin, 1997) to include savings decisions and borrowing constraints. In that article, the assumption of linear utility allowed us to ignore the capital market environment, essentially permitting individuals to make school attendance decisions independently of financing considerations. But, if individuals care about the timing of their consumption and there are borrowing constraints, the results of our earlier article, and in particular the finding that the present value of lifetime earnings (and utility) is largely determined by the skill "endowments" that youth possess at age 16, may be questionable. However, our finding that borrowing constraints, although they exist, have a negligible quantitative impact on school attendance decisions lends some further credibility to the results of our earlier modeling effort.

A number of limitations of our model are obvious. First, we do not model choice among colleges of different quality and cost. In estimates of a college choice model, Tierney (1980) finds that cost differential has a substantial effect on public vs. private school choice in sample of youth admitted to each. Cameron and Heckman (1999) present evidence that increases in tuition lead to reallocation of students among different types of colleges (four year private, four year public, community colleges). And Hearn (1991) finds that the average SAT of students in the college a youth attends is positively related to family income even after controlling for a rich set of background characteristics (an ability test, high school GPA, parents' education, etc.). Thus, an important extension would be to model school quality choice, in order to determine if parental transfers and/or borrowing constraints have an impact on the quality of the school a youth attends.

Second, our model does not allow for any effect of working while in school on school performance. If working while in school is detrimental to learning, this would obviously be an additional channel through which parental transfers could affect youth outcomes.[58]

[58] Eckstein and Wolpin (1999) find that working while attending high school does increase the probability of failing courses and thus of not graduating. However, they also find that forcing those

Finally, not all of the parameters we estimate are fundamental. The functions determining co-residence, marriage, and parental transfers are not themselves derived within the optimizing framework. Thus, aside from their potential misspecification, the policy experiments that we perform do not account for potential structural changes in these functions. For example, relaxing borrowing constraints or changing student loan policies might alter the incentive for parents to provide transfers. Allowing for the interactions between youth and parents in either a cooperative or noncooperative dynamic setting in a way that is empirically tractable is a challenging problem for future work.

APPENDIX A: EXACT FUNCTIONAL FORMS

In addition to the prior notation, we denote t^s as a semester indicator equal to one if the semester is Fall, equal to two if it is Spring and equal to 3 if it is Summer. Parental schooling has been discretized into four categories, $S^P = \{1, 2, 3, 4\}$. Chronological age at time t is denoted by age_t. There are assumed to be $k = 1, \dots, K$ types. Recall that $I(\cdot)$ is an indicator function equal to one if the term inside the parentheses is true and zero otherwise.

A.1. *Utility Function*.

$$
\begin{aligned}
u_t = {} & \mu_t \frac{1}{\lambda_0} c^{\lambda_0} + \lambda_1[I(h_t = 20) + \kappa^h I(h_t = 40)] \\
& + \lambda_2[I(s_t = .5) + \kappa^s I(s_t = 1)] + \lambda_3 I(h_t = 20) I(s_t = .5) \\
& + \lambda_4 I(h_t = 20) I(s_t = 1) + \lambda_5 I(h_t = 40) I(s_t = .5) \\
& + \lambda_6 I(h_t = 40) I(s_t = 1) + \lambda_7 I(\text{age}_t \geq 20) I(s_t = .5) \\
& + \lambda_8 I(\text{age}_t \geq 20) I(s_t = 1) + \lambda_9 I(s_t > 0) I(t^s = 3) \\
& + \lambda_{10} I(s_{t-1} = 0) I(S_t < 12) I(s_t = 1) \\
& + \lambda_{11} I(s_{t-1} = 0) I(S_t \geq 12)[I(s_t = 1) + I(s_t = .5)/\kappa^s] \\
& + \lambda_{12} I(s_{t-1} > 0) I(t^s = 2)[I(s_t = 1) + I(s_t = .5)/\kappa^s] \\
& \times \lambda_{13} I(S_{t-1} > 0) I(\text{age}_t < 22) I(t^s = 3)\left[I(h_t = 40) + \frac{1}{2} I(h_t = 20)\right] \\
& \times \lambda_{14} I(t^s = 3) I(\text{age}_t < 18)\left[I(h_t = 40) + \frac{1}{2} I(h_t = 20)\right]
\end{aligned}
\tag{A.1}
$$

who do not graduate to attend school and not work would induce only a small increase in the graduation rate.

