Women's College Decisions: How Much Does Marriage Matter?

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Abstract

This paper investigates the sequential college attendance decisions of young women and quantifies the impact of marriage expectations on their college decisions. A dynamic choice model of college attendance, labor supply, and marriage is formulated and structurally estimated using panel data from the National Longitudinal Survey of Youth 1979 (NLSY79). The model is used to simulate the effects of no marriage benefits and finds that the predicted college attendance rate would drop from 61% to 56%. Using the estimated model, I predict the college attendance behavior for a younger cohort from the NLSY97 to validate the behavioral model.

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1 Introduction

The primary motivation for going to college considered in existing empirical literature is the increase in earnings power that college education provides. However, this literature has ignored another potentially important benefit of college: college improves marriage opportunities by providing a social venue to meet potential spouses. Furthermore, a college-educated individual is substantially more likely to have a college-educated spouse. Thus, the individual enjoys educational balance in the household and benefits from the earnings power of the spouse. While this "marriage benefit" of college surely applies to both sexes, it is likely to be particularly important for women since married men on average have higher labor force participation rates and higher incomes than married women. If marriage benefit is a major component of returns to college, its omission will bias the estimated returns to college downward. Without knowing the relevant returns to college, neither can we understand gender and racial differentials in educational attainment nor can proper education policy inferences be drawn.

A large literature studies the effect of schooling on marriage and finds that one's own schooling can improve spousal schooling acquired in the marriage market (Boulier and Rosenzweig 1984; Behrman, Rosenzweig and Taubman 1994; and Weiss 1997). Little empirical work, however, has been done on measuring the impact of the marriage benefit on schooling decisions.¹ The first goal of the paper is to extend the existing model of schooling decisions (Willis and Rosen 1979; Keane and Wolpin 1997, 2001; Eckstein and Wolpin 1999) to allow for links between college and marriage. College and high school women may receive different numbers of marriage offers. As shown by the estimates, attending college increases marriage offer rate. In addition, women care about the educational balance in the household and there exists educational assortative mating (Becker 1973).² A college-educated woman enjoys her

 $^{^{1}}$ Two recent theoretical papers (Iyigun and Walsh 2005; Weiss 2006) investigate the interaction between education investment, assortative mating, and marriage outcome. Both papers call for empirical studies to test their implications.

²The fact that highly educated women marry highly educated men is well documented (Mare 1991; Pencavel 1998). Benham (1974) points out that women's education can improve a husband's productivity

marriage with a college-educated man and benefits from his income. The dynamic decision model I develop permits women to choose college attendance, labor supply, and marital status simultaneously over time. Various determinants of college decisions, including the cost of college, individual ability, and family background, as well as expected earnings benefit and marriage benefit, are estimated from the data.

The second goal of the paper is to assess the validity of the dynamic behavior model I develop by exploiting data from two comparable panel surveys. Todd and Wolpin (2003) discussed different types of model validation tests and provided an excellent example using a social experiment. In this paper, I use out-of-sample predictions, which compare two cohorts, to assess the validity of a structurally estimated model. I first estimate how exogenous sources determine individual behavior (for example, college attendance) based on data from a baseline cohort. Then, the validity of the model is assessed according to how well the variations over time in the exogenous sources predict the change in individual behavior based on data from a younger cohort.

A central empirical challenge in assessing the impact of marriage on college decisions is the dynamic simultaneity of the decisions. The dynamics of the decision process are due to the dependence of current choices on previous choices. Whether or not one will complete the senior year of college is largely determined by whether the individual finishes junior year; labor force participation depends on labor market experience; marital experience (marriage duration and children) is of crucial importance to marriage decisions. The simultaneity of the decision process is the nature of human behavior. For example, when a good job offer or marriage proposal comes along, it is likely to induce a woman to drop out of college. Without understanding the *dynamic* process of the *joint* decisions made by individuals, it is impossible to quantify what factors determine each choice, including the sequential college attendance decision.

A further challenge is due to the endogenous self-selection of the decision process. The

and earnings, but it is difficult to conclude whether this effect is due to human capital accumulation within the household or assortative mating. This paper will focus on the assortative mating aspect.

college premium, which is the relative wage between college and high school graduates, increases in individual skills or abilities, and those who have highest skills are the most likely to attend college. A statistical analysis could then attribute the effect of skills on college attendance to the earning gain. Similarly, self-selection exists in the marriage market. If exogenously less attractive women receive more schooling, ceteris paribus, than do more attractive women (Boulier and Rosenzweig 1984), the estimated effect of marriage on college attendance would be biased in a simple regression analysis. Self-selection is controlled in the behavior model by allowing for unobserved types in skills and in marriage.³ The dynamic decision process is solved for each type. Hence, the model implements a correction for the selection biases.

The model is estimated by using a sample of high school white females from the National Longitudinal Survey of Youth 1979 (NLSY79). To assess the importance of marriage on college attendance, a counterfactual economy is considered in which benefits from marriage are ruled out. The equilibrium choices are numerically simulated in such a hypothetical world and a comparison is made of predicted college enrollment with the actual economy. In the real economy, the college enrollment rate is 61% for high school females. With no benefits from marriage, the college enrollment rate would drop to 56%.

The estimation of the model is based on a NLSY79 sample of young women who were graduating from high school in the early 1980's. About 20 years later, the college enrollment rate of a NLSY97 sample increases to 80%. These two NLSY samples provide a unique source for model validation since almost identical survey instruments have been used by the Bureau of Labor Statistics. The estimated model based on the NLSY79 sample is able to predict well the college attendance behavior of the NLSY97 sample. The result is consistent with the stability of the structural model; that is, "fundamental" parameters of the individual are

³Modeling skill as multidimensional was pioneered by Willis and Rosen (1979) and Heckman and Sedlacek (1985), formally incorporating Roy (1951)'s self-selection model. More recently, Keane and Wolpin (1997, 2001), Eckstein and Wolpin (1999) integrated ability selection in a dynamic setting of employment and schooling choices. In this paper, both unobserved skill and marriage types are used in a broad sense. For example, skill types may differ in motivation, perseverance, and tastes for school, and marriage types may vary in attractiveness and preference for marriage.

invariant to changes in the environment.⁴

The next section provides an illustrative model and discusses the intuition for identification. Section 3 specifies the empirical model. Section 4 describes the NLSY data from which the model is estimated and validated. Section 5 discusses the estimation method. Estimation results are given in Section 6. Section 7 provides counterfactual simulations. Section 8 presents the conclusion.

2 A Simple Example

In this section, I use a simple two-period example to illustrate analytically how various sources determine college decisions, discuss the related empirical issues, and examine the identification of the model. Many assumptions will be relaxed in the empirical model specified in the next section to confront the data.

2.1 An Illustrative Model

Let us consider a sample of high school women, the size of which is normalized to one. Each woman lives for two periods and is endowed with ability δ , where $\delta \in {\delta_h, \delta_l}$ and $\delta_h > \delta_l$. A fraction π of the sample belongs to type δ_h .

In the first period, everyone stays single and makes her college attendance (and graduation) decision. Attending college requires a fixed cost cs, and no one works while in college. If a woman works, her labor earnings y_i take the form of $\ln y_i = \beta_0 (\delta_i) + \beta_1 S_i + \epsilon_{wi}$, where $S_i \in \{1, 2\}$ denotes high school and college respectively. The constant β_0 depends on individual ability with $\beta'(\delta) > 0$. The schooling coefficient β_1 measures the earnings benefit of college. The productivity shock ϵ_{wi} is assumed to be *i.i.d.* normal, with mean zero, variance σ_w^2 , and *c.d.f.* $F_w(\cdot)$.

In the second period, everyone works and the only choice is marital status. A marriage

 $^{^{4}}$ As discussed in Wolpin (1996), a major advantage of structural estimation is that it is capable of performing counterfactual policy experiments that entail extrapolations outside of the current policy regime.

is formulated only if a woman receives and accepts an offer from a man. Assume that there exists an infinite number of men (either high school or college graduates) in the economy and a proportion μ of them are college graduates. The meeting technology is such that college and high school women may receive different numbers of marriage offers. Let p^1 and p^0 be the marriage offer arrival rates for college and high school women respectively. A married woman can consume a fraction ψ of the husband's income, which depends on his schooling (S^H) and follows $\ln y_i^H = \rho_0 + \rho_1 S_i^H + \epsilon_{Hi}$, where $\epsilon_{Hi} \sim N(0, \sigma_H^2)$. Therefore, the schooling of the husband increases the marriage payoff for the woman. Let M_i be the net utility value of marriage and $M_i = a_0 + a_1(S_i - S_i^H)^2$. The value of marriage depends on the couple's homogeneity in educational background to capture educational assortative matching.⁵

The utility is separable in consumption and the value of marriage: $U_i = c_i + M_i m_i$. If a woman is married, $m_i = 1$; otherwise, $m_i = 0$. Each woman solves the following problem:

$$Max_{\{s_{i1},m_{i2}\}}E[c_{i1}+\beta(c_{i2}+M_{i2}m_{i2})]$$

s.t.
$$c_{i1} + cs \cdot s_{i1} \leq (1 - s_{i1})y_{i1}$$

 $c_{i2} \leq y_{i2} + \psi y_{i2}^H m_{i2},$

where s_i equals 1 if attendance is chosen and 0 otherwise, and β is the discount rate.

2.2 Determinants of College Decisions

The model can be solved backwards. At t = 2, a woman always marries if the utility value of marriage is positive. Otherwise, she marries if and only if

$$\epsilon_{Hi2} \ge \ln \frac{-a_0 - a_1 (S - S^H)^2}{\psi} - \left(\rho_0 + \rho_1 S^H\right).$$
 (1)

 $^{^5\}mathrm{See}$ the next section for discussions on various assumptions and the justification for the specifications in detail.

At t = 1, a woman attends college if and only if $\epsilon_{wi1} \leq \epsilon_w^*$, where ϵ_w^* is a function of the parameter vector of the model, θ . The parameters include π , cs, $\beta_0(\delta_h)$, $\beta_0(\delta_l)$, β_1 , σ_w , p^0 , p^1 , a_0 , a_1 , ψ , ρ_0 , ρ_1 , σ_H .⁶ College attendance rate in the economy is

$$\Pr(S=2) = F_w\left(\epsilon_w^*\right). \tag{2}$$

As equation (2) shows, when a woman makes her college attendance decision in the first period, not only does she take the cost of college into account, she also takes into account both the earning expectations and the marriage expectations in the future period. This equation is the key structural equation to be used to estimate how much a college decision is determined by various sources. A reduced form equation will be an approximation of equation (2). For example, the college attendance probability can be written as a probit of the cost of college, some proxy for ability, earnings gain, and marriage gain. Thus, reduced form coefficient estimates are functions of the fundamental parameters of the model. Inspection of equations (1) and (2) immediately implies the following results.

Proposition 1 The probability of attending college decreases in direct cost of college, and increases in marriage offer rate of college educated women. That is, $\partial \epsilon_w^*(\theta) / \partial cs < 0$ and $\partial \epsilon_w^*(\theta) / \partial p^1 > 0$.

How ability (through β_0), earnings return to schooling (β_1), and marriage sorting (a_1) affect college attendance depend on the parameters of the model.⁷ Once the parameters are estimated, the cross restrictions from the model, i.e., equations (1) and (2), will predict who attends college, and how individuals adjust their behavior if the cost and benefit of attending college changes. Counterfactural experiments like setting $\beta_1 = 0$ or $a_1 = 0$ then can be used to measure the effect of earnings benefits and assortative mating on college decision.

⁶It is well known that β is not well identified so it is given. Furthermore, we focus on women's decisions, so μ is also exogenously determined.

⁷As β_0 and β_1 increase, college attendance may increase because expected earning increases. But it may also decrease because forgone earnings in the first period also increase. Since normally people work for many years, the first effect dominates. The effect of the sorting parameter a_1 on college attendance will depend on the schooling distribution of potential husbands.

2.3 Identification

In general, the non-linearity makes it difficult to establish theoretical identification. One way to think about identification is that, as a necessary condition, each parameter should affect some moments in the distribution.

Let us first consider a homogeneous sample, where $\beta_0(\delta_i) = \beta_0$ for all δ_i . Women's earnings parameters are identified from a cross section OLS regression on $\ln y_{i2} = \beta_0 + \beta_1 S_{i2} + \epsilon_{wi2}$, since everyone works in the second period and schooling is predetermined.

