College Entry, Dropout and Re-enrollment: The Role of Tuition and Labor Market Conditions

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ABSTRACT

RONALD OERTEL: College Entry, Dropout and Re-enrollment: The Role of Tuition and Labor Market Conditions
(Under the direction of Wilbert van der Klaauw)

Industrial realignment in the United States, in part stemming from liberalized international trade, has motivated policymakers to encourage 'lifelong learning' and skill retooling. In light of these discussions it is important to understand current college going behavior, with a particular focus on college entry or re-entry at older ages, which is already a nontrivial phenomenon. I estimate a dynamic stochastic discrete choice model of schooling and labor force participation decisions over the life-cycle on a sample drawn from the National Longitudinal Survey of Youth (NLSY79). Employing value function interpolation methods in solving the dynamic programming problem, I estimate the model by Maximum Likelihood. My estimates fit the observed patterns reasonably well. I then ask how enrollment behavior would change in response to alterations in people's opportunities, including subsidies targeted at individuals already in the labor market. One such simulation shows that even a policy that fully eliminates tuition for persons with at least one year of work experience will raise the number of individuals who obtain a college degree by only 2.4%.

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Chapter 1

Introduction

Industrial realignment in the United States, in part stemming from liberalized international trade, has motivated policymakers to encourage 'lifelong learning' and skill retooling. In light of these discussions it is important to understand current college going behavior, with a particular focus on college entry or re-entry at older ages. The latter is already a non-trivial phenomenon, with those over 24 constituting roughly 40% of all male postsecondary enrollments.

1.1 Goals

The goal of this dissertation is to analyze decisions to enter, leave and re-enter college with the aid of a simple dynamic economic choice model. Using estimates of the model's parameters, the objective is to simulate the effects of several unprecedented policies aimed at increasing college enrollment and college completion. One specific objective of my research is to assess the effectiveness of policies aimed at inducing individuals to return to school. For example, I evaluate the impact of tuition subsidies restricted to individuals who have entered the labor market before attending or completing college. To accomodate this, I estimate a dynamic stochastic discrete choice model of schooling and labor force participation decisions over the life-cycle on a sample of 2313 young men drawn from the National Longitudinal Survey of Youth (NLSY79), covering the years 1978-2003.

My model incorporates a number of important features of college going behavior. First, the model accounts for persistence in behavior over time through preferences, human capital formation and learning. The model allows for habit persistence, where employment in the previous period may affect the disutility of working in the current period, and incorporates psychic costs of returning to school. Preference persistence is also captured through unobserved heterogeneity in preferences. In addition, past schooling and work decisions affect subsequent employment and education choices through their impact on wages. Secondly, in my model agents learn about the match between their educational background and the labor market. The quality of this match directly affects earnings, and it is assumed to remain constant for as long as an individual does not obtain additonal schooling. If they do return to school a new match quality is drawn. Initially unaware of the quality of their match, individuals infer it over time from the wage offers they receive. The distribution of match qualities is estimated in the model, and varies with the level of education and with the state unemployment rate. In this way my model captures any permanent effects of local labor market conditions at the time of leaving school.

Third, my model captures changes in the costs of college attendance and in labor market conditions. In my model agents make forecasts concerning future tuition and unemployment rates in their state of residence based on actual realizations of these variables in each year. Both of these affect their well-being and therefore condition their choices. Changes in college costs and labor market conditions over time may affect individual decisions to enter or leave college.

Employing value function interpolation methods in solving the dynamic programming problem, I estimate the model by Maximum Likelihood. My estimates fit the observed patterns reasonably well. I then ask how enrollment behavior would change in response to alterations in people's opportunities, including subsidies targeted at individuals already in the labor market. One such simulation shows that even a policy that fully eliminates tuition for persons with at least one year of work experience will raise the number of individuals who obtain a college degree by only 2.4%.

1.2 Literature

A substantial body of work exists that evaluates the sensitivity of enrollment to tuition and financial aid. Estimates of contemporaneous effects do not diverge very widely. Kane (1994) estimates the impact of a $1000 decrease in public tuition in 2004 dollars. He finds it associated with increases in the college attendance rates in the bottom and top income quartiles of 5.3 and 5.0 percentage points, respectively, among young 18- to 19-year-old African-American high school graduates, and by 2.9 and 0.7 percentage points among whites.[1] The same paper finds much smaller effects for an increase in Pell grants of similar size. Dynarski (2000) finds increases of 3.2 to 3.6 percentage points in Georgia's enrollment rate among 18- to 19-year-olds for each $1000 in the state's HOPE scholarship tuition subsidy. A study by van der Klaauw (2002) estimates that a $1000 fellowship offer raises the probability of attending the college making the offer by 2.8 to 3.8 percentage points. Additional studies, reviewed in Kane (2003), find similar estimates in this range. Older studies surveyed in Leslie and Brinkman (1987) also showed similar effects.

Another literature has examined the reasons for halting and resuming education. Chuang (1994) and Light (1996) find that ability measures, father's education, family income, and the local unemployment rate all have positive and significant effects on re-enrollment. In addition, Chuang finds negative effects for marriage, fertility, and employment on re-enrollment, while Light finds hourly wages, weekly hours, and tuition all negatively influencing the decision to re-enroll. The results are roughly consistent with the view that individuals re-enroll when the benefits are high (e.g. high ability) or the costs are low (e.g. high local unemployment, low current wages).

For policy purposes, researchers must take note of the fact that estimated behavioral rules reflect both agents' preferences and the constraints they face. Policies that are novel in scope or nature can alter these behavioral rules, a complication first laid out by Lucas (1976). Evaluating unprecedented policies thus requires having estimates of basic *structural* parameters that can be reasonably expected to remain robust to changes in policy. One

[1] The *rates* of increase in the college attendance rate corresponding to the percentage point increases quoted above are 14% and 8% for African-Americans and 7% and 1% for whites.

response to this challenge has been the development of dynamic structural models, which formalize the period-by-period decisions made by forward-looking agents. The evaluation of policy in this approach is a two-step process. In the first step the parameters that describe the agents' preferences are estimated. Once these estimates have been obtained, the second step forecasts the response to a policy change by a simulation of the agents' decision paths after certain parameters in the constraints facing the agent are altered.

In this vein, Keane and Wolpin (1997) investigate the 'career decisions of young men.' They estimate a model for five alternatives (home, school, military, blue-collar, white-collar). Permanent unobserved differences in aptitude for each of the five careers are formalized as different 'types' of agents, and the proportions of these in the population are estimated along with the remaining parameters in the model. Keane and Wolpin simulate the effect of a universal tuition subsidy. This policy is predicted to raise high school and college graduation rates.[2] On the other hand, it would have a negligible impact on lifetime utility, with the greatest benefits reaped by those who would have attended college anyway. The importance of allowing for permanent agent heterogeneity when performing policy simulations is further underscored by Eckstein and Wolpin (1999), who evaluate the impact of 'outlawing' work by high school students. They estimate a modest rise (from 82% to 84%) in the high school graduation rate.

With a similar model, Keane and Wolpin (2000) perform policy experiments aimed at reducing racial differences in school attainment. A bonus paid to all high school graduates would significantly reduce dropout rates, though it could not affect gaps attributable to endowment differences already in place by age 16. A wage subsidy, another policy experiment considered in the study, would close some of the gap in lifetime earnings but would reduce educational attainment, as working becomes relatively more attractive, even at young ages.

My research builds on the contributions just described by adopting the structural ap-

[2] One important caveat is that these are partial equilibrium models. In a general equilibrium model, by contrast, a policy that reduces the direct cost of schooling can be expected to lower the economic benefit from schooling, as the increased supply of educated workers makes them less valuable, thereby mitigating the policy's direct positive incentives. In recent work, Lee (2005) finds that the estimated general equilibrium responses to his tuition subsidy experiment are in fact somewhat smaller than the partial equilibrium estimates in Keane and Wolpin (1997).

proach taken by Keane and Wolpin (1997), Eckstein and Wolpin (1999), and Lee (2005) while extending their models to address the following considerations. First, the approach taken in this thesis is more sensitive to the timing of young persons' enrollment decisions. A fair number of individuals does return to school after an absence, but a return after a long absence is quite uncommon. One reason for this may be found in habit persistence - where the utility associated with non-schooling choices increases with the number of years the person opts for these alternatives - and increasing psychic costs (or lower nonmonetary benefits) associated with a return to schooling at older ages. Second, the framework I propose acccounts for the importance of realized and expected future labor market conditions and college tuition costs at the time of the choice decision to attend school, join the labor market or enter the nonschool-nonemployment state. Third, it more directly addresses the importance of imperfect information about how well one will fare in the labor market at the education level attained in a given year. There is heterogeneity across workers in the quality of the match between skills and the labor market, where some workers may return to school after discovering that their earnings potential at their current education level is worse than expected. In such a case they may acquire additional education in the hope of improving their future match with the labor market. The model I propose incorporates this type of learning, and incorporates individual expectations and stochastic realizations of college costs and local labor market conditions. In the next chapter I present this model and discuss how it will be estimated. This is followed by a discussion of the data in chapter 3, and a presentation and discussion of the estimates in chapter 4. Chapter 5 will present results from several policy experiments, while chapter 6 provides a conclusion.

Chapter 2

Model and Estimation Issues

I begin by describing the general choice-theoretic framework I will use to characterize schooling and employment decisions, followed by a more detailed discussion of the parametric specifications of the model's components.

2.1 Dynamic Stochastic Discrete Choice

My model belongs to the class of dynamic stochastic discrete choice models. In this kind of setting individuals aim to maximize their expected lifetime utility by choosing, in each period, one of a small number of mutually exclusive options. Utility will in general not be *intertemporally separable* because current utility depends crucially on past choices. However, tractability requires that utility be additively separable over time.

The options differ in their rewards, which are summarized by the choice-specific value function V_{itk}. The assumption of additive separability lets us write these rewards as the sum of current and discounted expected future rewards. For individual i choosing option k in period t this is expressed as

$$V_{itk}(S_{it}) \quad = \quad R_{itk}(S_{it}) + \delta E_t V_{t+1}(S_{it}, y_{itk} = 1),$$

where δ is the discount factor. As is made explicit here, present and future rewards will in general depend on both the current choice ($y_{itk} = 1$) and on the vector of *state variables* S_{it}, which include salient aspects of the individual's choice history.