$$+\lambda_{15}I(t^s=3)I(\text{age}_t<20)\left[I(h_t=40)+\frac{1}{2}I(h_t=20)\right]$$
$$+\lambda_{16}I(t^s=3)I(\text{age}_t\geq 22)\left[I(h_t=40)+\frac{1}{2}I(h_t=20)\right]$$
$$+\lambda_{17}I(s_t=.5)I(s_{t-1}=.5)+\lambda_{18}I(h_t=20)I(h_{t-1}=20)$$
$$+\lambda_{19}I(h_t=40)I(h_{t-1}=40)\kappa^h+\lambda_{20}I(h_t=0)I(h_{t-1}=0)I(\text{age}_t\geq 22)$$
$$+\lambda_{21}m_t+\lambda_{22}p_t+\lambda_{23}m_tp_t$$

where in addition

$$u_t=\exp\{\mu_1I(\text{age}_t<18)+\mu_2I(\text{age}_t<21)+\mu_3I(\text{age}_t<25)$$
$$+\mu_4I(\text{age}_t\geq 28)+\mu_5m_t+\mu_6s_t\}$$

(A.2)
$$\lambda_1=\tilde{\lambda}_{10}+\sum_{k=2}^{K}\tilde{\lambda}_{10k}I(\text{type}=k)+\tilde{\lambda}_{11}I(\text{age}_t<18)$$
$$+\tilde{\lambda}_{12}I(\text{age}_t<20)+\tilde{\lambda}_{13}I(\text{age}_t<22)$$
$$+\tilde{\lambda}_{14}I(\text{age}_t<25)+\tilde{\lambda}_{15}I(\text{age}_t<28)$$
$$+\tilde{\lambda}_{16}I(\text{age}_t<22)I[\text{age}_t\leq 22]\ +\epsilon_t^h$$
$$\lambda_2=\tilde{\lambda}_+20+\sum_{k=2}^{K}\tilde{\lambda}_{20k}I(\text{type}\equiv k)+\tilde{\lambda}_{21}I(\text{age}_t<18)\ +\epsilon_t^s$$
$$\lambda_4=\tilde{\lambda}_{40}+\tilde{\lambda}_{41}I(s_t\geq 12)$$
$$\lambda_6=\tilde{\lambda}_{60}+\tilde{\lambda}_{61}I(s_t\geq 12)$$
$$\lambda_9=\tilde{\lambda}_{90}+\tilde{\lambda}_{91}I(\text{age}_t\geq 21)$$

A.2. *Human Capital Function*.

(A.3)
$$\ln\Psi_t^0=\alpha_{01}+\sum_{k=2}^{K}\alpha_{0k}I(\text{type}=k)+\alpha_1S_t+\alpha_2H_t-\alpha_3H_t^2$$
$$+\alpha_4I(h_{t-1}=20)+\alpha_5I(h_{t-1}=40)$$
$$+\alpha_6\,\text{age}_t+\alpha_7I(\text{age}_t<18)$$

A.3. *Full- and Part-Time Hourly Wage Functions*.

(A.4)
$$w_t^F=\Psi_t^0\ \exp\{\epsilon_t^w\}$$
$$w_t^P=w_t\ \exp\{\alpha_8+\alpha_9S_t+\alpha_{10}H_t+\alpha_{11}\,\text{age}_t\}$$

A.4. *Parental and Marriage Transfer Functions*.

(A.5)
$$\text{tr}_t^p=\exp\left[\theta_0^p+\theta_1^pI(s_t>0)+\theta_2^pa_t+\theta_3^pa_t^2\right.$$
$$\left.+\theta_4^pI(S^P=2)+\theta_5^pI(S^P=3)+\theta_6^pI(S^P=4)\right]$$

and

$$\text{tr}_t^m = \theta_{01}^m + \sum_{k=2}^{K} \theta_{0k}^m (\text{type} = k) \tag{A.6}$$