Let P_S be the attendance rate and let $P_m(S, S^H)$ be the proportion of married women whose own schooling is S and whose husband's schooling is S^H . The model implies the following moment conditions if $M_{i2} < 0$:

$$P_m(1,1) = (1-P_S)(1-\mu)p^0[1-F_H(\ln(-\frac{a_0}{\psi})-\rho_0-\rho_1)], \qquad (3)$$

$$P_m(1,2) = (1-P_S) \mu p^0 [1 - F_H(\ln(-\frac{a_0 + a_1}{\psi}) - \rho_0 - 2\rho_1)], \qquad (4)$$

$$P_m(2,1) = P_S(1-\mu) p^1 [1 - F_H(\ln(-\frac{a_0+a_1}{\psi}) - \rho_0 - \rho_1)],$$
(5)

$$P_m(2,2) = P_S \mu p^1 [1 - F_H(\ln(-\frac{a_0}{\psi}) - \rho_0 - 2\rho_1)].$$
(6)

In equations (3) to (6), P_m 's and P_s are observed and μ is exogenously given. The model is not identified since there are four equations and eight unknowns: $\{p^0, p^1, a_0, a_1, \psi, \rho_0, \rho_1, \sigma_H\}$. Data on the husband's schooling and income provide additional moments. The conditional mean and the variance of the husband's earnings can be written as

$$E\left(\ln y_{i}^{H}|S_{i}^{H}=1\right) = \rho_{0} + \rho_{1} + E\left(\epsilon_{Hi}|S_{i}^{H}=1\right),$$
(7)

$$E\left(\ln y_{i}^{H}|S_{i}^{H}=2\right) = \rho_{0} + 2\rho_{1} + E\left(\epsilon_{Hi}|S_{i}^{H}=2\right), \qquad (8)$$

$$Var\left(\ln y_{i}^{H}\right) = \rho_{1}^{2} Var\left(S_{i}^{H}\right) + Var\left(\epsilon_{Hi}|m=1\right).$$

$$(9)$$

Note that $E(\epsilon_{Hi}|S_i^H = 1, 2)$ and $Var(\epsilon_{Hi}|m = 1)$ are functions of $\{p^0, p^1, a_0, a_1, \psi, \sigma_H\}$. In this model, the husband's earnings parameters can only be identified together with those pa-

rameters that determine marriage outcomes.⁸ From equations (3) to (9), $\left\{p^{0}, p^{1}, \frac{a_{0}}{\psi}, \frac{a_{1}}{\psi}, \rho_{0}, \rho_{1}, \sigma_{H}\right\}$ can be identified. a_{0}, a_{1} and ψ are not separately identified because the husband's earnings and marriage utility enter the individual utility function linearly. Finally, cs is identified from the attendance rate, $P_{S} = F_{w}\left[\epsilon_{w}^{*}\left(cs, \beta_{0}, \beta_{1}, \sigma_{w}, p^{0}, p^{1}, \frac{a_{0}}{\psi}, \frac{a_{1}}{\psi}, \rho_{0}, \rho_{1}, \sigma_{H}\right)\right]$, where cs is the only unknown variable.

Next let us consider a heterogeneous sample with two types. Using a similar argument, $\left\{p^{0}, p^{1}, \frac{a_{0}}{\psi}, \frac{a_{1}}{\psi}, \rho_{0}, \rho_{1}, \sigma_{H}\right\}$ are identified from the marriage distribution and the husband's income. The identification of the rest of the parameters relies on moments on wages and college attendance. Let $\beta_{0}(\delta_{k}) = \beta_{0k}, k = h, l$, and $\epsilon_{wk}^{*} = \epsilon_{w}^{*}(\theta^{-}, \beta_{0k})$, where θ^{-} includes all the parameters except for β_{0} . The college attendance rate is:

$$P_{S} = \pi F_{w} \left(\epsilon_{wh}^{*} \right) + (1 - \pi) F_{w} \left(\epsilon_{wl}^{*} \right).$$
(10)

At t = 1, wages are observed only for those who choose not to attend college. Therefore,

$$E(\ln y_1) = \pi \int_{\epsilon_{wh}^*}^{\infty} \left(\beta_{0h} + \beta_1 + \epsilon_w\right) f(\epsilon_w) d\epsilon_w + (1 - \pi) \int_{\epsilon_{wl}^*}^{\infty} \left(\beta_{0l} + \beta_1 + \epsilon_w\right) f(\epsilon_w) d\epsilon_w.$$
(11)

At t = 2, all wages are observed and following conditional moments can be computed.

$$E(\ln y_2|S=1) = \pi_1 \left(\beta_{0h} + \beta_1\right) + (1 - \pi_1) \left(\beta_{0l} + \beta_1\right), \qquad (12)$$

$$E(\ln y_2|S=2) = \pi_2 \left(\beta_{0h} + 2\beta_1\right) + (1 - \pi_2) \left(\beta_{0l} + 2\beta_1\right), \tag{13}$$

$$Var\left(\ln y_2 | S=1\right) = \pi_1 \left(1 - \pi_1\right) \left(\beta_{0h} - \beta_{0l}\right)^2 + \sigma_w^2, \tag{14}$$

$$Var\left(\ln y_2 | S=2\right) = \pi_2 \left(1 - \pi_2\right) \left(\beta_{0h} - \beta_{0l}\right)^2 + \sigma_w^2, \tag{15}$$

where $\pi_1 = \frac{\pi (1 - F_w(\epsilon_{wh}^*))}{1 - P_S}$ is the proportion of high school graduates with δ_h and $\pi_2 = \frac{\pi F_w(\epsilon_{wh}^*)}{P_S}$ is the proportion of college graduates with δ_h . Equations (10) to (15) can identify the

⁸This is the standard argument for selection models for the identification of the wage offer parameters. If all potential husbands' earnings are observed, $E\left(\epsilon_{Hi}|S_i^H=1\right) = E\left(\epsilon_{Hi}|S_i^H=2\right) = 0$ and $Var\left(\epsilon_{Hi}|m=1\right) = \sigma_H^2$, so ρ_0 , ρ_1 , and σ_H are identified from an *OLS* regression.

parameters $\{\pi, cs, \beta_{0h}, \beta_{0l}, \beta_1, \sigma_w\}$.⁹ The moment conditions incorporate the selection rules predicted by the model, and the functional form assumptions on the distributions of wage and unobserved heterogeneity. This is the standard argument for the identification of selection models (Heckman 1979).

3 The Empirical Model

By extending the simple example, I now specify a rich empirical model, in which young women make college attendance, labor supply, and marriage decisions simultaneously during each year after they graduate from high school.

3.1 The Basic Structure

The College Attendance Choice: Consider a young woman who makes a sequential college attendance decision every year after high school graduation. The annual cost of college, including tuition, room and board, is cs. A college attendee has the option to work, and/or get married at the same time. Employment and marriage in college may affect the value of school due to time constraints. A college degree is assumed to be completed in four years. When a woman attends graduate school, she pays an extra cost cg.

The Employment Choice: A woman receives job offers every year. The job offer rate depends on her schooling level (high school, some college, or college graduate), and whether she works in the previous year. The hourly wage offer follows:

 $\ln w_t = \beta_0 + \beta_1 S_t + \beta_2 H_t + \beta_3 H_t^2 + \beta_4 I(S_t \ge 16) + \epsilon_{wt},$

 9 For a homogenous sample, equations (12) to (15) become

$$\begin{split} E \left(\ln y_2 | S = 1 \right) &= \beta_0 + \beta_1, \\ E \left(\ln y_2 | S = 1 \right) &= \beta_0 + 2\beta_1, \\ Var \left(\ln y_2 \right) &= \sigma_w^2. \end{split}$$

Therefore, a simple OLS regression on second year wages will identify β_0 , β_1 , and σ_w .

where S_t and H_t are years of schooling and work experience, $I(\cdot)$ is an indicator function which equals one if the individual has a college degree, and $\epsilon_{wt} \sim N(0, \sigma_w^2)$. Coefficients β_1 and β_4 measure the effect of school attainment on the wage. The wage offer varies if she works while in college. The hourly wage offer in college is assumed to be log normal such that $\ln w_t = \beta_{0c} + \epsilon_{wct}$, where $\epsilon_{wct} \sim N(0, \sigma_{wc}^2)$. I allow for measurement error in observed wages, such that $\ln w^o = \ln w + u$, where w^o is the observed wage, w is the true wage, and the error term is normally distributed: $u \sim N(0, \sigma_u^2)$. Subscript for individual is suppressed here to simply notation.

The Marriage Choice: A single woman receives marriage proposals with probability Pr, which depends on her age and her schooling level. In particular, Pr follows:

$$\Pr_{t} = \frac{\exp(b_0 + b_1 age_t + b_2 age_t^2 + b_3 I(S_t > 12))}{1 + \exp(b_0 + b_1 age_t + b_2 age_t^2 + b_3 I(S_t > 12))}.$$

The meeting technology is such that high school and college women may receive different numbers of offers. The parameter b_3 determines the difference and will be estimated. If a college provides a social venue for young people to meet, b_3 may be positive. The distribution of potential husbands (men) is assumed to be exogenous and remains the same for all women. Let μ_{S^H} be the fraction of men with S^H years of schooling; then, the probability of receiving a proposal from a man with S^H is $\mu_{S^H} \operatorname{Pr}_t$. With probability $1 - \operatorname{Pr}_t$, no offer is received. If a woman is married, she always has the option to stay married. If she chooses to have a divorce, she becomes single in the next period.

Marriage decisions are based on a woman's evaluation of marriage.¹⁰ All emotional and biological values related to marriage are denoted by M. This marriage value depends on her own and husband's schooling, on her age, on whether they have children, and on marriage duration.

 $M_t = a_0 + a_1 \Delta S_t^2 + a_2 age_t + a_3 f_t + a_4 m dur_t,$

¹⁰For simplicity, marriage is modeled as a search process for women.

where $\Delta S_t = S_t - S_t^H$ is the couple's difference in schooling, f_t equals one if at least one child is in the household and zero otherwise. The constant a_0 can be interpreted as permanent preference for marriage. If educational imbalance in the household reduces marriage utility because of disagreement on the consumption of public goods, for example, a_1 is negative. This will lead to positive assortative matching in education.¹¹ a_2 reflects a woman's varying preference for marriage over time. a_3 and a_4 measure the impact of children and previous marriage choices. Children are likely to increase marriage utility. The dependence of M on marriage duration reflects a possible increase in the bond between spouses. The value of marriage varies as the marriage evolves.

At least two competing hypotheses can generate educational assortative matching. The first hypothesis is education complementarity; similar schooling backgrounds generate higher utility for marriage. The second hypothesis is geographic proximity; highly educated women meet highly educated men more often in college. Following Becker (1973), this study adopts the first hypothesis. Even though I observe who marries whom, I do not observe whom individuals meet and where these meetings take place. Therefore, it is difficult to empirically separate the two hypotheses without imposing some ad hoc assumptions.¹² Hitsch, Hortaçsu and Ariely (2006) provide evidence that women, in particular, have a preference for men with similar education levels based on the first-contact e-mails within an online dating service.¹³ This study shows that even without geographic proximity, the preferences for similar educational background play an important role in the matching process.

A married woman receives a monetary transfer from the husband. The net transfer depends on her work decision. The model focuses primarily on the female's decision process,

¹¹This is a simple way to model educational assortative mating. In Becker (1973), mating is positive assortative if schooling levels are complements in production. Shimer and Smith (2000) derive more complex sufficient conditions for assortative mating under search costs. Wong (2003) specifies the production function as the product of the types (e.g., education) in her empirical study of marriage matching.

¹²If I observe the sex ratio in college and the rate of marriage, I can potentially separate the effect of geographic proximity. Unfortunately, in the NLSY79 data used in this study, I have no information on which college each woman attends.

¹³Compared to high school educated men, men with a master's degree receive 48% fewer first-contact e-mails from high school educated women, 22% more e-mails from college educated women, and 82% more e-mails from women with (or working towards) a graduate degree (Hitsch, Hortaçsu and Ariely 2006).

and assumes that married men always work full time in the labor market.¹⁴ The earnings of a (potential) husband depend on his schooling and experience, and are specified as $\ln y_t^H = \rho_0 + \rho_1 S_t^H + \rho_2 E X_t^H + \rho_3 E X_t^{H2} + \epsilon_{y^H t}$. I also allow for a measurement error in observed husband's income. When a single woman receives an offer from a man, she knows his schooling and the distribution of ϵ_{y^H} . A married woman always observes the husband's true income; therefore, she knows both S_t^H and $\epsilon_{y^H t}$.