Determining the best choice in this period appears to be difficult because calculating the future rewards $E_t V_{t+1}$ requires a determination of the optimal choice in the next period:

$$E_t V_{t+1}(S_{it}, y_{itk} = 1) \quad = \quad E_t \max_{\tilde{k}} V_{t+1,\tilde{k}}(S_{it}, y_{itk} = 1), \tilde{k} = 1, ..., K.$$

The agent's decision problem can be solved by backward recursion, though, if we assume a finite time horizon. There is a terminal period T in which the individual chooses the alternative yielding the greatest reward. We do not observe all aspects of the rewards faced by the agents, but we can determine the probability that at T option k is the best alternative given the individual's state S_{iT}:

$$\begin{aligned} P_{iTk}(S_{iT}) &= P(y_{iTk} = 1 | S_{iT}) \\ &= P(V_{iTk}(S_{iT}) > V_{iT\tilde{k}}(S_{iT}), \forall \tilde{k} \neq k), \end{aligned}$$

Having computed the probabilities attached to each of the three options, we (and the agents) can determine the expected value of V_T from the perspective of T-1:

$$E_{T-1} V_T(S_{iT}) = \sum_{k=1}^{K} P_{iTk}(S_{iT}) E_{T-1} V_{iTk}(S_{iT}). \tag{2.1}$$

Backing up in time, we can consider choices in the penultimate decision period (T-1). Conditional on the values of the state variables, a given choice entails current rewards and a particular level of expected future utility, $E_{T-1} V_T(S_{iT-1}, y_{T-1k} = 1)$, a value we have already computed. We again calculate the utilities and probabilities attached to each option, and thus determine the expected 'remaining lifetime' utility ($E_{T-2} V_{T-1}(S_{iT-1})$), conditional on the state variables. This latter quantity will be required for computing the probability of choosing any option k in period T-2. We proceed in this manner, retreating period by period, all the way to the first possible point at which a decision can be made.

Such a 'solution' to the model is always conditional on the particular values taken by the parameters. When parameters are estimated, they will be updated during the search for a maximum. This change alters not only the current rewards of a choice but also the probabilities of any future choices. We will then need to re-compute $E_{t-1}V_t$ (or some approximation to it) for all t and for every feasible state vector, S_{it}.

2.2 Model Specification

In modelling schooling and work decisions, a period is taken to be a year, and we focus on the primary activity an individual chooses for a given year. From age a_0 onward until age $a_T = 67$, agents either work (unpaid) in the home ($y_{it1} = 1$), work for pay ($y_{it2} = 1$), or attend school. As long as an agent has not attended a total of 12 years of education, there is only one schooling type available, which is referred to as 'high school' ($y_{it3} = 1$). The age-of-first-choice a_0 is determined by the state's compulsory school attendance law. In the majority of states these laws require attendance until the 16th birthday, but certain states require attendance until the 17th or 18th birthday (Angrist and Krueger 1991). Once a person has attended 12 years of education, the number of options increases to four as agents may now opt to attend either a four-year college ($y_{it4} = 1$) or a two-year college ($y_{it5} = 1$). To avoid the need to model household formation decisions, which affect women's education and work choices to a larger extent than men's, I restrict consideration to the decisions of young men. For simplicity, in describing the model and the derivation of the optimal decision rule in each period, I will focus initially on a choice set that does not distinguish between the two- and four-year college options (a choice set with options 1 through 3). The extention to the larger choice set is straightforward and will be discussed later.

The per-period utility function can be written as

$$R_{itk} \quad = \quad R(C_{it}, D_{it}, y_{it-1,2}, Age_{it}, Race_i, \tilde{e}_{itk}; \beta_{\mathbf{k}}), k = 1, ..., K.$$

Here C_{it} represents the indvidual's consumption in period t. D_{it} stands for the number of years that have elapsed since the individual last left school,and $y_{it-1,2}$ is an indicator variable for whether the individual worked in the previous period. I include both as measures of the impact of past choices on preferences.[1] For example, having worked in the previous

[1]This kind of 'habit persistence' has been found to be of empirical importance, e.g. in the context of

period may alter the utility of working, in addition to raising whatever wage offer is received. Similarly, even for two individuals of the same age the psychic benefit of reentering school may well differ depending on how long each has been away from school. Rewards are also allowed to differ by age. Finally $\tilde{e}_{itk}$ is a taste shock, while $\beta_{\mathbf{k}}$ is a vector of utility parameters specific to option k. More specifically I adopt the following per-period utility function

$$\begin{aligned} R_{itk} &= \beta_0 C_{it} + \beta_{k1} + \beta_{k2} D_{it} + \beta_{k3} I[y_{it-1,2} = 1] \\ &+ f_k(Age_{it}) + \beta_{k4} I[\text{Race} \neq \text{`white'}] \\ &+ \tilde{e}_{itk}, k = 1, ..., K. \end{aligned} \tag{2.2}$$

This specification assumes a marginal utility of consumption (β_0) that is constant across choices. The influence of age on rewards is captured by a number of indicator variables for different age groups. Differences in preferences across races are captured by an indicator variable, with 'whites' being the excluded group.

In addition to differences in observed characteristics and transitory shocks, agents may also differ in permanent and unobserved traits. I interpret these as differences in preferences, and formalize such permanent heterogeneity by writing the unobserved determinants of utility as sums of permanent and transitory components,

$$\tilde{e}_{itk} = \tilde{\mathbf{u}}_{\mathbf{ik}} + \tilde{u}_{itk}, k = 1, ..., K.$$

The transitory taste shocks are jointly normally distributed, while the permanent components $\tilde{\mathbf{u}}_{\mathbf{ik}}$ are assumed to follow a discrete distribution with M points of support as in Mroz and Guilkey (1995) and Eckstein and Wolpin (1989). These mass points are interpreted as groups of persons in the population. The preferences of individuals differ across groups. Each group m has a representation of fraction π_m in the population. These fractions are estimated along with the other parameters. Groups are also allowed to differ in habit persistence. Permanent taste heterogeneity is therefore captured by group-specific intercepts $\beta_{k1}(m_i)$, and group-

women's labor supply (Eckstein and Wolpin 1989, van der Klaauw 1996).

specific parameters describing the influences of time away from school ($\beta_{k2}(m_i)$) and of work in the previous year ($\beta_{k3}(m_i)$). In the empirical implementation of the model M was set to 3. The population proportions of the three groups are parameterized as

$$\begin{aligned} \pi_1 &= (1+\exp\{\gamma_0\})^{-1}, \\ \pi_2 &= (1+\exp\{\gamma_1\})^{-1}(1-\pi_1), \text{ and} \\ \pi_3 &= 1-\pi_1-\pi_2. \end{aligned}$$

As only differences in current and future utility *levels* between the options matter for the determination of choices, some of the parameters will not be identified. Accordingly I normalize all parameters specific to the home alternative to zero. That is, $\beta_{1j}=0, j=1,...,4$ and $f_1(Age_{it})=0$. Thus the preference parameters $\beta_{kj}, j=1,...,4$ and $f_k(Age_{it})$, $k=2,...,K$ are to be interpreted as *relative to* home production. Similarly, I define differenced unobserved components

$$\begin{aligned} e_{itk} &= \tilde{e}_{itk}-\tilde{e}_{it1} \\ &= \tilde{\mathbf{u}}_{\mathbf{ik}}-\tilde{\mathbf{u}}_{\mathbf{i1}}+\tilde{u}_{itk}-\tilde{u}_{it1} \\ &\equiv \mathbf{u}_{\mathbf{ik}}+u_{itk}, k=2,...,K, \end{aligned} \tag{2.3}$$

where the difference is taken with respect to the unobserved components of the 'home' alternative. The differenced transitory taste shocks u_{itk} are jointly normally distributed, with variance $\sigma^2_{u_k}$ and covariance $\sigma_{u_k u_{k'}}$, and serially independent. I adopt the additional normalization $\sigma_{u_2}=1$ because the *scale* of the utility differences is also irrelevant to the determination of choices. As a result all preference parameters are measured relative to the variance of the transitory unobserved components of the reward to working.

An individual with preferences as defined is confronted with a simple budget constraint, which is given by

$$
\begin{aligned}
C_{it} &= N_{it} + W_{it} I[y_{it,2} = 1] \\
&- I(E_{it} \geq 12)[T_{1it} I[y_{it,4} = 1] + T_{2it} I[y_{it,5} = 1]],
\end{aligned}
\tag{2.4}
$$

where N_{it} is nonlabor income, W_{it} labor earnings, and T_{1it} and T_{2it} represent tuition at 4-year and 2-year colleges. Earnings are only generated when the individual engages in work in the sense of the model, and tuition must only be paid when attending school beyond 12 years of education ($E_{it} \geq 12$). This formulation assumes away saving or borrowing.

Potential annual earnings W_{it} are defined by the log-earnings equation:

$$
\begin{aligned}
\ln(W_{it}) &= \alpha_1(m_i) + \alpha_2 E_{it} + \alpha_3 X_{it} + \alpha_4 X_{it}^2 + \alpha_5 F_{it} \\
&+ \alpha_6 I[E_{it} \geq 12] + \alpha_7 I[E_{it} - (F_{it}/2) \geq 16] \\
&+ \alpha_8 UR_{it} + \alpha_9 I[\text{Race} \neq \text{`white'}] + \eta_{it} \\
&\equiv \overline{W}_{it} + \eta_{it}.
\end{aligned}
\tag{2.5}
$$

This is a standard Mincerian loglinear wage equation, here allowing for diploma effects and a contemporaneous effect of the local unemployment rate, UR_{it}, which is included as a measure of local labor demand conditions. The intercept is allowed to differ between the M groups of agents. The variables E_{it} and X_{it} are the accumulated stocks of education[2] and (general) work experience, which evolve according to $E_{it+1} = E_{it} + y_{it3} + y_{it4} + y_{it5}$ and $X_{it+1} = X_{it} + y_{it2}$. The number of years at a 2-year college (F_{it}) yields an increment to earnings ($\alpha(2) + \alpha(5)$) that may differ from the effect of other years of schooling. The college diploma effect, $\alpha 7$ requires some explanation. It is assumed that half of one year's worth of credits from a community college can be transferred over when attending a 4-year college. As the other half a year's credits are assumed to be nontranferable, this also means that a year of community college delays the time of obtaining a bachelor's degree by half a year. Finally, η_{it} is a normal, serially

[2] I do not distinguish between successful and unsuccessful attempts to complete a year of education. See Eckstein and Wolpin (1999) for an effort to use transcript information in estimation. Neither do I track the quality of education, as Strayer (2002) does, nor investigate the match between student ability and college quality. For such an attempt see Light and Strayer (2000).

uncorrelated earnings shock with variance σ_η^2. This shock is independent of shocks to utility *conditional on* the time-invariant components of unobserved heterogeneity.