A.5. *Parent Co-residence and (Currently) Married Probability Functions*. Define

$$\begin{aligned} L_t^j = \exp\Bigg(& \xi_{01}^j + \sum_{k=2}^{K} \xi_{0k}^j I(\text{type} = K) + \xi_1^j p_{t-1} + \xi_2^j m_{t-1} + \xi_3^j I(s_{t-1} > 0)\Bigg) \\ & + \xi_{41}^j \text{ age}_t + \sum_{k=2}^{K} \xi_{4K}^j I(\text{type} = k)\text{age}_t + \xi_5^j \text{ age}_t^2 + \xi_6^j I(\text{age}_t < 18) \\ & + \xi_7^j a_t + \xi_8^j \Psi_t^0 \qquad \text{for } j = p, m \end{aligned} \tag{A.7}$$

and

$$\xi_t^j \sim N(0, 1)$$

Then,

$$\begin{aligned} p_t &= 1 \qquad \text{iff} \quad L_t^p + \epsilon_t^p > 0 \\ m_t &= 1 \qquad \text{iff} \quad L_t^m + \epsilon_t^m > 0 \end{aligned}$$

Note that $\xi_7^p = 0$ and $\xi_8^m = 0$.

A.6. *Type Probability Functions*.

$$\begin{aligned} \pi_k = & \frac{\exp\left[\gamma_{0k} + \sum_{j=1}^{3} \gamma_{1jk} I(S^P = j) + \gamma_{2k} I(S_{16} < 10) + \gamma_{3k} I(S_{16} - 11)\right]}{1 + \sum_{\ell=1}^{K} \exp\left[\gamma_{0\ell} + \sum_{j=1}^{3} \gamma_{1j\ell} I(S^P = j) + \gamma_{2\ell} I(S_{16} < 10) + \gamma_{3\ell} I(S_{16} = 11)\right]} \\ & \text{for } k = 2, \ldots, K \\ & \sum_{k=1}^{K} \pi_k = 1 \end{aligned} \tag{A.8}$$

A.7. *Joint Initial Schooling and Parent Schooling Distribution*.

$$\begin{aligned} & \Pr(S_{16} = j, S^P = k) = \frac{\exp[\zeta_{0j} + \zeta_1 I(S^P \le 2) I(S_{16} \le 9)]}{1 + \sum_{j=7}^{10} \exp[\zeta_{0j} + \zeta_1 I(S^P \le 2) I_{16} \le 9]} \cdot \Pr(S^P = k) \\ & \qquad \text{for } j = 7, 8, 9, 10 \quad \text{and} \quad k = 1, 2, 3, 4 \\ & \sum_{j=7}^{11} \Pr(S_{16} = j, S^P = k) = \Pr(S^P = k) \quad \text{for } k = 1, 2, 3, 4 \end{aligned} \tag{A.9}$$

A.8. *Net Asset Lower Bound*.

$$a_t = -\exp[\phi_0 + \phi_1 \text{age}_t + \phi_2 \text{age}_t^2 + \phi_3 \Psi_t^0 + \phi_4 (\Psi_t^0)^2 + \phi_5 I(\text{age}_t \ge 22)] \tag{A.10}$$

A.9. *Terminal Emax Function*.

$$
\begin{aligned}
E\max_t = {} & +\beta_1\Psi_t^0 + \beta_2(\Psi_t^0)^2 + \beta_3 a_t + \beta_4(a_t)^2 \\
& + \beta_5 p_t + \beta_6 m_t + \beta_7 I(s_{t-1} > 0) + \beta_8 I(h_{t-1} = 20) \\
& + \beta_9 I(h_{t-1} = 40) + \beta_{10,}\Psi_t^0 a_t \\
& + \beta_{11} I(s_t \geq 12) + \beta_{12} I(s_t \geq 16) \\
& + \sum_{j=1}^{3} \beta_{12+j,\,t}\Psi_t^0 I(\text{type} = j+1) \\
& + \sum_{j=1}^{3} \beta_{15+j,\,t} a_t^0 I(\text{type} = j+1)
\end{aligned} \tag{A.11}
$$

where T^* is set equal to age 31.

In addition, prior to the terminal period, the interpolating regressions used to fit the E functions include: (1) an intercept; (2) type dummies; (3) interactions of assets with parents, marriage, and whether the parents' schooling is 3 or 4; (4) an interaction of Ψ_t^0 with whether the parents' schooling is 3 or 4; and (5) lagged part time school.

A.10. *Classification Error Rates*. Consider first the classification error process for full time school attendance:

$\prod_{0t}^{SF}$ = probability that *full*-time school is correctly recorded at time t.