Choice Set: Every year, a woman chooses from eight mutually exclusive and exhaustive alternatives if a job offer and a marriage proposal are received. Let s_t , h_t , m_t be the indicators for school attendance, employment, and marital status respectively; then, each alternative will be a triple (s_t, h_t, m_t) .¹⁵ Her choice set is $J = \{(s_t, h_t, m_t) : s_t \in \{0, 1\}, h_t \in \{0, 1\}, m_t \in \{0, 1\}\}$. The choice set is restricted if no job offer or marriage proposal arrives.

The Arrival of Children: In general, both the number and ages of children may be important in determining women's choices. However, I assume that the fertility effect can be adequately captured by a single indicator of the presence of any children. The stochastic process that governs fertility over time is specified as the following logit form:¹⁶

$$\Pr(f_t = 1 | f_{t-1} = 0) = \frac{\exp\{c_0 + c_1 S_t + c_2 m_{t-1} + c_3 age_t + c_4 age_t^2 + c_5 m dur_t\}}{1 + \exp\{c_0 + c_1 S_t + c_2 m_{t-1} + c_3 age_t + c_4 age_t^2 + c_5 m dur_t\}},$$

while $Pr(f_t = 1 | f_{t-1} = 1) = 1$. Note that the fertility rate is not necessarily zero for a single woman. A single mother is observed if this woman gives birth to a child before marriage or she is the custody parent after a divorce.

The Optimization Problem: The objective of a woman is to maximize the expected $14 As argued by Van Der Klaauw (1996), given that 95% of the male population works in a representative sample, this is not a very restrictive assumption.

¹⁵For example, $(s_t, h_t, m_t) = (0, 0, 0)$ corresponds to not attend school, not work, and being single.

¹⁶In this model fertility is exogenous. It is clear that a more complete model should explicitly incorporate fertility decisions as a choice variable. However, to avoid the modeling and estimation complications resulting from an increase in the choice set and the dimension of the state space, the focus here will be on the interaction of schooling, employment, and marriage decisions conditional on fertility in each period.

present discounted value of utility over a finite horizon; i.e.,

$$\max_{\{c_t, s_t, h_t, m_t\}} E\left[\sum_{t=1}^T \beta^{t-1} U_t(c_t, s_t, h_t, m_t | \Omega_t)\right],\$$

where $\beta > 0$ is the woman's subjective discount factor and Ω_t is the state space at time t. The state space consists of all factors known to the woman that affect current utilities or the probability distribution of the future utilities. Choice of the optimal sequence of control variables $\{c_t, s_t, h_t, m_t\}$ for $t = 1, \dots, T$ maximizes the expected present value.

The contemporaneous utility $U_t(c_t, s_t, h_t, m_t)$ is assumed to be linear in consumption and has the following form:

$$U_t(c_t, s_t, h_t, m_t) = (\alpha_1 + \alpha_2 s_t + \alpha_3 h_t + \alpha_4 m_t)c_t$$

+ $v_1 s_t (1 - h_t)(1 - m_t) + v_2 s_t h_t (1 - m_t) + v_3 s_t (1 - h_t) m_t + v_4 s_t h_t m_t$
+ $v_5 (1 - h_t) f_t + v_6 (1 - h_t)(1 - f_t) + M_t m_t + \epsilon_t^{(s,h,m)}.$

 v_1 to v_4 evaluate the net utility of attending school given employment and marital status. The utility of school interacts with labor supply since more involvement in market work may prevent individuals from engaging in school activities; this interaction represents the time constraint. The utility of school also depends on marital status if marriage requires leaving school or school utility is different when married. The value of nonemployment is assumed to depend on fertility as represented by v_5 and v_6 . M_t is the value of marriage as previously specified. Finally, $\epsilon_t^{(s,h,m)}$'s are alternative-specific random components representing random variations in the individual's preference for school and for work, as well as changes in the utility derived from marriage. They are jointly serially independent, noncorrelated, and have a joint normal distribution $F(\epsilon_t)$. They are known to the individual in period t, but unknown before t. The choice decision is subject to the budget constraint given by:

$$c_t + c_S \cdot s_t + cc \cdot f_t = y_t h_t + \psi(h_t) y_t^H m_t.$$

 c_S is the direct annual cost of college, $c_S = cs$ for $12 < S \leq 16$ and $c_S = cs + cg$ for S > 16. cc is the cost of children. y_t and y_t^H denote the annual earnings of the woman and her husband. $\psi(h_t)$ is the fraction of the husband's income that is available for the woman's consumption, which depends on her employment status. This transfer may be interpreted as the woman's share of accumulated common property. There are no borrowing and saving decisions. The budget constraint is assumed to be satisfied period by period.¹⁷

3.2 Heterogeneity

The model considered above corresponds to the decision problem of a representative woman. At high school graduation, however, young women differ in many aspects: their family backgrounds as measured by parental schooling, number of siblings, and family income; their cognitive backgrounds as measured by AFQT test scores; and their high school grades and SAT scores. The abilities and preferences of individuals are likely to vary, too, in unobserved ways (e.g., motivation, perseverance, or ambition) that are both persistent and correlated with observed traits. All of these characteristics may affect youth's college decisions. For example, those whose parents are highly educated may be more likely to have greater endowments of unobserved skills. They may be more likely to attend college, and postpone marriage and workforce entry.

Assume that there exist $k = 1, 2, \dots, K$ different skill types. Denote the *ex ante* probability that a woman *i* is of type *k* by P_i^k . P_i^k depends on her observed initial traits, including mother's schooling S_i^m , father's schooling S_i^f , number of siblings N_i^{sib} , household structure

¹⁷Cameron and Heckman (1998,2001) find that the short run liquidity constraints proxied by current family income play no significant role in college attendance decisions. Cameron and Taber (2004) also find no evidence that borrowing constraints play an important role in educational attainment. Keane (2002) reviews recent work on the importance of borrowing constraints, and the impact of financial aid programs.

at 14 HH_i , net family income Y_i^0 , AFQT score $AFQT_i$, and age at high school graduation AGE_i^0 , in the form of a multinomial logit.¹⁸ For $k = 2, \dots, K$,

$$P_i^k = \frac{\exp\left[\begin{array}{c} \lambda_0^k + \lambda_1^k S_i^m + \lambda_2^k S_i^f + \lambda_3^k N_i^{sib} + \lambda_4^k H H_i \\ + \lambda_5^k Y_i^0 + \lambda_6^k A F Q T_i + \lambda_7^k A G E_i^0 \end{array}\right]}{1 + \sum_{l=2}^K \exp\left[\begin{array}{c} \lambda_0^l + \lambda_1^l S_i^m + \lambda_2^l S_i^f + \lambda_3^l N_i^{sib} + \lambda_4^l H H_i \\ + \lambda_5^l Y_i^0 + \lambda_6^l A F Q T_i + \lambda_7^l A G E_i^0 \end{array}\right]},$$

and normalize P_i^1 as $1 - \sum_{k=2}^{K} P_i^k$.

I allow women of different skill types to have distinct tastes for school and for nonemployment, different skill rental prices, and different returns to schooling. Therefore, the parameters v_1 to v_6 , β_0 , β_{0c} , and β_1 will be type-specific.

Furthermore, women may also differ in taste for marriage and marriageability in the marriage market. I assume that there exist $m = 1, 2, \dots, M$ different marriage types.¹⁹ A woman of skill type k has probability π_k^m of being marriage type m, so that $\sum_{m=1}^M \pi_k^m = 1$ for all k. Each marriage type has distinct preferences for marriage (a_0 and a_1), and marriage offer rates (b_0).

3.3 Solution to the Decision Problem

To solve the optimization problem, I define the value function $V_{it}(\Omega_{it})$ as the maximal value of the individual *i*'s optimization problem at *t*:

$$V_{it}(\Omega_{it}) = \max_{\{c_{it}, s_{it}, h_{it}, m_{it}\}} E\left[\sum_{\tau=t}^{T_i} \beta^{\tau-t} U(c_{i\tau}, s_{i\tau}, h_{i\tau}, m_{i\tau} | \Omega_{it})\right].$$

¹⁸Achievement scores such as high school grades and SAT scores may affect college choice indirectly by the correlation with ability types like other background variables. They may also affect college entrance directly if college acceptance depends on the grades or SAT scores. Due to data limitations, I leave the introduction of grades to a schooling model such as this one to future research.

¹⁹I choose K = M = 3 after sensitivity analysis. In total, there are 9 discrete types.

The value function can be written as the maximum over alternative-specific value functions $V_{it}(\Omega_{it}) = \max_{(s_t,h_t,m_t)\in J} \{V_{it}^{(s,h,m)}(\Omega_{it})\},$ which obeys the Bellman equation:

$$V_{it}^{(s,h,m)}(\Omega_{it}) = U_{it}(c_t, s_t, h_t, m_t) + \beta E[V_{it+1}(\Omega_{it+1})|\Omega_{it}, (s_t, h_t, m_t) \text{ is chosen at } t].$$

The alternative-specific value function assumes that future choices are optimally made for any given current decision. The randomness in utility arises from the fact that Ω_{it+1} is observable to the individual at time t + 1 but unobservable at time t or before. The state space can be separated into a nonstochastic part and a stochastic part. Let $\overline{\Omega_{it}}$ be the nonstochastic part of the state space, which includes types, years of schooling, years of experience, marriage duration, age, choices, fertility, and husband's schooling in the previous period. Some of these state variables evolve endogenously: $S_{it} = S_{it-1} + s_{it}$, $H_{it} = H_{it-1} + h_{it}$, $mdur_{it} = m_{it}[mdur_{it-1} + m_{it}]$. The stochastic part of the state space includes the vector of the random shocks $[\epsilon_{it}^{(0,0,0)}, \dots, \epsilon_{it}^{(1,1,1)}, \epsilon_{iwct}, \epsilon_{iwt}, \epsilon_{iy_Ht}]$, as well as job offer, marriage offer, and fertility realizations.

The model does not have an analytical solution, but it can be solved backwards numerically. To simplify the model, I assume that the optimization problem is divided into two sub-periods, as in Eckstein and Wolpin (1999). During the first $T_i - 1$ periods, for each individual *i*, the model is solved explicitly. At the terminal period T_i ,

$$V_{iT_{i}}^{(s,h,m)}(\Omega_{iT_{i}}) = U_{iT_{i}}\left(c_{T_{i}}, s_{T_{i}}, h_{T_{i}}, m_{T_{i}}\right) + \beta \{V_{iT_{i}+1}(\Omega_{iT_{i}+1}) | \Omega_{iT_{i}}, (s_{T_{i}}, h_{T_{i}}, m_{T_{i}}) \text{ is chosen at } T_{i}\}.$$

The expected future utility is assumed to be a given linear function of the state variables: $V_{iT_i+1}(\Omega_{iT_i+1}) = \delta_1 S_{iT_i+1} + \delta_2 H_{iT_i+1} + \delta_3 H_{iT_i+1}^2 + \delta_4 I(m_{iT_i} = 1).$

Using the end condition, and assuming a known distribution of ϵ_{it} , each individual's optimization problem is solved recursively from the final period T_i . The numerical complexity arises because the value function requires high dimensional integrations for the computation of the "*E* max function" at each point of the state space. Following the procedure proposed

in Keane and Wolpin (1994), I use Monte Carlo integrations to evaluate the integrals.

4 Data

4.1 The NLSY79 Sample

The micro data are taken from the 1979-98 waves of the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. A key feature of these surveys is that they gather information in an event history format, in which dates are collected for the beginning and ending of important life events such as education, employment, and marriage.

My estimation sample consists of 487 white female high school graduates from the core random sample of the NLSY79. Sample restrictions and data aggregation are described in Appendix A. Selected individuals were born between 1961-1964 and graduated from high school between 1980-1983. They are followed since they leave high school and stay in the sample up to ten years as long as consecutive annual schooling, employment, and marriage profiles are observed.