I assume that exactly one wage offer is received in each period. Therefore unemployment is treated as voluntary in this model. The home alternative thus includes individuals who received wage offers below their reservation wage, and for whom schooling was similarly unattractive compared to home production. When earnings are observed, they are denoted by w_{it}, and the difference between the log of observed earnings $ln(w_{it})$ and $\overline{W}_{it}$ is defined as

$$\tilde{\eta}_{it} = ln(w_{it}) - \overline{W}_{it}. \tag{2.6}$$

Individuals cannot perfectly foresee the tuition charges and unemployment rates they will face over their lifetime in their state of residence. Instead I assume they make forecasts of these variables based on estimates of a state-specific AR(1) model. More specifically, in order to predict tuition at 4-year instituions in their (U.S.) state, agents are assumed to know the estimated coefficients from a regression of the logarithm of current (real median in-state 4-year) tuition on its lagged value, for a sample covering the years 1978 to 2004. Thus I assign each individual the constant, slope coefficient, and standard deviation that was estimated for their state of residence, and assume that individuals know and use these parameters to predict the following period's tuition given its current value. I followed an equivalent procedure for tuition at 2-year colleges and for the state-level unemployment rate. It is therefore assumed that individuals characterize the movement of tuition levels and unemployment rates as AR(1) processes, which they use in forecasting their future values conditional on current realizations.

Agents know their preferences as well as the stochastic process determining wage offers. At time t, but no earlier, they also observe the transitory components of their utilities prior to making their choice. The choice is probabilistic from our perspective because these transitory components are not observed in the data. I begin by deriving the choice probability for an individual whose earnings $w_{it} = \exp\{\overline{W}_{it} + \tilde{\eta}_{it}\}$ are observed.

A young man with the choice between home, work, and high school would choose the work alternative if both $V_{it2} > V_{it3}$ and $V_{it2} > V_{it1}$, or if

$$\varepsilon_{1it} = u_{it3} - u_{it2} \leq \overline{V}_{t2}(S_{it}, m_i) + \beta_0 w_{it} - \overline{V}_{t3}(S_{it}, m_i) \equiv \varepsilon^*_{1t}(S_{it}, m_i, \tilde{\eta}_{it})$$

and

$$\varepsilon_{2it} = -u_{it2} \leq \overline{V}_{t2}(S_{it}, m_i) + \beta_0 w_{it} - \overline{V}_{t1}(S_{it}, m_i) \equiv \varepsilon^*_{2t}(S_{it}, m_i, \tilde{\eta}_{it}).$$

where $\overline{V}_{tk}(S_{it}, m_i)$ is the nonstochastic component of $V_{tk}(S_{it}, m_i)$ for an individual with the unobserved permanent traits of group m_i. Thus conditional on the the time-invariant unobserved heterogeneity components, and given earnings w_{it} the probability of choosing work is given by

$$P^*_{it2}(m_i) \quad = \quad \Phi\left(\frac{\varepsilon^*_{1t}(S_{it}, m_i, \tilde{\eta}_{it})}{\sigma_1}, \frac{\varepsilon^*_{2t}(S_{it}, m_i, \tilde{\eta}_{it})}{\sigma_2}, \rho_{12}\right), \tag{2.7}$$

where $\sigma_1^2 = \sigma_{u_2}^2 + \sigma_{u_3}^2 - 2\sigma_{u_2 u_3}$, $\sigma_2^2 = \sigma_{u_2}^2$ and $\rho_{12} = \frac{\sigma_{u_2}^2 - \sigma_{u_2 u_3}}{\sigma_1 \sigma_2}$. When earnings are not observed, we need to integrate over potential earnings.

$$P_{it2}(m_i) = \int_{-\infty}^{\infty} \Phi\left(\frac{\varepsilon^*_{1t}(S_{it}, m_i, \eta_{it})}{\sigma_1}, \frac{\varepsilon^*_{2t}(S_{it}, m_i, \eta_{it})}{\sigma_2}, \rho_{12}\right) \phi\left(\frac{\eta_{it}}{\sigma_\eta}\right) d\eta_{it}. \tag{2.8}$$

The probabilities of choosing home and schooling can be defined similarly. For example, the home alternative will be chosen if

$$\varepsilon_{3it} = u_{it2} \leq \overline{V}_{t3}(S_{it}, m_i) - \overline{V}_{t2}(S_{it}, m_i) - \beta_0 w_{it} \equiv \varepsilon^*_{3t}(S_{it}, m_i, \eta_{it})$$

and

$$\varepsilon_{2it} = u_{it3} \leq \overline{V}_{t3}(S_{it}, m_i) - \overline{V}_{t1}(S_{it}, m_i) \equiv \varepsilon^*_{4t}(S_{it}, m_i).$$

Thus the probability of making this choice is given by

$$P_{it1}(m_i) = \int_{-\infty}^{\infty} \Phi\left(\frac{\varepsilon^*_{3t}(S_{it}, m_i, \eta_{it})}{\sigma_{u_2}}, \frac{\varepsilon^*_{4t}(S_{it}, m_i, \eta_{it})}{\sigma_{u_3}}, \rho_{u_2 u_3}\right), \phi\left(\frac{\eta_{it}}{\sigma_\eta}\right) d\eta_{it},$$

where $\rho_{u_2u_3} = \frac{\sigma_{u_2u_3}}{\sigma_3\sigma_4}$.

2.3 Contributions to the Likelihood

These probabilities form the basis of the sample likelihood function. Setting observed earnings aside for the moment, we can write the period-t likelihood contribution of individual i, who shares the preferences of group m, as $P_{it}(m) = \sum_{k=1}^{K} y_{itk}P_{itk}(m)$. Across all τ_i periods for which the individual is observed in the data, we have $P_i(m) = \prod_{t=1}^{\tau_i} P_{it}(m)$. With each individual's type being unobserved, we take a weighted average of type-specific contributions, $P_i = \sum_{m=1}^{M} \pi_m P_i(m)$, where π_m is the estimated share of group m in the population. Finally, the sample likelihood for a sample of I individuals is the product of individuals' contributions, $P = \prod_{i=1}^{I} P_i$. The log-likelihood is then given by

$$l = \ln P = \ln \prod_{i=1}^{I} P_i = \sum_{i=1}^{I} \ln(\sum_{m=1}^{M} \pi_m \prod_{t=1}^{\tau_i} \sum_{k=0}^{K} y_{itk}P_{itk}(m)). \tag{2.9}$$

Estimates are chosen to maximize the likelihood of observing the choices made by the agents in the sample. The likelihood function is successively evaluated at candidate sets of parameter values. Convergence is considered to be achieved when improvement in the function declines below a chosen level of accuracy. The algorithm for updating parameters between iterations and obtaining standard errors at the optimum follows Berndt, Hall, Hall and Hausman (1974). Specifically, the standard errors are given by the square roots of the diagonal elements of the inverse of a matrix formed by cumulating the outer product of the score vector over individuals.

When earnings are recorded, the likelihood contribution will be the joint probability of working and having earnings w_{it}. With $\tilde{\eta}_{it}$ defined as the difference between observed log earnings and those predicted by the deterministic part of the log earnings equation, the likelihood contribution for an individual from group m_i then consists of the product of a normalized wage density and the probability of working conditional on this wage draw[3]:

$$P_{it0}(m_i) \quad = \quad \frac{1}{\sigma_\eta}\phi\left(\frac{\tilde{\eta}_{it}}{\sigma_\eta}\right)\Phi\left(\frac{\varepsilon^*_{1t}(S_{it}, m_i, \tilde{\eta}_{it})}{\sigma_1}, \frac{\varepsilon^*_{2t}(S_{it}, m_i, \tilde{\eta}_{it})}{\sigma_2}, \rho_{12}\right). \tag{2.10}$$

2.4 Bayesian Updating

While individuals observe general labor market conditions in each period, and know the process generating wage offers, they do not know, ex ante, how well they will do individually in this market given their educational background. Over time, however, while out of school, individuals learn about the *match* between their skills and the current labor market. Persons finding the market unfavorable may withdraw from it and decide to return to school in the hope of receiving a more favorable match with a higher level of education.

I assume that there are two possible match qualities, $\theta = \theta_L, \theta_H$. These qualities are specific to the person's education level. That is to say, the match quality will remain the same as long as the individual does not obtain additional schooling. Individuals with a good match face a different intercept α_1^H and schooling coefficient α_2^H in the wage equation. With match quality being unobserved and varying across individuals, the wage error becomes heteroskedastic, with the variance of wages differing by the level of education. The individuals are aware that the difference exists, but do not know immediately whether they are in a good match or not. They do not observe the 'boost' to mean earnings, if any, separately from the transitory wage error, η_{it}. An individual who has just left school holds the initial belief that he has a good match with probability q_0. This belief is on average correct; that is, it corresponds to the available proportion of good matches. This proportion may vary by the level of education, and it also responds to the condition of the labor market in the state of residence. It is specified as

$$q_0 = (1 + e^{\gamma_2 + \gamma_3 E_{it} + \gamma_4 UR_{it}})^{-1}. \tag{2.11}$$

It is assumed that individuals use the wage offers they receive to infer the quality of their

[3] To distinguish workers with unobserved and observed earnings I let $y_{it2} = 1$ for the former case and $y_{it0} = 1$ for the latter.

current match with the labor market. This inference improves over time as long as individuals are out of school. The 'update,' that is, the factor by which the prior probability q_{t-1} is multiplied, is given by the ratio of the wage density for a good match to the weighted average of the wage densities for both match qualities, all evaluated at $\tilde{\eta_{it}}$. Thus the updated probability of having a good match is given by

$$q_t = q_{t-1} \frac{\phi\left(\frac{\tilde{\eta_{it}} - \alpha_1^H - \alpha_2^H E_{it}}{\sigma_\eta}\right)}{q_{t-1}\phi\left(\frac{\tilde{\eta_{it}} - \alpha_1^H - \alpha_2^H E_{it}}{\sigma_\eta}\right) + (1 - q_{t-1})\,\phi\left(\frac{\tilde{\eta_{it}}}{\sigma_\eta}\right)}. \tag{2.12}$$