$\prod_{1t}^{SF}$ = probability that *full*-time school is recorded when person did not attend school full time

$$\prod_{0t}^{SF} = \text{ES} + (1 + \text{ES}) f(s_t = 1)$$

$$\prod_{1t}^{SF} = \left(1 - \prod_{0t}^{SF}\right) f(s_t = 1)/[1 - f(s_t = 1)]$$

where $f(s_t = 1) = \frac{1}{\text{N}}\sum_{i=1}^{N} I(s_t = 1)$ and ES is a parameter to be estimated. Similarly, for part time school we have

$$\prod_{0t}^{SP} = \text{ES} + (1 - \text{ES}) f(s_t = .5)$$

$$\prod_{t}^{SP} = \left(1 - \prod_{0t}^{SP}\right) f(s_t = .5), [1 - f(s_t = .5)]$$

Similar classification error processes are assumed for work, initial school, parents' school, marriage, and living with parents. The corresponding parameters are EW, EIS, EPS, EM, EP.

A.11. *Measurement Error in Assets and Hourly Wages*.

A.11.1. *Hourly wages*.

$$w_t^{F,\,\text{observed}} = w_t^F \ \exp\{\epsilon_t^{w,\,m}\}$$

$$w_t^{P,\,\text{observed}} = w_t^P \ \exp\{\epsilon_t^{w,\,m}\}$$

$$\epsilon_t^{w,\,m} \sim N(0, \sigma_{w,\,m}^2)$$

A.11.2. *Assets*.

$$a_t^{\text{observed}} = a_t + \epsilon_t^{a,\,m}$$

$$\epsilon_t^{a,\,m} \sim N(0, \sigma_{a,\,m}^2)$$

$$\sigma_{a,\,m} = \sigma_{a,\,m,\,0} + \sigma_{a,\,m,\,1} a_t$$

If the person does not work but is incorrectly classified as working, the observed *hourly* wage is assumed to be drawn from the same distribution as full time wages, except multiplied by a factor $\exp\{\alpha_{12}\}$:

$$w_t^0 | h_t = 0 = \Psi_t^0 \ \exp\{\epsilon_t^w\} \exp\{\alpha_{12}\}$$

A.12. *Error Distribution*. Full- and part-time productivity shocks are proportional, $\epsilon_t^{wf} = \kappa^w \cdot \epsilon_t^{wp}$, so that the variance–covariance matrix of the joint normal distribution of the four shocks is restricted:

$$\begin{pmatrix} \epsilon_t^w \\ \epsilon_t^h \\ \epsilon_t^s \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \ \begin{pmatrix} \sigma_w^2 & & \\ \sigma_{wh} & \sigma_h^2 & \\ \sigma_{ws} & \sigma_{hs} & \sigma_s^2 \end{pmatrix} \right)$$

A.13. *Tuition Costs*. tc, tg.

A.14. *Discount Factor*. $\delta_t = \delta_0 + \delta_1 m_t$.

A.15. *Interest Rate for Borrowing*. $r_t^b = r_t^l + \eta$.

A.16. *Minimum Consumption*: CMIN. A person is guaranteed CMIN provided that he works and borrows the maximum.

The total number of parameters is 174.

APPENDIX B: PARAMETER ESTIMATES

Standard errors are multiplied by 100.

Utility Function

λ_0	$\tilde{\lambda}_{10}$	$\tilde{\lambda}_{20}$	λ_3	$\tilde{\lambda}_{40}$	λ_5	$\tilde{\lambda}_{60}$	λ_7
0.5174	−0.0712[a]	−0.0006[a]	−0.0110[a]	−0.0190[a]	−0.0204[a]	−0.0435[a]	0.0186[a]
(0.0068)	(0.0057)	(0.0065)	(0.0084)	(0.0071)	(0.0089)	(0.0181)	(0.0059)

λ_8	$\tilde{\lambda}_{90}$	λ_{10}	λ_{11}	λ_{12}	λ_{13}	λ_{14}	λ_{15}
0.0160[a]	−0.1300[a]	−0.0361[a]	−0.0366[a]	0.0430[a]	−0.0122[a]	−0.0289[a]	−0.0022[a]
(0.0063)	(0.0407)	(0.0142)	(0.0162)	(0.0113)	(0.0182)	(0.0243)	(0.0187)

λ_{16}	λ_{17}	λ_{18}	λ_{19}	λ_{20}	λ_{21}	λ_{22}	λ_{23}
−0.140[a]	0.0380[a]	.0053[a]	.0038[a]	0.0015[a]	0.0240[a]	−0.0291[a]	−0.0303[a]
(0.0154)	(0.0145)	(0.0041)	(0.0025)	(0.0057)	(0.0164)	(0.0225)	(0.0299)