Figure 1 presents college attendance, employment, marriage rates, and the fraction of women having children for the first ten years after high school graduation. Attendance falls by 4 to 5 percent annually throughout the first three years. After the fourth year, a more than 15 percent discrete drop is observed, corresponding to typical college graduation. The attendance rate continues to fall but stays around 9 percent after seven years. This pattern reflects the fact that some women return to school.²⁰ The labor force participation rate exhibits the well-known hump-shape. It increases from 43 percent to about 80 percent in

²⁰About one third of women in the sample have the experience of leaving and subsequently returning to school. This is very different from men. In Cameron and Heckman (2001), it is documented that only 2-6 percent of high school graduates and 6-12 percent of dropouts report at least one episode of leaving and then returning to school.

the first six years, then becomes flat and declines slightly. The percentages of women who are married and women who have children have increased over time. At a more disaggregate level, Table 1 shows the proportions of women who choose each of the eight alternatives. The participation rate of married women is significantly lower than that of single women except for the first few years when few women are married. Another interesting observation is that very few married women stay in college, which indicates low complementarity between marriage and college.

As a parsimonious way of describing the joint patterns of school attendance, marriage, and employment, I run probit regressions on these choices.²¹ Based on these regressions, single women who do not work are more likely to attend college. Employed women and college attendees are less likely to be married. Years of schooling and experience increase the probability of working, while college attendance, marriage, and husband's income reduce the participation rate. Furthermore, without controlling for husband's income, schooling has less effect on married women's employment. This result is likely due to the fact that a highly educated woman marries more often a man with higher education and income, and the husband's income induces her to work less. Therefore, without controlling for husband's income, the effect of schooling on employment probability is under estimated.

Real hourly wages are obtained as explained in Appendix A. In solving the dynamic programing problem, actual hours worked are ignored. Potential annual earning, obtained by multiplying hourly wage by 2000 hours, is used. Each woman is essentially assumed to be deciding about full-time work and the wage rate is assumed to be independent of hours worked. Among all the wage observations, wages of women who work while in school are much lower and less dispersed. Following the convention, I use wage observations while not in school to run an OLS log wage regression on years of schooling and experience. The regression yields the following coefficients with standard errors in parentheses: $\beta_0(\text{constant}) = 0.712$ $(0.051), \beta_1(\text{schooling}) = 0.081 (0.004), \beta_2(\text{experience}) = 0.122 (0.009), \beta_3(\text{experience}^2)$

²¹The results are available from the author.

= -0.005 (0.001). The concavity of the experience profile and the positive schooling effect are consistent with many other studies.

71 percent of the sample have married at least once. Married couples tend to share a common schooling background. At the time of the first marriage, 42 percent of the couples have the same educational attainment and the correlation between spousal years of schooling is 0.55. 60 percent of college women's husbands are college graduates, while less than 7 percent of high school women's husbands are college graduates.²² Even though the sample women are in their twenties, many of them have already undergone one or more changes in marital status. 142 women (29%) have remained single throughout the sample period, 25 (5%) have married twice, 54 (11%) have experienced at least one divorce. Most of the divorced women have never gone to college.²³

Detailed family and cognitive background variables are constructed for the selected sample. Table 2 illustrates the potential importance of background in determining school outcomes. Both parents' education levels have strong positive correlation with women's schooling outcome. Women whose family income is greater than twice the median obtain almost two years more schooling than women whose family income is less than half of the median. AFQT scores are strongly correlated with schooling outcome. 79 percent of women in the top 20 percentile of AFQT scores complete college, while 77 percent of women in the bottom 20 percentile AFQT scores never attend college. Furthermore (not shown in Table 2), the number of siblings has little effect on schooling outcome if it is less than four and reduces schooling otherwise. Women who live with both parents at age 14 obtain a half year more schooling than those from broken families. Those who graduate from high school earlier do

 $^{^{22}}$ If schooling homogamy provides positive value to marriage, I expect marriages in which partners share similar educational background to be more stable. Due to the small number of observations, however, the joint schooling distributions are not statistically different for marriages survived and divorced during the sample periods.

²³From a life cycle perspective, this number is probably biased since college graduates get married later. Therefore, it is less likely for us to observe their divorce over the same time span. However, some aggregate data show the same pattern. According to data from the National Survey of Family Growth (NSFG), among non-Hispanic 20 to 44 years old white women in 1995, the probability of first marriage disruption after 15 years is 55% for high school dropouts, 45% for high school graduates, and 36% for women with more than a high school education.

significantly better subsequently in school than those who graduate later.

4.2 The NLSY97 Sample

For the purpose of model validation, a comparable sample is constructed from the National Longitudinal Survey of Youth 1997 (NLSY97) rounds 1-6. The NLSY97 sample consists of 8,984 youths who were at the age of 12-16 as of December 31, 1996. Since both surveys use the same instruments, they provide a unique source for the comparison of lifetime behavior between a cohort born in the early 60's and a cohort born in the early 80's. In constructing the NLSY97 sample, all of the restrictions are the same or kept as close as possible to those on the NLSY79 sample. A selected 537 women, who graduated from high school between 1997-2000, are observed for up to five years.

A dramatic increase in college enrollment from 61% to 80% is observed when I compare the NLSY79 and the NLSY97 samples.²⁴ Figure 2 compares the two college attendance profiles. Note that only four-year data are available for the NLSY97 sample conditional on having a large enough number of observations. The two attendance profiles are almost parallel with each other for the first four years.²⁵

The two samples differ in many respects, which may lead to the different schooling outcomes. First, as shown in Table 3, the NLSY97 women's parental education, family income, and AFQT scores are significantly higher than those of the NLSY79 women. Second, the schooling distribution of potential husbands has changed from 1980 to 2000 (Table 4). Third, between 1980 to 2000, the relative wage between some college and high school females increases by 50%, while the relative wage between college and high school females doubles

²⁴These are enrollment rates of white females with a high school diploma based on the NLSY79 and the NLSY97 samples. The enrollment rates from the National Center for Education Statistics (NCES) and CPS are lower since their high school graduates include individuals who completed GED (General Equivalency Diploma). It is well known that a GED is not equivalent to a high school diploma (Cameron and Heckman 1993).

²⁵At the same time, the labor force participation pattern for the young cohort stays the same. The young cohort tends to marry less or later. But if I take cohabitation into account, the proportion of having a partner/spouse converges to the marriage profile of the old cohort.

(Figure 3).²⁶ Fourth, the cost of college has been increasing dramatically in the last two decades according to the National Center for Education Statistics (Figure 4). The underlying structure of economic relations is estimated based on the data from the NLSY79 sample. The validity of the model is assessed according to how well estimates of the model predict the change in individual lifetime choices, especially college enrollment, given observed changes in background, husbands, wages, and schooling cost.

5 Estimation Method

The solution of the model serves as an input to the estimation procedure. The model is estimated by the simulated method of moments (McFadden 1989; Pakes and Pollard 1989). Specifically, the sum of squared differences between sample moments and simulated moments is minimized with respect to the parameters of the model.

The model is restricted to have an exogenous process on fertility and exogenous schooling distribution of potential husbands. I estimate the probability of a first birth separately and use it as an input to the estimation algorithm.²⁷ The results from the logit estimation are presented in Appendix B. Schooling has a negative impact on the probability of having children. Married women are more likely to have children than single women. As women become older, their probability of having at least one child increases but at a diminishing rate. I calculate the schooling distribution of 22 to 35-year-old white males between 1980 to 1983 from CPS and use it as non-parametric estimates of potential husbands' schooling distribution. Furthermore, the discount factor β is set to be 0.96, i.e., an annual rate of time preference of 4 percent.

For the selected sample indexed by $i = 1, \dots, 487$, I observe their family and cognitive background; schooling, employment, and marital status every year $(s_{it}^D, h_{it}^D, m_{it}^D)$; observed

²⁶The increase in college premium is well documented in the literature; see Katz and Murphy (1992), Card and DiNardo (2002), and Eckstein and Nagypál (2004).

²⁷The probability of the first birth depends on schooling and marital status, which are correlated with unobservables (ability, taste for marriage, etc.). Therefore, the logit estimates may be biased and inconsistent. I assume that the potential bias is small and adopt a two-step procedure as in Van Der Klaauw (1996).

wages if employed (w_{it}^{oD}) ; and the characteristics of the first marriage (husband's schooling S_{it}^{HD} and annual income y_{it}^{HD}) if married, for $t = 1, \dots, T_i$, where the superscript D denotes the data. The choice model is simulated in a consistent way as in the data. For each individual i, I first simulate her type conditional on her background. At the beginning of the first year, $t_i = 1$, all of the uncertainty in that period is realized: preference and productivity shocks are known, as well as whether job offer, marriage offer or child arrives, and the type of offers received. Using the distribution of the shocks, she also forms expectations about future utility and earnings given her current decision. She makes a joint decision on schooling, employment, and marriage $(s_{i1}^S, h_{i1}^S, m_{i1}^S)$. Her wage w_{i1}^S is recorded if employed and her husband's schooling S_{i1}^{HS} and income y_{i1}^{HS} are recorded if married. The states are then updated. Now at $t_i = 2$, conditional on the current states and all the idiosyncratic shocks, $(s_{i2}^S, h_{i2}^S, m_{i2}^S)$, $w_{i2}^S, S_{i2}^{HS}, y_{i2}^{HS}$ are simulated. If a woman is working and her wage is observed, I simulate the measurement error to obtain the "observed" wage according to $w_{it_i}^{oS} = w_{it_i}^S \exp(u)$. Observed husband's income is simulated in a similar way. Given the value of parameters, I simulate data from the model for $N^S = 25$ times for each individual.

The moments used in the estimation include the proportions of women who choose each of the eight alternatives in each year (Table 1) and the aggregated proportions attending college, working, and married (Figure 1); the proportions of high school graduate, some college, and college graduate women; mean transition moments, defined as the probability of moving to one state at t+1 given the choice at t (Table 7); husband's schooling distribution conditional on married women's education (Table 8); mean and standard deviation of husband's annual income; as well as observed mean wage and wage decile moments. In total, there are 254 data moments. For each simulation, the same moments are computed and the simulated moments are averaged over all simulations.

The simulated method of moments is implemented by using these moments. Let m_j^D be moment j in the data and $m_j^S(\theta)$ be moment j from the model simulation given the

parameter vector θ . The moment vector is

$$g'(\theta) = [m_1^D - m_1^S(\theta), \cdots, m_j^D - m_j^S(\theta), \cdots, m_J^D - m_J^S(\theta)],$$

where J is the total number of moments and J = 254. The estimation procedure iterates between the solution of the dynamic program and the minimization of the objective function $J(\theta) = g(\theta)'Wg(\theta)$ with respect to θ , where the weighting matrix W is set to be the identity matrix. I bootstrap the standard errors.

A simplified version of the model is used in Section 2 to illustrate how each of the key parameters of the model is determined by certain moments in the data.²⁸ The basic intuition is that the choice model provides selection rules, without which a reduced form analysis will generate biased estimates. Moments from a structural model, on the contrary, incorporate those selection rules.

Potentially, the decision process can be estimated by a multinomial probit model. The reduced form parameters of a probit are unspecified functions of the structural parameters of the optimization model. In order to fit the observed distributions of data with all the transitions, I will need to specify eight nested multinomial simultaneous equations for every year, and all of them should include individual fix effects. This system of equations would probably have more parameters than the structural model I estimate.

6 Results

6.1 Parameter Estimates

Parameter estimates, and their standard errors, are reported in Appendix C. Some of the parameters are not of direct interest, although parameters on background, earnings, and

²⁸The cost of college *cs* enters the model linearly with the value of schooling v_1 to v_4 . So I set cs = 7,515 in the estimation based on the estimates from the National Center for Education Statistics (NCES, Digest of Education Statistics, 1990, pp285, Table 281) during 1980-1988. In addition, a_0 , and ψ are not separately identified and I set $\psi(0) = 0.5$.

marriage are worth highlighting.

The model is fit with three skill types. According to the estimated correlation between background and skill types, the λ 's, higher parental education, fewer siblings, living with both parents at 14, higher family income, good AFQT score, and graduation from high school at an early age imply higher probability of being skill type two. Similarly, parental schooling, family income, and AFQT score also have a positive (but less) impact on the probability of being skill type three. I expect these two types to have higher skills relative to the first type. The estimated utility values of school indicate significant heterogeneity among skill types. According to the rank order of the values of v_1 , v_2 , v_3 , and v_4 's, type three has the highest value of school, type two the next, and type one the lowest, independent of working and marital status.