Learning about match quality implies that the probability of a good match now becomes an additional state variable. This means that the state vector S, on which the expected value function $E_t V_{t+1}$ (defined earlier) is conditioned, now includes the prior probability q_{t-1}. With learning, we also need to modify an individual's period-specific likelihood function. We now have a mixture over two contributions, with the prior probabilities q_{t-1} and $(1-q_{t-1})$ serving as weights. For a worker with observed wages this contribution is

$$\begin{aligned} P_{it0}(m_i) &= P(y_{it2} = 1, \tilde{\eta}_{it} | m_i) \qquad (2.13) \\ &= \Phi\left(\frac{\varepsilon_{1t}^*(S_{it}, m_i, \tilde{\eta}_{it})}{\sigma_1}, \frac{\varepsilon_{2t}^*(S_{it}, m_i, \tilde{\eta}_{it})}{\sigma_2}, \rho_{12}\right) \\ &\times \frac{1}{\sigma_\eta}\left(q_{i,t-1}\phi\left(\frac{\tilde{\eta}_{it} - \alpha_1^H - \alpha_2^H E_{it}}{\sigma_\eta}\right) + (1 - q_{i,t-1})\,\phi\left(\frac{\tilde{\eta}_{it}}{\sigma_\eta}\right)\right) \end{aligned}$$

For individuals who did not choose work, and for a small number of workers whose earnings are not observed, we need to 'integrate out' over the unobserved wage offers. The probability of choosing work when wages are not observed is then computed as

$$\begin{aligned} &P_{it2}(m_i) \\ &= q_{i,t-1} \int_{-\infty}^{\infty} \Phi\left(\frac{\varepsilon_{1t}^*(S_{it}, \eta_{it}, m_i)}{\sigma_1}, \frac{\varepsilon_{2t}^*(S_{it}, \eta_{it}, m_i)}{\sigma_2}, \rho_{34}\right) \phi\left(\frac{\eta_{it}|\theta_H}{\sigma_\eta}\right) d\eta_{it} \\ &+(1 - q_{i,t-1}) \int_{-\infty}^{\infty} \Phi\left(\frac{\varepsilon_{1t}^*(S_{it}, \eta_{it}, m_i)}{\sigma_1}, \frac{\varepsilon_{2t}^*(S_{it}, \eta_{it}, m_i)}{\sigma_2}, \rho_{34}\right) \phi\left(\frac{\eta_{it}|\theta_L}{\sigma_\eta}\right) d\eta_{it}. \end{aligned}$$

2.5 Interpolation

The probability q_t affects the wages expected for future periods. Similarly, the current values in tuition and unemployment rates, as well as the coefficients used to forecast their future values, help determine the future attractiveness of the available options. With the introduction of such continuous state variables an exact evaluation of future utilities for every possible state vector S_{it+1} becomes impossible. However, we are able to approximate these future utilities by interpolation (Keane and Wolpin 1994). To do this, we select a subset of state space points for evaluation. We then compute the expected value function values (i.e. quantities like (2.1)) at those points, and regress these on the state variables themselves as well as interactions between them[4]. Having obtained coefficient estimates from this regression we can interpolate the value function at every possible state vector value.

Specifically, for each of the $M = 3$ permanent heterogeneity groups, for both having and not having worked in the previous period, and for both 'white' and 'non-white' individuals, I draw 250 state vectors, for a total of 3000 observations to be used in an age-specific interpolation regression. The ranges of the state variables are chosen to mimic those observed in the data. Within these ranges, the values are randomly chosen by transforming draws from the uniform $U[0, 1]$ distribution. The 17 variables assigned randomly are the current values, constants, slope coefficients, and standard deviations for both tuition variables and the unemployment rate (for a total of 12 variables), the prior probability of being in a good match, as well as the years of (1) general schooling, (2) 2-year college education, (3) work experience, and (4) years since last leaving school. For each of these 3000 observations, the expected maximum over the alternative-specific value functions is simulated with 60 draws from a vector of shocks to utility, earnings, both kinds of tuition and the unemployment rate. The simulated $E_t \max_k V_{t+1,k}$ becomes the dependent variable in the interpolation regression. The state variables, transformations of them (for example, indicator variables for having attended 12 and 16 years of education), and interaction terms then combine for a total of 58

[4]Keane and Wolpin (1994) suggest the differences between the choice-specific value functions and the maximum over these, as well as the square root of these differences, as regressors in the interpolation regression. I follow the approach taken by van der Klaauw and Wolpin (2005), where the interpolation regression function is a polynomial in the state variables themselves.

regressors.

2.6 Simulation of Choice Probabilities

Probit models for more than two choices require approximations to the multivariate cumulative normal distribution. These approximations become less accurate as the number of choices increases. A commonly employed alternative approach, and the one pursued here, is to use simulation to compute these multivariate probabilities. The most popular simulation algorithm for multinomial probit models was developed by Geweke, Hajivassiliou, and Keane (GHK), as reported in Geweke, Keane and Runkle (1994). A detailed description of the implementation of this algorithm is given in Train (2003). The key insight is that a joint probability like (2.7) can be written as the product of conditional probabilities defined on uncorrelated normal variates. The first step is to specify the distribution of the relevant error differences. I will again first describe the process when there are only three options, and then extend it to four options.

For the first alternative ('home'), the covariance of the transitory shocks is summarized by the 2×2 matrix

$$\Omega = \begin{pmatrix} 1 & \sigma_{u_2 u_3} \\ \sigma_{u_2 u_3} & \sigma^2_{u_3} \end{pmatrix}$$

For this matrix, the Cholesky factor L_1, where $L_1 L_1' = \Omega$, is

$$\begin{pmatrix} a & 0 \\ b & c \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \sigma_{u_2 u_3} & (\sigma^2_{u_3} - (\sigma^2_{u_2 u_3}))^{0.5} \end{pmatrix}$$

We can then transform the correlated errors u_{itk} into functions of uncorrelated standard normal errors,

$$\begin{pmatrix} u_{it2} \\ u_{it3} \end{pmatrix} = L_1 \begin{pmatrix} z_{1it} \\ z_{2it} \end{pmatrix} = \begin{pmatrix} a & 0 \\ b & c \end{pmatrix} \begin{pmatrix} z_{1it} \\ z_{2it} \end{pmatrix}.$$

For a given wage draw, η_{it}, the probability of choosing the home alternative is

$$\begin{aligned} P_{it1}(m, \eta_{it}) &= P(u_{it2} \leq \overline{V}_{t1}(S_{it}, m) - \overline{V}_{t2}(S_{it}, m) - \beta_0 \exp\{\overline{W}_{it} + \eta_{it}\}, \\ &\quad u_{it3} \leq \overline{V}_{t1}(S_{it}, m) - \overline{V}_{t3}(S_{it}, m)) \\ &\equiv P(u_{it2} \leq \overline{V}_{12}, u_{it3} \leq \overline{V}_{13}) \\ &= P(az_{1it} \leq \overline{V}_{12}) \times P(cz_{2it} \leq \overline{V}_{13} - bz_{1it} \,|\, az_{1it} \leq \overline{V}_{12}) \\ &= \Phi(\frac{\overline{V}_{12}}{a}) \int_{-\infty}^{\overline{V}_{12}/a} \Phi(\frac{\overline{V}_{13} - bz_{1it}}{c}) \phi(z_{2it})\, dz_{2it}. \end{aligned}$$

The integral in this expression is simulated by taking repeated draws of pseudo-random numbers z_{2it} from the standard normal distribtution truncated at $\overline{V}_{12}/a$, computing the probability inside the integral, and taking an average across draws. The result is then multiplied by the first probability $\Phi(\frac{\overline{V}_{12}}{a})$. The algorithm applies to a given wage draw η_{it}. As the wage error is unobserved, several draws are taken from the distribution of wages, and the procedure is repeated for each of them. Finally an average is taken across wage draws, and this average represents the simulated probability of choosing the home alternative. In my implementation of this procedure I use 20 draws of z_{2it} for each individual and, where necessary, 40 draws of the wage shock η_{it}.

The distribution of the error differences will differ between the K options, but they all must be consistent with each other. To ensure this, all distributions are specified with reference to the same matrix Ω. Adding a column of zeros to the left, and row of zeros at the top of Ω yields $\hat{\Omega}$:

$$\hat{\Omega} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & \sigma_{u_2 u_3} \\ 0 & \sigma_{u_2 u_3} & \sigma^2_{u_3} \end{pmatrix}$$

The covariance matrix Ω_k of the error differences for option k can then be obtained from $\hat{\Omega}$. First a 'selector matrix' S_k is created by a inserting a column of $-1's$ as the k-th column of a $(K-1) \times (K-1)$ identity matrix. For instance, with K=3 and k=2, this matrix is

$$S_2 = \begin{pmatrix} 1 & -1 & 0 \\ 0 & -1 & 1 \end{pmatrix}$$

Ω_k is computed as $\Omega_k = S_k \hat{\Omega} S_k'$. The coefficients of the Cholesky factor of Ω_k can then be used to simulate the probability of choosing k in the same way as the coefficients a, b, and c in the algorithm outlined above are used to simulate the probability of choosing the home alternative.