Taste for Leisure Shifters

$\tilde{\lambda}_{102}$	$\tilde{\lambda}_{103}$	$\tilde{\lambda}_{104}$	$\tilde{\lambda}_{11}$	$\tilde{\lambda}_{12}$	$\tilde{\lambda}_{13}$	$\tilde{\lambda}_{14}$	$\tilde{\lambda}_{15}$	$\tilde{\lambda}_{16}$
0.0036a	0.0141[a]	0.0099[a]	0.0113[a]	−0.0027[a]	−0.0000[a]	0.0021[a]	−0.0010[a]	0.0018[a]
(0.0022)	(0.0026)	(0.0028)	(0.0069)	(0.0053)	(0.0052)	(0.0047)	(0.0061)	(0.0006)

Taste for School Shifters

$\tilde{\lambda}_{202}$	$\tilde{\lambda}_{203}$	$\tilde{\lambda}_{204}$	$\tilde{\lambda}_{21}$	$\tilde{\lambda}_{41}$	$\tilde{\lambda}_{61}$	$\tilde{\lambda}_{91}$
−0.0382[a]	−0.0646[a]	−0.1357[a]	0.1044[a]	0.0052[a]	−0.0111[a]	0.0626[a]
(0.0120)	(0.0168)	(0.0441)	(0.0302)	(0.0081)	(0.0342)	(0.0745)

Taste for Consumption Shifters

μ_1	μ_2	μ_3	μ_4	μ_5	μ_6
0.0239	0.0104	0.0344	−0.0724	−0.0509	−0.0998
(0.1021)	(0.0686)	(0.0690)	(0.1311)	(0.0657)	(0.0636)

Full-Time/Part-Time Multipliers

κ^h	κ^s
2.2910	1.9373
(0.0387)	(0.1155)

Wage Equation Parameters

α_{01}	α_{02}	α_{03}	α_{04}	α_1	α_2	α_3	α_4
7.4747	−0.0717	−0.2545	−0.2583	0.0749	0.0273[b]	−0.0191[c]	0.0122
(0.0403)	(0.0472)	(0.0612)	(0.0573)	(0.0043)	(0.0015)	(0.0030)	(0.0075)

α_5	α_6	α_7	α_8	α_9	α_{10}	α_{11}	α_{12}
0.0338	0.0026	−0.0442	−0.2698	0.0099	0.0010	0.0020	0.0923
(0.0086)	(0.0023)	(0.0705)	(0.0831)	(0.0059)	(0.0035)	(0.0036)	(1.1319)

Parental Transfer Function

θ_0^P	θ_1^P	θ_2^P	θ_3^P	θ_4^P	θ_5^P	θ_6^P
7.1179	0.9750	0.0459[d]	−0.0951[e]	0.2124	0.6614	1.1251
(0.2648)	(0.2630)	(0.0280)	(0.0346)	(0.2653)	(0.3093)	(0.2496)

Marriage Transfer Function

θ_0^m	θ_{02}^m	θ_{03}^m	θ_{04}^m
0.0946[f]	−0.0152[f]	−0.0292[f]	−0.0574[f]
(0.0286)	(0.0370)	(0.0375)	(0.0352)

Continued...

Parent Co-residence Probability Function

ξ_0^P	ξ_{02}^P	ξ_{03}^P	ξ_{04}^P	ξ_1^P	ξ_2^P	ξ_3^P
5.7094	−0.0010	−0.3638	−0.9421	1.2144	−0.6552	0.4124
(0.2458)	(0.3112)	(0.2599)	(0.3184)	(0.2626)	(0.3855)	(0.1135)
ξ_{41}^P	ξ_{42}^P	ξ_{43}^P	ξ_{44}^P	ξ_5^P	ξ_6^P	ξ_8^P
−0.4323	−0.0000	0.0151	0.0352	0.7025[g]	−0.2000	−0.1475[d]
(0.0058)	(0.0081)	(0.0067)	(0.0072)	(0.0340)	(0.1537)	(0.1117)