According to the estimates of the wage equation parameters, both skill rental price and return to schooling are the lowest for the first type. Type two's have the highest skill rental price while type three's have the highest return to schooling. Each additional year of schooling increases wages by 4.2%, 5.5%, 6.2% respectively for each type. Note that the estimated returns to schooling are much lower than the OLS estimates, providing evidence that without controlling for self selection, the earning return to schooling is upward biased.²⁹ College graduation increases wage by 29.6% conditional on years of schooling and experience. Even though skill type 1's have much lower skill rental price and returns to schooling for the formal labor market, they seem to have a comparative advantage for jobs available at school as indicated by the highest β_{0c} .

In the estimated marriage evaluation rule, the negative a_1 confirms that education attainment of both spouses are complements within the family. The value of marriage increases with age, children, and marriage duration. The estimated b_3 in the marriage offer probability function shows that college attendance increases the marriage offer rate significantly. Considerable heterogeneity is also observed among marriage types. Marriage type 1's fixed

 $^{^{29}}$ See Card (2001) for a recent survey on the complexity in estimating the earnings return to schooling.

value for marriage (a_0) is the lowest and the difference in schooling with the husbands gives them the largest disutility (a_1) . So they seem to be the most choosy ones. At the same time, they seem to be the most attractive type since they receive marriage offers most often (highest b_0). Interestingly, almost all skill type 2's belong to this marriage type.

6.2 Observed and Unobserved Heterogeneity

As shown in the estimated parameters, there is considerable variation in type-specific skill endowments and preferences. According to simulations using the estimated model, skill types differ substantially in their education attainment. College attendance rates are 18%, 96%, and 100% for skill type 1, type 2, and type 3 respectively. None of skill type 1 finish four-year college. For skill type 2, 64% of them graduate from college, while for skill type 3, an overwhelming 97% graduate. Basically, Type 1 is the high school type, type 2 is the college type, and type 3 is the graduate school type.³⁰

The model predicts a strong correlation between observed background variables and unobserved types. Although I cannot determine each individual's actual type, I can assign a set of type probabilities conditional on her family and cognitive background. Table 5 shows the correlation between selected background variable with unobserved skill types. I consider the marginal contribution of each variable on the skill type distribution. For example, to study the correlation between mother's schooling and young women's skill type, I fix other background variables at the sample means and then compute the type probabilities conditional on mothers being high school incomplete, high school graduates, some college or college graduates. As Table 5 shows, family and cognitive background variables have strong predictive power on the probabilities of being skill type 1 and type 2. Higher completed schooling of parents, higher family income, and higher AFQT scores imply a higher proportion of skill type 2 and a lower proportion of skill type 1. Mother's schooling has stronger correlation with the skill types than father's schooling. The probability of being type 3, however, is not

³⁰Each skill type also consists of a different composition of marriage types.

strongly correlated with background variables.

6.3 Within-Sample Fit

This section presents evidences on the within-sample fit of the model. Given the estimated parameters, I calculate the predicted proportions of women who choose each alternative in every year after high school. Figure 5 depicts the fit of the model to the choice proportions. Each of the profiles implied by the estimated model has approximately the right shape and matches the levels of the data quite closely. More formally, Table 6 presents the withinsample χ^2 goodness of fit statistics for the model with respect to choice proportions. The model prediction is statistically the same as the data moments at the five percent level. As for the overall schooling distribution, the model predicts that 61.2% of the sample attend college and 38.0% finish four-year college as compared with what is in the data: 61.4% attend at least one year college and 37.8% complete four years. Table 7 presents the predicted mean transitions based on the same simulations that generate the choice distributions in Figure 5. The model can match transitions reasonably well. The data demonstrates much persistence in each state; the model recovers persistence in attendance status and marital status but somewhat underpredicts the persistence in nonemployment. Individual heterogeneity and state dependency generate persistence in the model. The estimated model can also fit well the trend and the levels of women's wage and married men's annual income.

As Table 8 presents, the predicted husband's schooling distribution conditional on married women's schooling level matches the data closely. In the model, even though high school graduate women like to marry college men for their high income, they suffer from the difference in educational background and receive fewer marriage proposals. The model underpredicts their probability of marrying college men. Women who attend college but never finish four years behave more like high school graduates. Overall, the model can fit the conditional schooling distribution of husbands.

6.4 Model Validation: Out of Sample Predictions for the NLSY97 Sample

Given the parameter estimates and the exogenous changes in women's background, men's schooling distribution, college premiums, and cost of college, it is straightforward to predict these variables' impact on college attendance. Figure 6 presents the prediction of college attendance profile for the NLSY97 sample. The model, which is estimated based on a sample attending college in the early 1980s, predicts well the enrollment behavior in the early 2000s.

In the first simulation as shown by the line with dots, potential husbands' schooling distribution, the earning processes, and the cost of college are fixed at the levels of the NLSY79 sample, and the NLSY97 sample's background variables are used. College enrollment would increase by 11 percentage points, from 61% to 72%. Background has a lasting effect: as seen in the graph, it improves both attendance and graduation. The background effect is due to the increased number of high-skilled women.

In the second simulation as shown by the dash line, young women face potential husbands with a new schooling (Table 4) distribution. The model predicts that females' college enrollment would increase by an additional 1 percentage point due to educational assortative mating. The effect, however, is small and tentative because the change in husbands' educational attainment is very small.

In the third simulation as shown by the line with circles, females expect the dramatic increase in earning returns to schooling. The earning returns to schooling for the NLSY79 sample are estimated in the structural model to control for selection. Without a similar structural model estimated for the new cohort, we cannot obtain a consistent estimate for the new returns. I adopt a much more parsimonious method. As Figure 3 shows, the relative wage between some college and high school graduate females increased by 50%, while the relative wage between college graduate and high school graduate females doubled between the early 1980s and the early 2000s.³¹ I assume that, for the new cohort, the returns to each additional year of schooling (β_1 's) would increase by 50% and the returns to college graduation (β_4) would double. Since most of the premium is due to a college degree, the effect of increasing college premium on college enrollment is small but it has a large effect on college graduation.³²

In the last simulation as shown by the line with triangles, women in the NLSY97 sample pay a higher cost of college (around \$11,030 in 2000 dollars). College enrollment would drop by 1 percentage point. The tuition effect is small.

Overall, the prediction for the NLSY97 sample indicates that the individual preference parameters are invariant to the environment. Furthermore, to account for the dramatic increase in educational attainment, the shift in the skill distribution (through background) plays an essential role; the marriage market could play an important role in college enrollment. The rising skill premium has small effects on college enrollment but large effects on graduation, and the rising tuition plays an insignificant role.

7 Simulations

7.1 How Much Does Marriage Matter to College Decisions?

I run counterfactual simulations to study the effects of marriage on women's college decision. I compare women's schooling distribution from each simulation with the baseline distribution predicted by the model given the estimated parameters. Table 9 presents the simulation results.

The first simulation analyzes the case when women do not care about the relative schooling background of husbands. Setting $a_1 = 0$, the model predicts no correlation between

³¹These premiums may be attributed to the returns to ability or the returns to college (Taber 2001). I simply treat the premiums as the returns to college to have an upper bound for the changes in college premium for the new cohort.

³²Changes in men's college premium have insignificant effects.

couples' educations because matching is random. The only gain through the marriage market in this case is that college attendance increases marriage offer rate. Therefore, I observe that women cluster at the level of some college. College enrollment would increase slightly by 1.1 percentage points and graduation would drop by 1.6 percentage points. Type 1's have more incentive to attend college and type 2's have less tendency to graduate.

In the second simulation, I assume that college does not increase the marriage offer rate, i.e., $b_3 = 0$. College graduation rate would increase by 3 percentage points but college enrollment would drop by 4.5 percentage points. Based on the type-specific simulations, type 1's are the type who attend college for more marriage opportunities. If college has no effect on the marriage offer rate, their enrollment rate would drop by half. The marriage offer rate has little effect on type 2's enrollment. In fact, setting b_3 to zero would increase their college graduation rate because they are less likely to get married and drop out of college when the marriage offer rate is lower.

Women benefit from expected marriage from educational assortative mating and the marriage offer rate. When I zero out both benefits in the third simulation, college enrollment would drop by around 5 percentage points (from 61% to 56%) and the college graduation rate would drop slightly by 0.2 percentage points. The drop in enrollment is mainly because fewer type 1's attend college to meet more potential spouses. On the other hand, the fact that type 2's have less incentive to graduate to match their schooling with college graduate men contributes to the drop in graduation.

To see the effects of assortative mating in education, I run an experiment in which all potential husbands are college graduates. The model predicts that college enrollment for women would increase by almost 10 percentage points and graduation would increase by 11 percentage points. Under this scenario, type 1's attend college much more often. All type 2's would attend college and 89% of them would graduate. When there is a dramatic change in men's schooling distribution, as shown in this experiment, it can have a large impact on women's schooling decisions through educational assortative matching.

7.2 The Impact of the Earning Return to Schooling

Table 10 shows the impact of the earning return to schooling.³³ With a 10% increase in the return of each additional year of schooling (β_1 's), the enrollment rate would stay the same and the graduation rate would increase by 0.7 percentage points. When β_1 goes up, the opportunity cost of college goes up and type 1's are less likely to attend college. For type 2's the benefits outweigh the cost and they increase their schooling investment. If the return of each additional year of schooling increases by 50%, college enrollment would still have almost no change and graduation rates would increase by 4.1 percentage points. Graduation increase is from type 2's. On the other hand, a 10% increase in returns to college graduation (β_4) would have almost no effect on enrollment and increase graduation by 0.8 percentage points. Even with a 50% increase β_4 , college enrollment would increase only by 0.2 percentage points and graduation would increase by 3.8 percentage points. These effects are due to the response of type 2's.

7.3 Education Policy Experiments

In Table 11, I present evidence on the impact of two policy interventions to increase educational attainment: college tuition subsidies and college graduation bonuses. These education policy experiments assume that the impact of policy-induced skill supply responses on equilibrium skill rental prices are negligible.³⁴

College Tuition Subsidies I first simulate the effect of an experiment that provides a 50% tuition subsidy (a reduction in *cs* by 50%) for each year of college attendance. Average completed schooling level would increase by 0.1 years, from 14.3 to 14.4 years. College

³³This exercise considers the wage elasticity of college enrollment. The wage elasticity of labor supply has been a topic of considerable interest in both labor and macro economics; it correlates with both marriage and schooling choices. In Van Der Klaauw (1996), marital status is a choice variable. Eckstein and Wolpin (1989) and Imai and Keane (2004) include post-school human capital accumulation in a life cycle labor supply model.

³⁴Two recent papers, by Donghoon Lee (2005) and Heckman et al (1998), start developing solution and estimation methods that can account for the general equilibrium feedbacks. However, their results are very different.

attendance rate would increase from 61.2% to 62.3% and graduation rate would increase from 38% to 40%. Because college graduation is so prevalent among type 3's regardless of the subsidy, the increases in college graduation rates are mostly from type 2's. At the same time, more type 1's would attend college with the tuition subsidy.

Graduation Bonuses In contrast to tuition subsidies, which are based only on attendance, graduation bonuses reward individuals for years of schooling that are completed. Graduation bonus schemes provide monetary payment for college graduation. In the second policy experiment, reported in panel (2) of Table 11, the effect of a \$5000 graduation bonus is presented. College attendance rate would increase slightly by 0.3 percentage points and graduation rate would increase from 38% to 42.4%. The low skill type 1's are not affected by the policy intervention.

8 Concluding Remarks

In this paper, I have formulated and empirically implemented a structural dynamic model of high school graduate women's sequential decisions on college attendance, work, and marriage. The model is estimated on longitudinal data that include information about school attendance, labor force participation, marital status, wages, and spousal characteristics. The estimates of the model are used to quantify the importance of alternative reasons for college attendance and graduation. In particular, the estimates of the model are used to assess the effect of the expectations of marriage on college choice due to educational assortative mating, potential husband's income, and the marriage offer rate.

The main results can be summarized as follows: First, marriage plays a significant role in a female's college attendance decision. When the benefits from marriage are ruled out in the estimated model and everything else is kept the same, the predicted college enrollment would drop by 5 percentage points, from 61 percent to 56 percent. In contrast, earning return has negligible effects on college attendance but significant effects on college graduation. Overall, the observed and unobserved heterogeneity is the most important determinant of women's college decisions. Second, the estimated model from the early 1980s does well in predicting college enrollment behavior in the early 2000s. The prediction for the new sample is not only a validation of the model, it also provides evidence of the stability of the structural model for policy analysis.