The covariance structure changes when the choice set is enlarged to four choices. Again, taking the first alternative ('home') as an example, the covariance of the transitory shocks is summarized by the 3×3 matrix

$$\Omega = \begin{pmatrix} 1 & \sigma_{u_2 u_4} & \sigma_{u_2 u_5} \\ \sigma_{u_2 u_4} & \sigma^2_{u_4} & \sigma_{u_4 u_5} \\ \sigma_{u_2 u_5} & \sigma_{u_4 u_5} & \sigma^2_{u_5} \end{pmatrix}$$

Again, the Cholesky factor L_1 such that $L_1 L_1' = \Omega$ is computed:

$$L_1 = \begin{pmatrix} d & 0 & 0 \\ e & f & 0 \\ g & h & i \end{pmatrix}$$

We can then transform the correlated errors u_{itk} into functions of uncorrelated standard normal errors,

$$\begin{pmatrix} u_{it2} \\ u_{it4} \\ u_{it4} \end{pmatrix} = L_1 \begin{pmatrix} z_{1it} \\ z_{2it} \\ z_{3it} \end{pmatrix} = \begin{pmatrix} d & 0 & 0 \\ e & f & 0 \\ g & h & i \end{pmatrix} \begin{pmatrix} z_{1it} \\ z_{2it} \\ z_{3it} \end{pmatrix},$$

and write the joint probability of satisfying the relevant inequalities as the product of conditional probabilities:

$$
\begin{aligned}
P_{it1}(m) &= P(u_{it2} \leq \overline{V}_{t1}(S_{it},m) - \overline{V}_{t2}(S_{it},m) - \beta_0 \exp\{\overline{W}_{it} + \eta_{it}\}, \\
& \quad u_{it4} \leq \overline{V}_{t1}(S_{it},m) - \overline{V}_{t4}(S_{it},m), \\
& \quad u_{it5} \leq \overline{V}_{t1}(S_{it},m) - \overline{V}_{t5}(S_{it},m)) \\
&\equiv P(u_{it2} \leq \overline{V}_{12}, u_{it4} \leq \overline{V}_{14}, u_{it5} \leq \overline{V}_{15}) \\
&= P(dz_{1it} \leq \overline{V}_{12}) \\
&\times P(fz_{2it} \leq \overline{V}_{14} - ez_{1it} \,|\, dz_{1it} \leq \overline{V}_{12}) \\
&\times P(iz_{3it} \leq \overline{V}_{13} - gz_{1it} - hz_{2it} \,|\, dz_{1it} \leq \overline{V}_{12}, fz_{2it} \leq \overline{V}_{14} - ez_{1it}) \\
&= \Phi(\frac{\overline{V}_{12}}{d}) \\
&\times \int_{z_{2it}=-\infty}^{\overline{V}_{12}/d} \Phi(\frac{\overline{V}_{14} - ez_{1it}}{f}) \\
&\times \int_{z_{3it}=-\infty}^{\frac{\overline{V}_{14}-ez_{1it}}{f}} \Phi(\frac{\overline{V}_{15} - gz_{1it} - hz_{2it}}{i})\phi(z_{3it})\phi(z_{2it})\, dz_{3it}\, dz_{2it}.
\end{aligned}
$$

Similar probabilities are computed for the other options, each with its own Cholesky factor derived from the same underlying covariance matrix.

Chapter 3

Data

I obtain information on personal characteristics and choices from the National Longitudinal Survey of Youth 1979 (NLSY79). The survey interviewed its subjects annually from 1979 through 1994 and biennially thereafter.

My goal was to define a single primary activity (work, school, home) for each individual reaching back to their 16th birthday. Using retrospective data contained in the survey allowed me to include individuals born as early as August 1961. In a similar vein, I used the information reported in the post-1994 biennial interviews to construct annual activities through 2004, which is the most recent interview year on which data is publicly available.

3.1 School Enrollment

The earliest readily available school enrollment variable in the NLSY79 is the enrollment status as of May 1, 1979. However, it is possible to construct a school enrollment variable for the year prior to that because individuals reported a fair amount of retrospective information in their initial 1979 interview. I began by defining school enrollment in 1979 using the individual's enrollment status as of May 1, 1979 (NLSY79 Variable R02166.01). I then assigned a positive school enrollment status for 1978 for individuals enrolled at some point between March 1978 and May 1979 if they were too young to drop out before May 1978. Given the school attendance laws prevailing in most states at the time, this meant they had to be born in or after May 1962. This cutoff could be relaxed by one year for states with compulsory school attendance until the 17th birthday (ME, NV, NM, PA, TX, VA), and by two years for states with compulsory school attendance through age 18 (HI, OH, OK, OR, UT, WA).

In addition, individuals enrolled at some point between March 1978 and May 1979 were considered to have attended school in 1978 if they met a highest-grade-completed (hgc) test for their birth cohort as of May 1, 1979. The rationale went as follows. Individuals born in September 1961 or later were too young to start first grade in 1967 in the vast majority of states. If they started school in 1968 and did not repeat any grade they would have completed tenth grade in 1978, which would be reflected in the highest grade completed as of May 1 1979 (recorded in R00173.00 and/or R02167.01). Similarly, those born in September 1960 or later would have completed the eleventh grade in 1978. Allowing for one grade repetition relaxed this hgc-test by one year. I opted for this latter, more permissive interpretation because it helps smooth out the series of enrollment rates by birthyear. I also assigned a positive 1978 enrollment status for persons who graduated from high school in 1977 (R00183.00) but had completed 13 years of schooling by May 1, 1979, with equivalent cutoffs for earlier graduating years.

All the individuals defined as enrolled in 1978 according to the criteria just discussed were also considered 'observed without gap,' meaning that we know their primary activity for every year since their 16th birthday. Regardless of their 1978 enrollment status, I also considered individuals to be observed without gap if they were too young to have left school by May 1977. Again, "too young" was defined by birthday cutoffs which varied by state. For those old enough to have dropped out, but who last enrolled between April 1977 and March 1978 (inclusive), I defined another hgc-test equivalent to that described above, but relaxed by one year. Persons meeting that hgc-test were then also considered to be observed without a gap in their choice history. Across all birth-years, the coding described above left me with 4558 young men who were observed without gap, and 1845 who were not. Beginning with a sample containing only the youngest individuals, I successively decreased the birth-year cutoff, observing the fraction of individuals with gaps in their choice history. This fraction is nil for the youngest (born in 1964), and increases monotonically as the birthyear is reduced, crossing the treshold of 0.05 among men born in 1961. I then varied the birth-month cutoff for that year, and thus established an inclusion criterion of being born after July 1961. This left 2605 individuals, 46 of whom still showed gaps and were therefore deleted as well. I also deleted 105 individuals who appeared to be out of school in violation of the mandatory school attendance law for their state.

Further, a few individuals had an improbably low 'highest grade completed' as of 1978. This latter variable, the highest grade completed as of 1978, was imputed by subtracting the indicator for school attendance in 1978 from the highest grade attended as of 1979 (R02167.01). Thus, to remain in the sample, men born in or after May 1964 had to have completed 5 years of schooling, those born between May 1963 and April 1964 required 6 years, those born between May 1962 and April 1963 7 years, and those born before May 1962 needed 8 years. This led to the deletion of 46 more individuals, with 2408 remaining in the sample.

School enrollment variables for the years 1980 through 1994 were again based on the enrollment status as of May 1 of the survey year, as was the case for 1979 (already noted above). For the years after 1994, I assigned a school enrollment status of 0 if the individual declared having not been enrolled since the last interview, or was not interviewed and declared at the subsequent interview having not been enrolled since the last interview. I further assigned an enrollment status of 1 if the individual was in school either in all of the four months of September, October, March and April, or was enrolled in May, assigning a status of zero for the complement. For the even (interview) years, this was overridden by the available May 1 enrollment status. For these years we have one more source of information. Individuals not interviewed in year t may report in their interview in year t+2 that they were enrolled in either March and April or in May of year t. In this case they were also considered enrolled for the entire school year ending in year t. This criterion deviates from that defined earlier because recollections in year t+2 are only recorded as far back as January of year t. For this reason I could not require them to have been enrolled in September and October of year t-1 as well as March and April of year t.

3.2 Two-year Colleges

For a number of survey years, the NLSY provides information on the type of college last attended, and in some cases for two additional colleges. For most of the early survey years the college type is not recorded if the most recent college remained the same between interviews. Beginning with the 1998 survey year the college type is recorded even if the college had been recorded previously; this interviewing policy had also been in place briefly for the 1984 survey year. In 1987 and 1991 the questions about college type and dates of enrollment at colleges were not asked at all. Further, no surveys took place in the odd years after 1994.

I adopted the following conventions for the college type variable. For most of the years prior to 1994 I was able to use the type of the college last attended, but things were less straightforward for the years in which these variables were not available. For the years 1987, 1988 and from 1992 onward, the college type in year t was taken to be that reported, provided the person had first enrolled at that college the year before and last enrolled there in the current year or later. Further, for the years 1987, 1988 and 1992 to 1996, if the person indicated having been enrolled at the same college as in the most recent previous even year or earlier, then that year's college type was substituted, provided that the student last enrolled there in the current year or later.

I was not able to assign a college type for every individual enrolling at school after accumulating 12 years of education. This was the case for 561 person-years. Conversely, though, there were also 73 person-years who did indicate a college type even though they had *not* yet attended twelve years of education. In each of these two scenarios, an individual's person-years occuring prior to the problem case were retained, but those occuring after were lost. Altogether these deletions then led to a sample containing 37,449 (instead of 42,180) person-years.

3.3 Work Choices

From the weekly work history arrays, available going back to January 1978, I constructed the number of weeks in the year spent in each of the four categories of "no information," "not working," "employed," and "military." For the years 1978 through 1993, I assigned individuals to the activity of "work" if they were not in school in the sense already described and employed more than half the year according to both of two conditions: their number of weeks employed had to exceed 26, and their annual hours worked had to exceed 1000. They were considered to be engaged in "home production" if they were not in school and failed one or both of the 'more-than-half-time' work conditions. For the years 1994 and onward, annual hours are not available for the odd years. I replaced the two work conditions by a single condition of having worked more than 26 weeks. Individuals with positive weeks in the military were dropped from the point of enlistment onward. I further deleted person-years from that point onward where no assignment to one of the three primary activities had been made, even if such an assignment was possible for later years. This was predicated on the transition laws of the years of education and years of work experience, two crucial state variables in the model.

By construction, agents younger than 16 do not *choose* their primary activity; these person-years are excluded from the sample. For the year 1978, for example, this meant that persons born after April 1962 would not be used in the estimation until (at least) 1979. In states with compulsory attendance through age 17 even 16-year-olds cannot be considered to be choosing their activity, nor do 17-year-olds in states that compell attendance until the 18th birthday. Therefore these person-years were also excluded from the sample. With these adjustments we observe 2313 individuals for 1-26 years, for a total of 32,718 person-years.