Marriage Probability Function

ξ_0^m	ξ_{02}^m	ξ_{03}^m	ξ_{04}^m	ξ_1^m	ξ_2^m	ξ_3^m
−7.618	0.0079	0.3757	1.1207	0.0211	3.910	−0.3368
(0.2567)	(0.2579)	(0.1825)	(0.2132)	(0.2122)	(0.1017)	(0.0868)
ξ_{41}^m	ξ_{42}^m	ξ_{43}^m	ξ_{44}^m	ξ_5^m	ξ_6^m	ξ_7^P
0.4469	−0.0000	−0.0149	−0.0448	−0.8776[g]	0.2000	0.0438[d]
(0.0038)	(0.0050)	(0.0047)	(0.0048)	(0.0286)	(0.2556)	(0.0126)

Type Probability Function

γ_{02}	γ_{112}	γ_{122}	γ_{132}	γ_{22}	γ_{32}
−1.4279	1.2833	1.0083	0.8417	1.1833	−0.9917
(18.42)	(46.49)	(25.85)	(32.18)	(37.65)	(32.24)
γ_{03}	γ_{113}	γ_{123}	γ_{133}	γ_{23}	γ_{33}
−0.4261	1.3532	1.0241	1.0246	1.5278	−1.2833
(14.49)	(41.86)	(20.44)	(30.70)	(32.10)	(31.74)
γ_{04}	γ_{114}	γ_{124}	γ_{134}	γ_{24}	γ_{34}
−3.7103	4.1175	1.7653	1.4875	3.3241	−3.6905
(27.93)	(46.37)	(31.72)	(40.07)	(35.52)	(45.98)

Joint Initial schooling and Parent schooling distribution

ζ_{07}	ζ_{08}	ζ_{09}	$\zeta_{0,10}$	ζ_1
−3.7000	−1.5169	−0.1406	1.9609	1.1340
(49.40)	(26.44)	(19.34)	(13.41)	(19.12)
$\Pr(S^P = 1)$	$\Pr(S^P = 2)$	$\Pr(S^P = 3)$		
0.1653	0.4500	0.1525		
(1.421)	(1.938)	(1.444)		

Net Asset Lower Bound

ϕ_0	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5
9.3542	−0.1674	−0.0504[g]	−0.4558[d]	0.0328[c]	0.7910
(1.0404)	(0.0761)	(0.0549)	(0.5231)	(0.0254)	(0.6656)

Terminal Value Function

β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
0.2615	−0.0360[d]	0.0131	−0.0069[c]	−0.0903[a]	0.4082[a]	0.0376[a]	−0.0191[a]	−0.0353[a]
(0.0172)	(0.0109)	(0.0013)	(0.0160)	(0.2743)	(0.1623)	(0.0646)	(0.1003)	(0.0538)
β_{10}	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{16}	β_{17}	β_{18}
−0.0835[c]	0.1008[a]	0.0193[a]	0.0021	0.0060	0.0220	0.0002	0.0009	0.0031
(0.1180)	(0.0604)	(0.0478)	(0.0063)	(0.0071)	(0.0073)	(0.0011)	(0.0012)	(0.0013)

Continued...

Classification Error Rate Parameters					
ES	EW	EM	EP	EIS	EPS
0.8685	0.7559	0.9325	0.9296	0.9487	0.8795
(0.2369)	(0.2945)	(0.1507)	(0.1604)	(0.4378)	(0.8605)
Measurement Error in Assets and Hourly Wages					
$\sigma_{w,m}$	$\sigma_{a,m,0}$	$\sigma_{a,m,1}$			
0.5501	2.6757[a]	0.4701			
(0.1082)	(3.290)	(0.4015)			
Error Distribution					
σ_w	σ_h	σ_s	ρ_{wh}	ρ_{ws}	ρ_{hs}
0.2584	.0047[a]	0.0165[a]	−0.5962	0.2531	0.0962
(0.0207)	(0.0042)	(0.0091)	(0.6533)	(0.5307)	(0.5537)
Other Parameters					
tc	tg	δ_0	δ_1	η	CMIN
3.6728[a]	5.2364[a]	0.9758	0.0164	0.0128	0.5749[a]
(0.5302)	(1.1710)	(0.0043)	(0.0067)	(0.0077)	(0.8409)

NOTES: [a]Parameter *divided* by 1000.
[b]Parameter multiplied by 1000.
[c]Parameter multiplied by 10^6.
[d]parameter multiplied by 10,000.
[e]parameter multiplied by 10^8.
[f]parameter *divided* by 10,000.
[g]parameter multiplied by 100.

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