An important caveat to the measured impact of marriage on college decision is that the current study is based on a partial equilibrium analysis. As women make their college decisions based on the schooling distribution of men, men are making the same decisions. Therefore, both genders' schooling distributions are an equilibrium outcome. A complete analysis would require a general equilibrium model of the marriage market, which is left for future work.³⁵

The U.S. labor market has experienced some striking changes over the past few decades. First of all, female college enrollment and graduation rates have been expanding constantly. At the same time, the labor force participation rate of married females has increased dramatically. These two trends are consistent with each other because as women become more educated, the returns from working are higher. However, for cohorts born since the mid 1950s and the early 1960s, women's college enrollment rate and graduation rate exceed those of men but their labor force participation is much lower than men's labor force participation, especially for married women. If the increase in earnings power were the only gain from investing in education and there were no discrimination towards females, we would not expect the labor force participation rate of females to be much lower than that of males. The marriage market may be a promising direction to explore based on the results of this paper.

 $^{^{35}}$ To empirically implement such a model, we need to observe *both* spouses' sequential choices. In addition, in a general equilibrium model of the marriage market, we may extend our discussion on heterogeneity to both women and men.

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Appendix A: Data Construction

The NLSY79 sample is restricted such that all women graduated from high school during May to August between 1980-1983, at ages between 17 and 19. They were single and with no children at high school graduation.³⁶ I keep those who reported consistent and complete schooling, employment, and marital history and family background. This leaves me with a sample of 487 women born between 1961-1964. A comparable sample is constructed from the NLSY97. All of the restrictions are the same or kept as close as possible to those on the NLSY79 sample.

In the model, each period is a year. This characterization of the decision process implies that some of the data must be aggregated to match the model. The details of the data construction follow.

Timing: I follow each woman in the model after she graduates from high school. A year in the model is defined as a school year from September to August. Suppose a woman receives her high school diploma in June 1985; the first year corresponds to calendar month September 1985 to August 1986.

Schooling: In order to construct the annual school attendance, I first derive monthly attendance on the basis of a question concerning whether the youth enrolled in regular school in each month of the previous year. This question starts in 1981. I thus have the individual's monthly schooling status from January 1980. I treat a woman as an attendee if she reports having attended school for at least 6 months in the school year³⁷. Questions on the month and year that respondents receive a high school diploma are used to determine the graduation date. Combining this date with respondent's date of birth, her age at graduation is computed.

Employment and wage: NLSY79 workhistory records weekly hours worked for each week

³⁶Complete schooling history is not available before 1980; therefore, the sample is restricted to high school graduates after 1980. 7 individuals graduated after 1983. 9 individuals graduated before 17 or after 19. More than 96% of the sample received a high school diploma during May to August. 24 women were married or had children at graduation.

³⁷Measurement error on choices is not considered.

since the beginning of 1978. Annual hours worked is based on accumulating weekly hours worked over the school year. A woman in the model is defined as employed if her working hours are reported during at least 26 weeks of the year, and annual hours worked are at least 1000 hours.

The employment history information is employer-based. All references to a "job" should be understood as references to an employer. The variable "hourly rate of pay job #1-5" in the work history file provides the hourly wage rate for each job. The associated wage on multiple jobs held is the average, and data are constructed such that maximum number of jobs held in a year is five. I use coded real hourly wage in 2000 dollars. Nominal wage data are deflated by CPI from BLS CPI-U. The hourly wages are top coded at \$300 and bottom coded at \$1.

Marital status and fertility: Month/year in which the first, the second and the third marriage began and month/year in which the first and the second marriage ended are recorded in NLSY79. I aggregate monthly marital status into annual status according to the following criteria: an individual is defined as married in a year if she is married for at least 6 months in the year. This definition of marriage does not include those who cohabit. Detailed cohabitation information is not available in the NLSY79 until the 1990 survey and the decision to cohabit is quite different from the decision to marry (see Brien et al 1999). Cohabitation is not treated as a separate choice to limit the state space. Based on a question about the birth date of the first child born to NLSY79 respondents, the fertility history on the first child can be constructed. For simplicity, I follow the birth of the first child only and ignore child mortality.

Spouses' characteristics: NLSY ask every year how much a respondent's spouse receives from "wages, salary, commissions or tips from all jobs before deductions for taxes or anything else". I use this question to construct husbands' annual earnings, which are converted to real income in 2000 dollars. NLSY household roster provides each family member's highest grade completed and their relationship to the youth respondent. I first obtain the spouse's household number, then link it to corresponding family member characteristics such as age and highest grades completed.

Background: Highest grade completed of a woman's mother and father, number of siblings, and whether the woman came from a broken family (i.e., one or both biological parents were absent) are measured at age 14. Family income measures parental income for dependent respondents. A dependent is defined by the NLSY as a person living at home or not at home but living in a dorm or military barrack. A two-year average is constructed for family income at ages 15 and 16 if available. Family income at age 14 and age 17 is used if the data are missing at age 15 or 16. Family income is measured in 2000 dollars.

Three surveys, conducted independently of the regular NLSY79 interviews, collected aptitude and intelligence score information: (1) The Armed Services Vocational Aptitude Battery (ASVAB), a special survey administered in 1980 to NLSY79 respondents (94% of the 1979 sample participated); (2) the 1980 survey of high schools, which collected scores from various aptitude/intelligence tests and a variety of college entrance exams such as the Preliminary Scholastic Aptitude Test (PSAT), the Scholastic Aptitude Test (SAT), and the American College Test (ACT); and (3) the 1980-83 collection of high school transcript information. The ASVAB consists of a battery of 10 tests that measure knowledge and skill in 10 different areas. The Armed Forces Qualifications Test score (AFQT) is a composite score derived from 4 sections of the battery (namely, arithmetic reasoning, word knowledge, paragraph comprehension and math knowledge) and is widely used as a cognitive ability indicator. AFQT89 percentile scores are used in the estimation.

For NLSY97, the AFQT score is not available. However, ASVAB math and verbal percentile score generated by NLS is an age-adjusted, weighted average percentile score of four batteries from ASVAB: Mathematical Knowledge (MK), Arithmetic Reasoning (AR), Word Knowledge (WK), and Paragraph Comprehension (PC). The formula is essentially the same as for AFQT scores and I treat them as comparable variables.

College entrance examination scores may be important for college applications. They

are not included in the analysis since the number of respondents for whom these scores are available is low. Consider three major college entrance exams, namely PSAT, SAT, and ACT, within my sample: 93 individuals report SAT scores, 109 report PSAT scores, and 102 report ACT scores. Overall, only 40% of the sample has at least one usable test score. When evaluating applications, schools use an SAT type of achievement score as a signal for individual ability. I assume that SAT scores or high school grades are of second order importance conditional on ability.

Appendix B: Inputs of the Model

Coefficient	Estimates (Std. Err.)
c_0 : Constant	-12.385 (3.460)
c_1 : Education	-0.343 (0.026)
c_2 : Last period's marital status	1.461(0.126)
c_3 : Age	$1.041 \ (0.291)$
$c_4: \mathrm{Age}^2$	-0.018 (0.006)
c_5 : Marriage duration	$0.310\ (0.031)$