3.4 Earnings and Tuition

In order to create an earnings variable, I divided the individual's reported annual earnings by annual work hours. This was multiplied by 2000 to generate a full-time equivalent income. In the estimation earnings are thus treated as missing when either of the annual measures were not reported, but the observation remains part of the sample. Information on state-level average tuition was obtained from the Integrated Postsecondary Education Data System (IPEDS) for the years 1980, 1984 to 1998, and 2000 to 2004, and from the Higher Education

General Information Survey (HEGIS) for the years 1978 and 1983. The 4-year tuition rate applicable to an individual was given by the median undergraduate tuition for all public 4-year colleges or universities in the state of residence at age 14. The 2-year tuition variable was defined analogously. The lack of a consistent measure of financial aid for large parts of the sample precludes the measurement of net tuition. Tuition figures used in this study are to be taken as 'gross' or 'sticker price' tuition. For the years in which no tuiton measures were available from the two sources mentioned (1979, 1981, 1982, and 1999) I imputed tuition by linear interpolation. Both earnings and tuition were deflated using the Consumer Price Index for May of the relevant year, and as a result are measured in 2004 dollars.

3.5 Sample Overview

A summary of the annual activity proportions in the sample used for estimation is given in Table 3.1. As is shown there, the proportion working full-time increases monotonically from a low of 2.5% at age 16 to 88.44% at age 35, and remains at roughly that level until age 39.

Full-time school enrollment when fewer than 12 years have been previously attended will be referred to as "high school attendance." This activity begins at its high of 93.8% at age 16 and falls below 1% by age 20. Two things are worth noting about the high school series. The fraction enrolled at age 16 only represents the proportion of those who have a legal choice about enrolling. As noted, those individuals who are required by state law to attend until age 17 or 18 are not represented in the sample until they reach that age. Second, it is highly unlikely that 0.21% of 37-year-olds are enrolled in high school. These apparent late bloomers reflect observations on individuals who enroll in their eleventh or twelfth year of schooling at these later ages, and do *not* indicate being enrolled in one or the other college type at that time. Enrollment in 4-year colleges and universities peaks at age 21, and declines thereafter, but does not drop below 1% until age 35. Enrollment at 2-year colleges peaks even earlier, at age 19, when 10.9% choose this option. The final option, labeled 'out-of-the-labor-force' (OLF) includes individuals who were employed for less than half of the year. This proportion

Table 3.1: Activity Proportions in Data, by Age

Ages	N	Work	High School	4-year College	2-year College	OLF
All (16-41)	32718	.6277	.1456	.0727	.0237	.1302
16	1742	.0247	.938	0	0	.0373
17	2059	.0578	.8679	.0019	.001	.0714
18	2068	.1673	.5561	.0895	.044	.1431
19	1862	.369	.0806	.217	.109	.2245
20	1756	.4761	.0046	.2221	.0871	.2101
21	1702	.5452	.0024	.2274	.0517	.1733
22	1631	.6137	.0031	.1882	.0319	.1631
23	1548	.7132	.0013	.1189	.0233	.1434
24	1482	.7726	.0047	.0769	.0182	.1275
25	1428	.8039	.0021	.063	.0126	.1183
26	1354	.8102	.0007	.051	.0192	.1189
27	1263	.8131	.0016	.0435	.015	.1267
28	1176	.8206	.0017	.0408	.0085	.1284
29	1118	.8301	.0018	.0268	.0089	.1324
30	1093	.8435	.0009	.021	.0064	.1281
31	1062	.8512	.0009	.0188	.0085	.1205
32	1038	.8661	0	.0164	.0048	.1127
33	1024	.8682	.002	.0127	.0029	.1143
34	1014	.8797	0	.0118	.003	.1055
35	995	.8844	.001	.006	.004	.1045
36	970	.8773	0	.0062	.001	.1155
37	938	.8795	.0021	.0053	.0032	.1098
38	923	.8884	0	.0033	.0011	.1073
39	762	.8766	0	.0026	.0026	.1181
40	493	.8621	0	.0081	.0041	.1258
41	217	.8618	0	.0138	.0046	.1198

reaches a high of 22.45% at age 19, and declines below 14% by age 24.

As Table 3.2 shows, there is a great degree of persistence in choices from year to year. For all ages taken together, the transition rates shown in the diagonal elements in the table, which reflect the proportions remaining in their primary activity from one year to the next, are the largest within their rows and columns. For 16- to 22-year-old men working in a given year, about five in six will also be working in the next year, and this persistence is even greater for the older age group. A similar proportion of younger men who enrolled in a 4-year college or university will also be found in that activity in the following year.

Table 3.2: Transition Rates in Data

			Activity at t					
Ages	Activity at $t-1$	N	Work	HS	4-year	2-year	OLF
16-22	Work	2839	.844	.004	.018	.020	.114
16-22	High School	6642	.111	.706	.064	.035	.084
16-22	4-Year College	1337	.129	.	.817	.019	.035
16-22	2-Year College	507	.306	.	.144	.487	.063
16-22	OLF	1495	.334	.025	.023	.020	.597
23-41	Work	16352	.931	.001	.009	.005	.055
23-41	High School	26	.577	.077	.	.	.346
23-41	4-Year College	955	.416	.	.537	.012	.036
23-41	2-Year College	224	.473	.	.067	.415	.045
23-41	OLF	2341	.36	.006	.009	.004	.622
All (16-41)	Work	19191	.918	.001	.011	.007	.064
All (16-41)	High School	6668	.113	.703	.064	.034	.085
All (16-41)	4-Year College	2292	.249	.	.700	.016	.035
All (16-41)	2-Year College	731	.357	.	.120	.465	.057
All (16-41)	OLF	3836	.350	.013	.014	.010	.612

Individuals are less likely to *re-enroll* at later ages. About 2% of young men enroll in 4-year and 2-year colleges, respectively, after working full-time the previous year, and similar proportions return to school from outside the labor force. Among men of ages 23 to 41, about 1% will resume their education after an absence at a 4-year college, and about 0.5% do so at a 2-year college. Direct transfers from a 2-year to a 4-year college are much more likely than transfers in the opposite direction. For all ages taken together, about 12% of men studying at community colleges students will enroll in a 4-year college or university in the , but less than 2% do the reverse.

Tables 3.3 to 3.6 provide an indication of the prevalence of leaving and returning to school in the data. 1968 individuals are observed leaving school at most once (Table 3.3), while 345 are observed leaving school multiple times. For those leaving school only once, Table 3.4 shows the frequency counts for the six possible transitions from schooling into non-schooling states. The greatest frequencies here occur for individuals who leave during or after high school for either full-time work or part-time work/home production, with a substantial minority (of about 42%) making the latter transition. This is much less common for those leaving postsecondary education, where 87% and 86% immediately transition into full-time

Table 3.3: Number of Times Observed Leaving School

Times Leaving School	Individuals	Proportion
0	484	20.93
1	1484	64.16
2	266	11.50
3	60	2.59
4	16	0.69
5	2	0.09
6	1	0.04
Total	2,313	100.00

Table 3.4: Transitions for Individuals Leaving School Once

	Activity at t		
Activity at $t-1$	Work	OLF	Total
High School	624	448	1072
4-year College	260	38	298
2-year College	98	16	114
Total	982	502	1484

employment.

As Table 3.5 shows, 1925 persons are never observed returning to school, while 388 return at least once, for a total of 506 re-enrollment spells. For the people who return, Table 3.6 gives an idea of the relative importance of the three schooling types among the re-enrollment spells. 65 persons return to high school after an absence, and 9 do so multiple times. 187 or about 48% of any first re-enrollment spell occurs in order to attend a 4-year college, and 64% of later re-enrollment spells occur at such institutions. As for the pre-return activities, there is a significant difference between first and later re-enrollment, as 130 or about one third of all

Table 3.5: Number of Times Observed Returning to School

Times Returning to School	Individuals	Proportion
0	1925	83.23
1	294	12.71
2	74	3.20
3	17	0.73
4	2	0.09
5	1	0.04
Total	2,313	100.00

Table 3.6: Transitions if Returning to School

First Return				
	Activity at t			
Activity at $t-1$	High School	4-year College	2-year College	Total
Work	20	138	100	258
OLF	45	49	36	130
Total	65	187	136	388

Later Returns				
	Activity at t			
Activity at $t-1$	High School	4-year College	2-year College	Total
Work	3	69	31	103
OLF	6	6	3	15
Total	9	75	34	118

first re-enrollment spells commence after part-time work/home production, while only 13% (15/118) of later spells come from that source.

Chapter 4

Estimates

Parameter estimates and their asymptotic standard errors are presented in Table 4.1. The signs of most coefficients in the wage equation[1] accord with commonly held priors. For example, years of work experience raise earnings at a decreasing rate. The return to work experience starts just below 10% for the first year, and declines from there. According to these estimates, the earnings-experience profile reaches a maximum around 16 years of work experience ($-\frac{\alpha_3}{2\alpha 4} = 16$).

Good matches receive a boost equal to $\alpha_1^H + \alpha_2^H E_{it}$. At 12 years of schooling, this amounts to a boost of 66% of earnings, and at 16 years of schooling it stands at about 61%. The proportion of available good matches, q_0, appears to not vary systemically with the level of education and the unemployment rate when entering the labor market. These two coefficients, γ_3 and γ_4, while implying economically meaningful effects, are imprecisely estimated. Given the coefficients, the availability of a good match with 16 years of education and at an unemployment rate of 5% is $(1 + exp\{.296 + 1.9315(0.05) - .0148(16)\})^{-1} = 0.46$. In addition to reducing the fraction of good matches, an increase in unemployment also directly reduces wages, with an average loss of about 2.3% per percentage point increase in the unemployment rate.

The coefficient on the indicator variable for having 12 or more years of schooling is large and negative, likely reflecting problems with treating all individuals who have attended 12 years of schooling identically, regardless of whether they graduated from high school. By contrast, I find a large and positive premium for 16 or more years of education (about 51%).

[1] All dollar figures are in 2004 dollars. Monetary values (earnings and tuition) are measured in $10000.

Residual variation in the log of annual earnings is estimated to be quite high, with an estimated standard deviation of 0.49. All else equal, an incremental year of schooling raises wage offers by 4.5%. A year of education at a community college adds less than that, but the difference ($\alpha_8 = -.0085$) is very imprecisely estimated. Relative to the exluded group of 'whites,' and all else equal, other racial groups receive wage offers that are about 18% lower.

The estimate of the marginal utility of consumption is positive and highly significant. Relative to the utility of home production, the nonpecuniary utility associated with working increases steeply until reaching the age range 28-32 after which it flattens out, and finally falls somewhat at higher ages. While the utility of attending high school drops after age 18, the nonpecuniary component of the utility associated with attending 4-year colleges rises at age 20, but generally falls with age. The utility associated with attending a 2-year college is highest below age 20, and falls prior to rebounding eventually. Relative to 'whites,' other groups have a greater disutility of working, and higher consumption values of high school and community college education.