Tabel B: Logit Estimates of the Arrival Probability of the First Child

	$\frac{\text{Type}}{\lambda_{0}^{2}} \frac{\lambda_{1}^{2}}{\lambda_{2}^{2}} \frac{\lambda_{2}^{2}}{\lambda_{3}^{2}} \frac{\lambda_{4}^{2}}{\lambda_{5}^{2}} \frac{\lambda_{5}^{2}}{\lambda_{7}^{3}} \frac{\lambda_{6}^{3}}{\lambda_{1}^{3}} \frac{\lambda_{3}^{3}}{\lambda_{3}^{3}} \frac{\lambda_{3}^{3}}{\lambda_{5}^{3}} \frac{\lambda_{6}^{3}}{\lambda_{7}^{3}} \frac{\lambda_{1}^{3}}{\pi_{1}^{1}} \frac{\lambda_{1}^{2}}{\pi_{1}^{2}}$	$\begin{array}{r} \hline \text{proportions} \\ \hline -6.729 \ (0.307) \\ 0.411 \ (0.017) \\ 0.120 \ (0.009) \\ -0.571 \ (0.030) \\ 1.077 \ (0.053) \\ 0.063 \ (0.003) \\ 0.071 \ (0.004) \\ -0.189 \ (0.007) \\ -7.150 \ (0.287) \\ 0.240 \ (0.014) \end{array}$	$ \begin{array}{c} a_{0}^{1} \\ a_{0}^{2} \\ a_{0}^{3} \\ a_{1}^{3} \\ a_{1}^{2} \\ a_{1}^{3} \\ a_{2} \\ a_{3} \end{array} $	$\begin{array}{r} \hline \text{age value} \\ \hline -7.878e+3 \ (519) \\ -1.111e+3 \ (44.6) \\ 5.953e+4 \ (3102) \\ -6.060e+3 \ (868) \\ -4.908e+3 \ (186) \\ -3.304e+3 \ (126) \\ 0.858e+3 \ (36.9) \\ 1.396e+4 \ (940) \end{array}$
$\begin{array}{c} -0.026 \ (0.001) \\ -0.016 \ (0.001) \\ -0.003 \ (0.001) \\ -6.154e+4 \ (5017) \\ 3.952e+4 \ (2888) \\ 6.255e+4 \ (2888) \\ 6.255e+4 \ (3199) \\ -1.181e+5 \ (4975) \\ 2.562e+4 \ (1373) \\ 1.117e+5 \ (1.05e+4) \\ 5.206e+5 \ (2.35e+4) \\ 2.778e+5 \ (3.70e+4) \end{array}$	$ \begin{array}{c} \lambda_{0}^{2} \\ \lambda_{1}^{2} \\ \lambda_{2}^{2} \\ \lambda_{3}^{2} \\ \lambda_{4}^{2} \\ \lambda_{5}^{2} \\ \lambda_{6}^{2} \\ \lambda_{7}^{3} \\ \lambda_{1}^{3} \\ \lambda_{2}^{3} \end{array} $	$\begin{array}{c} 0.411 & (0.017) \\ 0.120 & (0.009) \\ -0.571 & (0.030) \\ 1.077 & (0.053) \\ 0.063 & (0.003) \\ 0.071 & (0.004) \\ -0.189 & (0.007) \\ -7.150 & (0.287) \end{array}$	$a_0^2 \\ a_0^3 \\ a_1^1 \\ a_1^2 \\ a_1^3 \\ a_2^2 \\ a_3$	$\begin{array}{c} -1.111e{+}3 \ (44.6) \\ 5.953e{+}4 \ (3102) \\ -6.060e{+}3 \ (868) \\ -4.908e{+}3 \ (186) \\ -3.304e{+}3 \ (126) \\ 0.858e{+}3 \ (36.9) \end{array}$
$\begin{array}{c} -0.016 \ (0.001) \\ -0.003 \ (0.001) \\ -6.154e+4 \ (5017) \\ 3.952e+4 \ (2888) \\ 6.255e+4 \ (3199) \\ -1.181e+5 \ (4975) \\ 2.562e+4 \ (1373) \\ 1.117e+5 \ (1.05e+4) \\ 5.206e+5 \ (2.35e+4) \\ 2.778e+5 \ (3.70e+4) \end{array}$	$ \begin{array}{c} \lambda_{1}^{2} \\ \lambda_{2}^{2} \\ \lambda_{3}^{2} \\ \lambda_{4}^{2} \\ \lambda_{5}^{2} \\ \lambda_{6}^{2} \\ \lambda_{0}^{3} \\ \lambda_{1}^{3} \\ \lambda_{2}^{3} \end{array} $	$\begin{array}{c} 0.120 & (0.009) \\ -0.571 & (0.030) \\ 1.077 & (0.053) \\ 0.063 & (0.003) \\ 0.071 & (0.004) \\ -0.189 & (0.007) \\ -7.150 & (0.287) \end{array}$	$a_0^2 \\ a_0^3 \\ a_1^1 \\ a_1^2 \\ a_1^3 \\ a_2^2 \\ a_3$	5.953e+4 (3102) -6.060e+3 (868) -4.908e+3 (186) -3.304e+3 (126) 0.858e+3 (36.9)
$\begin{array}{c} -0.003 \ (0.001) \\ -6.154e{+}4 \ (5017) \\ 3.952e{+}4 \ (2888) \\ 6.255e{+}4 \ (3199) \\ -1.181e{+}5 \ (4975) \\ 2.562e{+}4 \ (1373) \\ 1.117e{+}5 \ (1.05e{+}4) \\ 5.206e{+}5 \ (2.35e{+}4) \\ 2.778e{+}5 \ (3.70e{+}4) \end{array}$	$\lambda_{2}^{2} \lambda_{3}^{2} \lambda_{4}^{2} \lambda_{5}^{2} \lambda_{6}^{2} \lambda_{7}^{2} \lambda_{0}^{2} \lambda_{1}^{3} \lambda_{2}^{3}$	$\begin{array}{c} -0.571 & (0.030) \\ 1.077 & (0.053) \\ 0.063 & (0.003) \\ 0.071 & (0.004) \\ -0.189 & (0.007) \\ -7.150 & (0.287) \end{array}$	$a_1^1 \\ a_1^2 \\ a_1^3 \\ a_2 \\ a_3$	$\begin{array}{c} -6.060\mathrm{e}{+3} (868) \\ -4.908\mathrm{e}{+3} (186) \\ -3.304\mathrm{e}{+3} (126) \\ 0.858\mathrm{e}{+3} (36.9) \end{array}$
$\begin{array}{c} -6.154e+4 \ (5017) \\ 3.952e+4 \ (2888) \\ 6.255e+4 \ (3199) \\ -1.181e+5 \ (4975) \\ 2.562e+4 \ (1373) \\ 1.117e+5 \ (1.05e+4) \\ 5.206e+5 \ (2.35e+4) \\ 2.778e+5 \ (3.70e+4) \end{array}$	$\lambda_{3}^{2} \ \lambda_{4}^{2} \ \lambda_{5}^{2} \ \lambda_{6}^{2} \ \lambda_{7}^{2} \ \lambda_{0}^{3} \ \lambda_{1}^{3} \ \lambda_{2}^{3}$	$\begin{array}{c} 1.077 \; (0.053) \\ 0.063 \; (0.003) \\ 0.071 \; (0.004) \\ -0.189 \; (0.007) \\ -7.150 \; (0.287) \end{array}$	$a_1^1 \\ a_1^2 \\ a_1^3 \\ a_2 \\ a_3$	$\begin{array}{c} -4.908\mathrm{e}{+3} (186) \\ -3.304\mathrm{e}{+3} (126) \\ 0.858\mathrm{e}{+3} (36.9) \end{array}$
$\begin{array}{c} 3.952e{+}4 (2888) \\ 6.255e{+}4 (3199) \\ -1.181e{+}5 (4975) \\ 2.562e{+}4 (1373) \\ 1.117e{+}5 (1.05e{+}4) \\ 5.206e{+}5 (2.35e{+}4) \\ 2.778e{+}5 (3.70e{+}4) \end{array}$	$\lambda_4^2 \ \lambda_5^2 \ \lambda_6^2 \ \lambda_7^2 \ \lambda_0^3 \ \lambda_1^3 \ \lambda_2^3$	$\begin{array}{c} 0.063 & (0.003) \\ 0.071 & (0.004) \\ -0.189 & (0.007) \\ -7.150 & (0.287) \end{array}$	$a_1^2 \\ a_1^3 \\ a_2 \\ a_3$	-3.304e+3 (126) 0.858e+3 (36.9)
$\begin{array}{c} 6.255e{+4} (3199) \\ -1.181e{+5} (4975) \\ 2.562e{+4} (1373) \\ 1.117e{+5} (1.05e{+4}) \\ 5.206e{+5} (2.35e{+4}) \\ 2.778e{+5} (3.70e{+4}) \end{array}$	$\lambda_5^2 \lambda_6^2 \lambda_7^2 \lambda_0^3 \lambda_1^3 \lambda_2^3$	$\begin{array}{c} 0.071 & (0.004) \\ -0.189 & (0.007) \\ -7.150 & (0.287) \end{array}$	a_1^3 a_2 a_3	0.858e + 3 (36.9)
$\begin{array}{c} -1.181e+5 (4975) \\ 2.562e+4 (1373) \\ 1.117e+5 (1.05e+4) \\ 5.206e+5 (2.35e+4) \\ 2.778e+5 (3.70e+4) \end{array}$	λ_6^2 λ_7^2 λ_0^3 λ_1^3 λ_2^3	-0.189 (0.007) -7.150 (0.287)	a_2 a_3	
$\begin{array}{c} 2.562e{+}4 \ (1373) \\ 1.117e{+}5 \ (1.05e{+}4) \\ 5.206e{+}5 \ (2.35e{+}4) \\ 2.778e{+}5 \ (3.70e{+}4) \end{array}$	$\lambda_7^2 \\ \lambda_0^3 \\ \lambda_1^3 \\ \lambda_2^3$	-7.150 (0.287)		
$\begin{array}{l} 1.117e+5 & (1.05e+4) \\ 5.206e+5 & (2.35e+4) \\ 2.778e+5 & (3.70e+4) \end{array}$	$\lambda_0^{\dot 3}\ \lambda_1^3\ \lambda_2^3$	()		1.000074 (040)
$\begin{array}{l} 1.117e+5 & (1.05e+4) \\ 5.206e+5 & (2.35e+4) \\ 2.778e+5 & (3.70e+4) \end{array}$	$\lambda_1^{\overset{\mathrm{o}}{3}}\ \lambda_2^{\overset{\mathrm{o}}{3}}$	()	a_4	5.519e + 3(245)
2.778e+5 (3.70e+4)	$\lambda_2^{\frac{1}{3}}$		_	
2.778e+5 (3.70e+4)	4	0.113(0.006)	Marria	age offer
· · · · · ·	λ_3^3	-0.115 (0.014)	b_{0}^{1}	-6.185 (0.57)
	λ_4^3	-0.334 (0.024)	b_0^2	-12.78 (0.39)
-6.101e+5 (3.0e+4)	$\lambda_5^{\frac{3}{5}}$	0.027(0.001)	$b_0^{\dot{3}}$	-8.429 (0.41)
6.268e+5 (2.61e+4)	λ_6^3	0.035(0.002)	b_1^0	0.220(0.01)
-2.336e+4 (1090)	λ_7^3	0.018(0.002)	b_2	-0.957e-4 (0.001)
3.490e + 3(165)	π_1^1	0.732(0.088)	b_3^2	0.677 (0.054)
9.956e + 3(561)	π_{1}^{2}	0.260(0.087)		nd's earning
		· · · · ·		9.379 (0.407)
· · · ·	π^{2}_{2}			0.043(0.012)
	$\pi_{3}^{\tilde{1}}$	· · · · ·		0.058(0.011)
	π_{3}^{2}	· · · ·		-0.151e-2 (0.002)
		· /		0.550(0.061)
		-	-	0.158(0.007)
nstraint	β_0^2			· · · · ·
	β_0^3			3.459e+4 (2786)
	β_1^1			1.302e+4 (608)
· · · ·	β_1^2			1.122e + 4 (498)
0.110 (0.000-)	β_1^3			1.298e+4 (628)
		. , , ,		4.129e+4 (1827)
		· · · · ·		1.684e + 5 (6892)
	β_{A}			7.642e + 4 (2837)
0.772(0.056)	β_0^4	· · · · ·		2.267e+5 (1.94e+4)
, ,	β_{2}^{2}			ondition
· · · ·	β_{α}^{3}			2.484e+4 (1228)
· · · ·		· · · · ·		3.932e+4 (4304)
$3.3000 \pm (1.100)$		0.114 (0.005)	δ_3	· · · ·
9.999e-1 (2.3e-5)				-0.265e+2 (1.16)
	$\begin{array}{c} 8.116e+3 \ (341) \\ 1.533e+4 \ (1023) \\ 2.582e+4 \ (2447) \\ 9.718e+3 \ (398) \\ \hline \\ \hline \\ nstraint \\ \hline \hline \\ 3.734e+4 \ (1396) \\ 4.322e+4 \ (3726) \\ 0.145 \ (0.004) \\ \hline \\ \hline \\ \hline \\ 0.145 \ (0.004) \\ \hline \\ \hline \\ \hline \\ 0.772 \ (0.056) \\ 0.798 \ (0.022) \\ 0.707 \ (0.033) \\ 9.996e-1 \ (7.4e-5) \\ 9.999e-1 \ (2.3e-5) \\ \hline \end{array}$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

Appendix C: Parameter Estimates

Year	No. Obs	NNS	ANS	NWS	AWS	NNM	ANM	NWM	AWM
1	(487)	15.2	37.6	30.6	10.5	3.5	0.2	2.3	0.2
2	(486)	9.5	31.7	32.7	11.5	4.1	0.4	9.5	0.6
3	(485)	8.0	26.8	33.0	10.5	6.6	1.9	13.0	0.2
4	(481)	6.2	21.0	33.9	10.8	7.5	1.5	18.5	0.6
5	(478)	4.2	6.7	44.6	7.9	8.4	1.5	25.1	1.7
6	(475)	4.0	4.4	42.1	5.7	10.7	1.1	30.9	1.1
7	(472)	4.0	3.0	38.6	3.8	13.6	0.8	33.9	2.3
8	(470)	3.2	1.9	32.8	4.0	14.0	1.3	40.4	2.3
9	(469)	3.2	1.9	30.1	3.4	16.2	1.5	41.2	2.6
10	(467)	3.0	0.9	27.0	3.4	18.6	1.9	42.6	2.6

Table 1: Choice Proportions by Years After High School

Note:

NNS denotes not-attend, not-work, single; ANS denotes attend, not-work, single; NWS denotes not-attend, work, single; AWS denotes attend, work, single; NNM denotes not-attend, not-work, married; ANM denotes attend, not-work, married; NWM denotes not-attend, work, married; AWM denotes attend, work, married.

	No. of	HGC	% HS	% some	% college
	Obs.		graduate	$\operatorname{college}$	graduate
All	487	14.3	38.6	23.6	37.8
Mother's Schooling:					
Non-high school graduate	100	12.9	64.0	24.0	12.0
High school graduate	267	14.2	39.7	25.5	34.8
Some college	60	15.2	21.7	28.3	50.0
Collge graduate	60	16.3	8.3	10.0	81.7
Father's Schooling:					
Non-high school graduate	114	13.2	59.7	21.0	19.3
High school graduate	205	13.9	44.4	26.8	28.8
Some college	64	14.8	23.4	31.3	45.3
College graduate	104	16.1	13.5	15.4	71.1
Net Family Income:					
$Y \ll 1/2$ median	40	13.8	47.5	25.0	27.5
1/2median $< Y <=$ median	204	13.9	44.1	29.4	26.5
median < Y <= 2median	210	14.6	33.8	19.5	46.7
Y > 2median	33	15.6	24.2	12.1	63.6
AFQT Percentile Score					
$AFQT \le 20$	48	12.5	77.1	18.7	4.2
20 < AFQT < =50	173	13.3	57.2	26.0	16.8
50 < AFQT < =80	191	14.9	25.1	25.7	49.2
AFQT>80	75	16.3	5.3	16.0	78.7

Table 2: Background and Schooling Outcomes

Variable Name	NLSY79	NLSY97
Highest grade completed of mother at 14	12.3(0.09)	13.6(0.10)
Highest grade completed of father at 14	$12.6\ (0.13)$	13.8(0.12)
Number of siblings at 14	2.8(0.08)	3.4(0.10)
Broken home at 14	0.14(0.01)	0.16(0.02)
Family income (in thousands 2000 dollars)	65.3 (1.50)	78.5(2.68)
$AFQT \ score^*$	53.9(1.08)	63.5(1.00)
Age at high school graduation	17.9(0.02)	17.8(0.02)

Table 3: Background Differencs: NLSY79 v.s. NLSY97

Note: Standard errors of the means are in parentheses

* See Appendix A for changes in definition.

Table 4: Schooling Distribution of NLSY79 and NLSY97 Sample's Potential Husbands

Cohort\Yrs of school	11 or less	12	13	14	15	16	17	18 or more
NLSY79	6.88	41.69	8.65	11.03	5.30	16.16	3.53	6.77
NLSY97	8.03	40.41	8.53	11.97	4.40	18.24	2.60	5.83

Note: statistics are based on 22 to 35 years old white males whose years of schooling are at least 10 years from CPS 1980-1983 and 1997-2000. CPS changed schooling classification in 1992. Prior to 1991, information on the number of grades attended and completed was collected up to 18 years. After 1992, however, education attainment is categorized to highest degree received. I use the test from the February 1990 CPS (details see Kominski and Siegel 1993), in which both questions were asked to the same individuals, to reclassify the degrees into highest grades completed.

	% Skill Type 1	% Skill Type 2	% Skill Type 3
Mother's Schooling:			
Non-high school graduate	62.6	25.7	11.7
High school graduate	43.0	43.0	14.0
Some college	28.5	57.6	13.9
Collge graduate	13.2	75.0	11.8
Father's Schooling:			
Non-high school graduate	51.0	37.2	11.8
High school graduate	42.0	44.3	13.7
Some college	36.8	48.3	14.9
College graduate	28.9	54.8	16.3
Net Family Income:			
Y <= 1/2median	46.0	39.6	14.4
1/2median $< Y <=$ median	43.0	42.8	14.2
median < Y <= 2median	38.6	47.5	13.9
Y > 2median	29.6	57.5	12.9
AFQT Percentile Score			
$AFQT \le 20$	86.3	6.2	7.5
20 < AFQT < =50	64.8	23.0	12.2
50 < AFQT < =80	25.5	62.2	12.3
AFQT>80	6.7	85.8	7.5

 Table 5: Relationship of Selected Family Background Characteristics to Skill Types

Note: Results are based on 5,000 simulations.

Table 6: Chi-Square Goodness-of-Fit Tests of the Within-Sample Choice Distribution

				Cł	noices				
Year	NNS	ANS	NWS	AWS	NNM	ANM	NWM	AWM	$\chi^2 \text{ Row}$
1	0.89	0.73	0.15	0.01	0.90	0.01	0.16	0.00	2.85
2	0.10	0.05	0.28	0.02	0.01	0.10	0.10	0.01	0.67
3	0.29	0.05	0.16	0.02	0.01	0.83	0.04	0.44	1.85
4	0.10	0.17	0.04	0.01	0.50	0.16	0.02	0.20	1.21
5	0.22	0.95	0.54	0.02	1.19	0.12	0.19	0.12	3.35
6	0.06	0.00	0.07	0.00	0.36	0.11	0.12	0.03	0.75
7	0.29	0.17	0.00	0.29	0.07	0.38	0.00	0.77	1.97
8	0.94	0.46	0.20	0.16	0.12	0.08	0.17	0.33	2.47
9	1.04	3.01	0.06	0.32	0.07	0.04	0.00	0.63	5.16
10	0.09	0.02	0.00	0.41	0.10	0.02	0.06	0.72	1.43

Note: $\chi^2 = \sum_{i=1}^k \frac{(O_i - E_i)^2}{E_i}$, where O_i is the observed frequency for bin *i* and E_i is the expected frequency for bin *i*, $\chi^2_7(0.05) = 14.07$.

	Fit of the Mean	Transitions
$\operatorname{From} \mathbf{To}$	Attend	Not-Attend
Attend	$61.65\ (66.45)$	$38.35\ (33.55)$
Not-Attend	6.34(5.31)	$93.66\ (94.69)$
From\To	Work	Not Work
Work	82.69(88.76)	17.31(11.24)
Not Work	46.83(34.77)	$53.17\ (65.23)$
From\To	Single	Married
Single	86.64(87.71)	$13.36\ (12.29)$
Married	5.53(3.63)	94.47 (96.37)

Note: Data moments are in parentheses.

Table 8: Predicted Matching in Education at The First Marriage

Married Women's		Husbands' School	ing
Schooling	HS Graduates	Some College	College Graduates
HS Graduates	73.0 (77.7)	24.4(15.7)	2.6(6.6)
Some College	42.8(42.9)	38.5(38.5)	18.7(18.7)
College Graduates	12.1 (19.5)	30.6(20.7)	57.3(59.8)

Note: Data moments are in parentheses.

	All	Type 1	Type 2	Type 3
Baseline Model				
Mean HGC	14.3	12.2	15.3	19.5
% HS Graduate	38.8	82.3	4.3	0.01
% Some College	23.2	17.7	31.4	3.0
% College Graduate	38.0	0	64.3	97.0
(1) No Educational Assor	tative Mat	ting $(a_1 = 0)$		
Mean HGC	14.3	12.2	15.3	19.3
% HS Graduate	37.7	79.7	3.9	0.0
% Some College	25.9	20.3	37.1	1.8
% College Graduate	36.4	0	59.0	98.2
(2) College Does Not Incr	ease Marr	iage Offers (b	$p_3 = 0)$	
Mean HGC	14.3	12.1	15.5	19.9
% HS Graduate	43.3	91.0	5.2	0.01
% Some College	15.7	9.0	24.8	3.0
% College Graduate	41.0	0	70.0	97.0
(3) Both (2) and (3) Hold	$l(a_1 = 0,$	$b_3 = 0)$		
Mean HGC	14.3	12.1	15.3	19.7
% HS Graduate	43.7	90.9	5.8	0.0
% Some College	18.5	9.1	32.7	1.6
% College Graduate	37.8	0	61.5	98.4
(4) All Husbands Are Col	llege Grad	uates		
Mean HGC	14.8	12.5	16.0	19.2
% HS Graduate	29.2	64.8	0	0
% Some College	21.8	34.9	11.1	0.5
% College Graduate	49.0	0.3	88.9	99.5

Table 9: The Impact of Returns to Schooling on Education Outcome by Skill Types

	All	Type 1	Type 2	Type 3
Baseline Model				
Mean HGC	14.3	12.2	15.3	19.5
% HS Graduate	38.8	82.3	4.3	0.01
% Some College	23.2	17.7	31.4	3.0
%College Graduate	38.0	0	64.3	97.0
(1) 10% Increase in Retur	rn to One [*]	Year of Schoo	oling $(\beta_1$'s)	
Mean HGC	14.3	12.2	15.4	19.3
% HS Graduate	38.8	82.6	4.2	0.01
% Some College	22.4	17.4	30.1	3.0
% College Graduate	38.7	0	65.7	97.0
(2) 50% Increase in Retur	rn to One	Year of Schoo	oling $(\beta_1$'s)	
Mean HGC	14.3	12.2	15.5	18.3
% HS Graduate	38.8	83.3	3.6	0.01
% Some College	19.0	16.7	23.0	3.2
% College Graduate	42.1	0	73.4	96.8
(3) 10% Increase in Retur	rn to Colle	ge Graduatio	on (β_4)	
Mean HGC	14.3	12.2	15.4	19.4
% HS Graduate	38.8	82.3	4.2	0.01
% Some College	22.4	17.7	29.8	2.9
% College Graduate	38.8	0	66.0	97.1
(4) 50% Increase in Return	rn to Colle	ge Graduatio	on (β_4)	
Mean HGC	14.4	12.2	15.5	19.2
% HS Graduate	38.6	82.3	3.8	0.01
% Some College	19.6	17.7	23.6	2.7
% College Graduate	41.8	0	72.6	97.3

Table 10: The Impact of Returns to Schooling on Education Outcome by Skill Types

	All	Type 1	Type 2	Type 3
Baseline Model		-JF	-JF	-JF
Mean HGC	14.3	12.2	15.3	19.5
% HS Graduate	38.8	82.3	4.3	0.01
% Some College	23.2	17.7	31.4	3.0
% College Graduate	38.0	0	64.3	97.0
(1) 50% College Tuition Subsidy				
Mean HGC	14.4	12.2	15.5	19.7
$\%~{\rm HS}$ Graduate	37.7	80.0	3.7	0
% Some College	22.3	20.0	28.2	2.5
% College Graduate	40.0	0	68.1	97.5
(2) \$5000 Graduation Bonus				
Mean HGC	14.4	12.2	15.5	19.4
% HS Graduate	38.5	82.3	3.7	0.01
% Some College	19.1	17.7	22.9	2.7
%College Graduate	42.4	0	73.4	97.3

Table 11: Education Policy Experiments

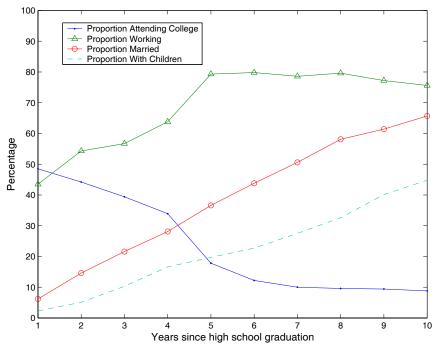


Figure 1: Proportions Attending College, Working, Married and Having Children

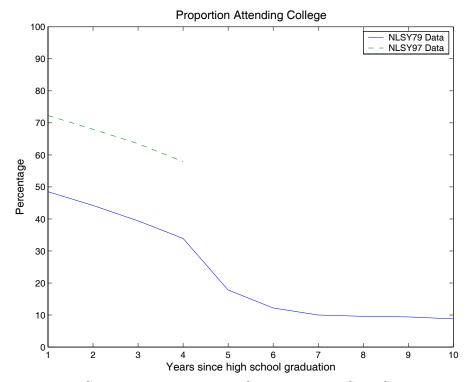


Figure 2: College Enrollment: the NLSY79 and the NLSY97 Samples

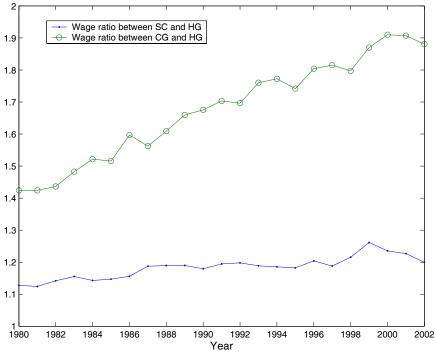


Figure 3: Relative Wages of White Females from CPS 1980-2002

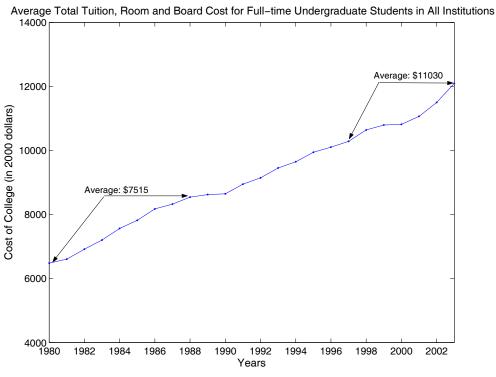


Figure 4: Changes in Direct Cost of College

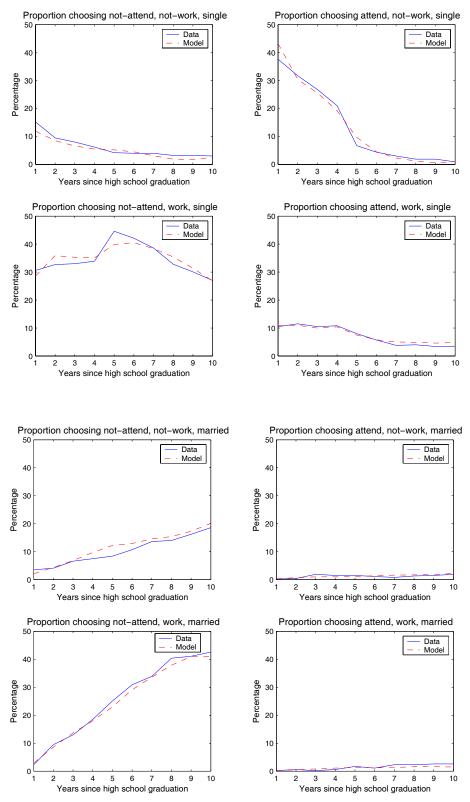


Figure 5: Fit of Choice Proportions

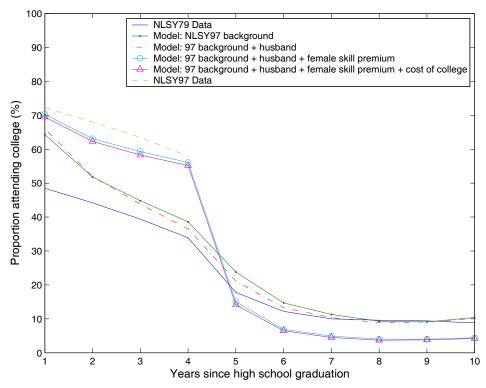


Figure 6: Out of Sample Prediction: College Attendance Profile for NLSY97 Sample