The proportions for the three heterogeneity groups are given by

$$\begin{aligned}
\pi_1 &= (1 + exp\{.617\})^{-1} = 0.35, \\
\pi_2 &= (1 + exp\{.258\})^{-1}(1 - \pi_1) = .28, \text{ and} \\
\pi_3 &= 1 - \pi_1 - \pi_2 = .37
\end{aligned}$$

Conditional on years since leaving school and on work status in the previous year, group 2 has a greater preference for work ($\beta_{21}(2) > 0$) and 2-year college ($\beta_{51}(2) > 0$) than group 1 (the default), while the reverse is true for high school and 4-year college. Group 2 also faces lower wage offers than group 1 ($\alpha_{12}(2) < 0$). Group 3 receives the highest wage offers among the three. It also has the greatest preference for work, high school, and 2-year college. For all three groups, recent time away from school reduces the disutility of work ($\beta_{22} > 0$, $\beta_{22} + \beta_{22}(2) > 0$, and $\beta_{22} + \beta_{22}(3) > 0$), and reduces the consumption value of all 3 schooling choices. For the most part, having worked the year before makes work now less onerous, and schooling less attractive, with the exception of 4-year college for group 2, and 2-year college for group 1.

As discussed in chapter 3 and shown in Table 4.2, the choice patterns in the data reveal a rapid transition from high school to college, employment and non-employment, followed by a transition from college to employment. As shown in Table 4.3, the model is able to capture the following main features in the data. First, the full-time employment rate increases rapidly with age. Secondly, college attendance rates rise initially and then decline. Thirdly, the non-school/non-employment rate increases initially, then declines, and finally stabilizes. However, the Table also shows that the model has trouble fitting the observed choice patterns in the 16-18 age range, underestimating the rate at which individuals attend high school at those ages. This is likely to be related to the negative estimate on high school completion in the earnings equation discussed earlier. The model also has some trouble in capturing the decline in college attendance rates (and the associated increase in employment) with age. As indicated by the chi-squared statistics in Table 4.3 the overall fit is not great, but given the large sample sizes at each age interval as well as the well-known tendency of simple structural dynamic models to be rejected by the data, this does not come as a great surprise.

The model's fit of the data would likely improve with a more careful distinction between high school and college grade attendance and grade completion, but this would generally require a considerable expansion in the choice set and state variables in the model. It is not obvious, though, that the model's inability to capture these specific features in the activity-age patterns in the data will lead to meaningful biases in the model's implied estimates of the effect of tuition and labor market conditions on choice behavior.

Table 4.1: Parameter Estimates

	Variable	Coefficient	Std. Error
β_0	Consumption	.0211	.0020
Utility when working			
β_{21}	Constant	-1.9355	.0497
$\beta_{21}(2)$	$I[m_i = 2]$	.1483	.0550
$\beta_{21}(3)$	$I[m_i = 3]$	.8937	.0675
β_{22}	Years out of school	.0151	.0021
$\beta_{22}(2)$	$I[m_i = 2]$ Years out of school	-.0090	.0024
$\beta_{22}(3)$	$I[m_i = 3]$ Years out of school	-.0054	.0035
β_{23}	Work in previous period	1.7486	.0419
$\beta_{23}(2)$	$I[m_i = 2]$ Work in previous period	-.4322	.0490
$\beta_{23}(3)$	$I[m_i = 3]$ Work in previous period	-.6107	.0565
	$18 \leq Age < 20$	.3423	.0274
	$20 \leq Age < 22$	.5079	.0410
	$22 \leq Age < 24$	.6245	.0423
	$24 \leq Age < 28$	.7543	.0383
	$28 \leq Age < 32$	.6479	.0431
	$32 \leq Age < 36$	.6962	.0435
	$36 \leq Age$	.5586	.0435
β_{24}	indicated race other than 'white'	-.1430	.0134
Utility when at high school			
β_{31}	Constant	.4580	.0404
$\beta_{31}(2)$	$I[m_i = 2]$	-.4067	.0358
$\beta_{31}(3)$	$I[m_i = 3]$	1.508	.0696
β_{32}	Out of school last year	-.3471	.0662
$\beta_{32}(2)$	$I[m_i = 2]$ Out of school last year	.0514	.0614
$\beta_{32}(3)$	$I[m_i = 3]$ Out of school last year	-.9906	.1073
β_{33}	Work in previous period	-.4201	.0568
$\beta_{33}(2)$	$I[m_i = 2]$ Work in previous period	.2509	.0534
$\beta_{33}(3)$	$I[m_i = 3]$ Work in previous period	-.6903	.0965
	$Age \geq 19$	-.2844	.0273
β_{34}	indicated race other than 'white'	.1163	.0106

Table 4.1 (continued): Parameter Estimates

	Variable	Coefficient	Std. Error
Utility when at 4-year college			
β_{41}	Constant	.2334	.0326
$\beta_{41}(2)$	$I[m_i = 2]$	-.4872	.0486
$\beta_{41}(3)$	$I[m_i = 3]$	-.5128	.0544
β_{42}	Years out of school	-.0438	.0106
$\beta_{42}(2)$	$I[m_i = 2]$ Years out of school	-.3406	.0603
$\beta_{42}(3)$	$I[m_i = 3]$ Years out of school	-.0178	.0160
β_{43}	Work in previous period	-.1361	.0647
$\beta_{43}(2)$	$I[m_i = 2]$ Work in previous period	.2574	.1194
$\beta_{43}(3)$	$I[m_i = 3]$ Work in previous period	.0143	.0594
	$20 \leq Age < 22$	.1266	.0259
	$22 \leq Age < 24$	.1577	.0279
	$24 \leq Age < 28$	.1046	.0289
	$28 \leq Age < 32$	.0351	.0330
	$32 \leq Age < 36$	-.0236	.0389
	$36 \leq Age$	.0742	.0295
β_{44}	indicated race other than 'white'	-.0204	.0155
Utility when at 2-year college			
β_{51}	Constant	-.7684	.1283
$\beta_{51}(2)$	$I[m_i = 2]$	.0744	.0471
$\beta_{51}(3)$	$I[m_i = 3]$	.6627	.1070
β_{52}	Years out of school	-.3765	.3242
$\beta_{52}(2)$	$I[m_i = 2]$ Years out of school	.3148	.3233
$\beta_{52}(3)$	$I[m_i = 3]$ Years out of school	.2739	.3230
β_{53}	Work in previous period	.1716	.3441
$\beta_{53}(2)$	$I[m_i = 2]$ Work in previous period	-.3068	.3479
$\beta_{53}(3)$	$I[m_i = 3]$ Work in previous period	-.4621	.3456
	$20 \leq Age < 22$	-.0872	.0397
	$22 \leq Age < 24$	-.1993	.0560
	$24 \leq Age < 28$	-.0765	.0502
	$28 \leq Age < 32$	-.0504	.0570
	$32 \leq Age < 36$	-.1123	.0681
	$36 \leq Age$	.2308	.0555
β_{54}	indicated race other than 'white'	.0870	.0296

Table 4.1 (continued): Parameter Estimates

	Variable	Coefficient	Std. Error
Wage Offer Equation			
α_1	Constant	-.0521	.0298
$\alpha_1(2)$	Constant $I[m_i = 2]$	-.5809	.0116
$\alpha_1(3)$	Constant $I[m_i = 3]$	.3447	.0099
α_2	Years of Schooling	.0452	.0021
α_3	Years of Work Experience	.0991	.0021
α_4	Years of Work Experience squared	-.0031	.0001
α_5	Years at 2-year college	-.0085	.0168
α_6	Schooling ≥ 12	-.2561	.0116
α_7	Schooling ≥ 16	.5064	.0138
α_8	Current Unemployment Rate	-2.2534	.2157
α_9	indicated race other than 'white'	-.1806	.0077
α_1^H	$I[\theta = \theta_H]$	.8146	.0267
α_2^H	$I[\theta = \theta_H]$ Years of Schooling	-.0127	.0020
Heterogeneity			
4-year College	Utility Shock Cholesky coefficient 1	-.0361	.0387
4-year College	Utility Shock Cholesky coefficient 2	-.3117	.0298
2-year College	Utility Shock Cholesky coefficient 1	-.2790	.0772
2-year College	Utility Shock Cholesky coefficient 2	.4044	.0713
2-year College	Utility Shock Cholesky coefficient 3	.1865	.0686
High School	Cholesky coefficient 1	-.2076	.0176
High School	Cholesky coefficient 2	.0083	.0011
σ_η	Std. Deviation of Wage Offers	.4924	.0010
γ_0	Constant in π_1	.6170	.0664
γ_1	Constant in π_2	.2584	.0708
γ_2	Constant in q_0	.2960	.2277
γ_3	Current Unemployment Rate in q_0	1.9315	1.7196
γ_4	Years of Schooling in q_0	-.0148	.0121
δ	Discount Factor	.935	Fixed
Individuals		2313	
Observations		32717	
Log-likelihood		-28552.3367	

Table 4.2: Activity Proportions in Data, by Age Group

Ages	N	Work	School	4-year	2-year	OLF
16-18	5869	.0866	.7788	.0322	.0158	.0866
19-21	5320	.4607	.0305	.2220	.0835	.2034
21-24	4661	.6973	.0030	.1298	.0247	.1453
25-27	4045	.8089	.0015	.0529	.0156	.1211
28-30	3387	.8311	.0015	.0298	.0080	.1296
31-33	3124	.8617	.0010	.0160	.0054	.1159
34-36	2979	.8805	.0003	.0081	.0027	.1084
37-39	2623	.8818	.0008	.0038	.0023	.1113
40-41	710	.8620	0	.0099	.0042	.1239
All (16-41)	32718	.6277	.1456	.0727	.0237	.1302

Table 4.3: Activity Proportions in Baseline Simulation, by Age Group

Ages	N	Work	School	4-year	2-year	OLF	χ^2 (Row)
16-18	5869	.2841	.6135	.0293	.0184	.0546	1181
19-21	5320	.4299	.1286	.2186	.0473	.1756	581
22-24	4661	.5901	.0696	.1535	.0308	.1560	414
25-27	4045	.7083	.0488	.0879	.0311	.1239	331
28-30	3387	.7331	.0374	.0656	.0286	.1352	279
31-33	3124	.7854	.0280	.0452	.0204	.1210	198
34-36	2979	.8035	.0251	.0383	.0263	.1068	229
37-39	2623	.7644	.0409	.0565	.0431	.0951	388
40-41	710	.7443	.0647	.0577	.0443	.0889	123
All (16-41)	32718	.5940	.1604	.0939	.0310	.1207	343

Chapter 5

Policy Experiments

In this chapter I present the results of four sets of policy simulations. The first of these concerns universal tuition subsidies, and a second set restricts these subsidies to particular groups. Another group of experiments alters parameters in the wage equation, and a final set is concerned with the effects of increases in the unemployment rate on choices.

5.1 Universal Tuition Subsidies

Table 5.1 compares the results of two universal tuition subsidies with the baseline simulation. A \$1000 reduction in tuition is shown to result in modest increases in the proportions enrolled in high school and at 4-year colleges, in every age group, with smaller changes in the proportions enrolled at 2-year colleges. The corresponding enrollment rates at the two college types for ages 18 to 19, shown in Table 5.2, increase by 0.11 and 0.05 percentage points, or about 0.16 percentage points for both college types combined. The share of 38-year-olds with 16 of more years of schooling is also shown to increase by 1.7 percentage points, or about 6% of its level in the baseline simulation, which is in line with estimates of the effects of federal aid and tuition on college enrollment and completion found in prior studies.

A complete elimination of tuition generates greater though still modest changes in behavior. Both work and the nonwork-nonschool alternative are chosen less frequently in every age group, while all three kinds of schooling are chosen more often, also in every age group. By age 38 an additional 2.15% have accumulated 16 of more years of schooling as a result of eliminating tuition. By this measure 'free' postsecondary education achieves only about

Table 5.1: Simulated Activity Proportions, by Age Group

Ages	Work	School	4-year	2-year	OLF
Baseline					
16-20	.331	.436	.103	.030	.100
21-25	.584	.071	.155	.033	.156
26-30	.727	.041	.073	.029	.129
31-35	.796	.026	.041	.020	.117
36-41	.766	.042	.054	.043	.095
All (16-41)	.594	.160	.094	.031	.121
Tuition Reduced by $1000					
16-20	.328	.437	.104	.031	.099
21-25	.581	.072	.158	.034	.156
26-30	.724	.042	.075	.030	.129
31-35	.793	.027	.043	.020	.116
36-41	.763	.042	.057	.044	.095
All (16-41)	.591	.161	.096	.031	.120
Tuition Eliminated					
16-20	.324	.440	.106	.033	.096
21-25	.573	.074	.164	.036	.153
26-30	.716	.044	.081	.032	.127
31-35	.787	.028	.048	.022	.115
36-41	.755	.043	.062	.048	.093
All (16-41)	.585	.163	.100	.034	.118

Table 5.2: Effect on Educational Attainment

Experiment	Enrollment Rate, Ages 18-19		$E_{it} \geq 16$ by Age 38
	4-year	2-year	
Baseline	.1398	.0420	.2881
Tuition Reduced by $1000	.1409	.0425	.3051
Tuition Eliminated	.1439	.0456	.3096

26% more than a $1000 subsidy. The persistent negative effect on the proportion engaged in full-time work requires some explanation because we might expect the increased earnings to draw individuals back into employment. Earnings do in fact increase in the free tuition experiment[1], but it appears that this effect is dominated by the high consumption value of schooling and the high psychic cost of returning to it once an individual has left.

5.2 Targeted Subsidies

In contrast with such universal policies, incentives for additional schooling might be targeted at older workers. Tables 5.3 and 5.4 show the results of two such subsidies. In two separate experiments, tuition is eliminated for workers with at least 1 year of (full-time) work experience, and for those who are at least 28 years of age. It is intructive to note that high school enrollment, while already 'free', increases as a result of both of these policies, as the option value of completing secondary education has now increased. By age 38, the policy providing the subsidy conditional only on age has raised the 'college completion rate' by 1.24 percentage points, while the policy that explicitly requires work experience only raises that rate by 0.68 percentage points.

5.3 Changes in Wage Offers

A further set of experiments was conducted that directly acted on the earnings offered to individuals, the results of which are shown in Tables 5.6 and 5.7. In one experiment wage offers were increased by 10%. This wage subsidy encourages work at all ages, increasing the time devoted to full-time work by about 1 percentage point across all ages at the expense of all other activities. By age 38, the rate of BA degree completion is reduced from 28.8% to 28.1%. By contrast, this rate increases to 29.2% in an experiment that raises the wage of college graduates by increasing α_7 from .506 to .606. This kind of change raises the proportions working at all ages, while schooling increases slightly at most age groups. The activity most

[1]Median Earnings at age 38 increase from $41,463 in the baseline simulation to $41,786 for those choosing work, and median offers to those who end up choosing to remain at a 4-year college or university at that age increase from $37,090 to $38,659.

Table 5.3: Simulated Activity Proportions, by Age Group

Ages	Work	School	4-year	2-year	OLF
Baseline					
16-20	.331	.436	.103	.030	.100
21-25	.584	.071	.155	.033	.156
26-30	.727	.041	.073	.029	.129
31-35	.796	.026	.041	.020	.117
36-41	.766	.042	.054	.043	.095
All (16-41)	.594	.160	.094	.031	.121
Tuition Eliminated After 1 Year of Work					
16-20	.330	.437	.103	.031	.099
21-25	.582	.072	.156	.034	.155
26-30	.725	.042	.075	.031	.127
31-35	.794	.027	.043	.021	.115
36-41	.763	.042	.056	.046	.093
All (16-41)	.592	.161	.095	.032	.119
Tuition Eliminated from Age 28 on					
16-20	.326	.439	.105	.032	.099
21-25	.577	.073	.159	.035	.156
26-30	.719	.043	.079	.031	.128
31-35	.788	.028	.047	.022	.115
36-41	.757	.041	.062	.047	.093
All (16-41)	.587	.162	.098	.033	.120

Table 5.4: Effect on Educational Attainment

Experiment	Enrollment Rate, Ages 18-19		$E_{it} \geq 16$ by Age 38
	4-year	2-year	
Baseline	.1398	.0420	.2881
Tuition Eliminated if $X_{it} \geq 1$	.1398	.0425	.2949
Tuition Eliminated if Age≥ 28	.1415	.0433	.3005

Table 5.5: Simulated Activity Proportions, by Age Group

Ages	Work	School	4-year	2-year	OLF
Baseline					
16-20	.331	.436	.103	.030	.100
21-25	.584	.071	.155	.033	.156
26-30	.727	.041	.073	.029	.129
31-35	.796	.026	.041	.020	.117
36-41	.766	.042	.054	.043	.095
All (16-41)	.594	.160	.094	.031	.121
Wages Increased by 10% at All Ages					
16-20	.337	.433	.102	.030	.098
21-25	.594	.069	.151	.033	.152
26-30	.739	.040	.068	.029	.125
31-35	.806	.026	.037	.020	.112
36-41	.775	.046	.047	.042	.091
All (16-41)	.603	.159	.090	.030	.117
College Premium Raised by 10%					
16-20	.331	.436	.104	.031	.098
21-25	.585	.071	.157	.034	.154
26-30	.729	.042	.073	.030	.126
31-35	.798	.028	.040	.020	.114
36-41	.767	.047	.050	.043	.092
All (16-41)	.595	.162	.094	.031	.118

clearly discouraged in both cases is the non-work, non-employment option, which decreases for every age group.

5.4 Changes in Labor Market Conditions

The final set of experiments contrasts the results of a single-period increase in the unemployment rate with those of a longer-term recession. Specifically, in the first experiment, the local unemployment rate is increased by 2 percentage points for every individual at age 21. At that time, agents will update their forecasts of future unemployment rates, and make their choices in light of those forecasts. In the next year, the local unemployment rate is no longer augmented, and agents' expectations of future unemployment rates will be identical to

Table 5.6: Effect on Educational Attainment

Experiment	Enrollment Rate, Ages 18-19		$E_{it} \geq 16$ by Age 38
	4-year	2-year	
Baseline	.1398	.0420	.2881
Wages Increased by 10% at All Ages	.1384	.0418	.2810
College Premium Raised by 10%	.1407	.0421	.2920

the forecasts agents used in the baseline simulation. In the second experiment, the increase in the unemployment rate above the rates found in the data lasts for ten periods, and thus continues through to age 30.

Even the single-period increase in the unemployment rate has effects on behavior for several years. The proportion choosing work, for example, is reduced for all age groups from age 21 on. For most individuals the time thus freed up is spent in the out-of-the-labor-force state. For others, though, time spent on schooling increases. This is reflected in increased proportions engaged in secondary and university education, and this increase is still noticeable for the 31-35 age group.

In the case of the longer-term recession, the 'substitution into leisure,' that is, the transfer of time from work into voluntary unemployment is even more pronounced, and persists for as long as the unemployment rate remains above the baseline. The increase in the proportion enrolled at 4-year colleges and universities, while small, continues for even longer, and registers even for the oldest age group. It is worth noting, though, that the contemporaneous effects of this ten-period recession lie primarily in the increased proportions in the nonwork-nonschool state. In both experiments, the rate of college completion as of age 38 increases beyond that found in the baseline simulation, but this increase is very small.

Table 5.7: Simulated Activity Proportions, by Age Group

Ages	Work	School	4-year	2-year	OLF
Baseline					
16-20	.331	.436	.103	.030	.100
21-25	.584	.071	.155	.033	.156
26-30	.727	.041	.073	.029	.129
31-35	.796	.026	.041	.020	.117
36-41	.766	.042	.054	.043	.095
All (16-41)	.594	.160	.094	.031	.121
Single-period recession at age 21					
16-20	.331	.436	.103	.030	.100
21-25	.582	.072	.156	.033	.158
26-30	.726	.041	.074	.030	.129
31-35	.795	.027	.042	.020	.117
36-41	.765	.042	.054	.043	.095
All (16-41)	.593	.161	.094	.031	.121
Ten-period recession beginning at age 21					
16-20	.330	.436	.103	.030	.100
21-25	.581	.072	.156	.033	.160
26-30	.723	.042	.074	.029	.132
31-35	.794	.027	.042	.020	.117
36-41	.765	.042	.055	.043	.095
All (16-41)	.592	.161	.094	.031	.122

Table 5.8: Effect on Educational Attainment

Experiment	Enrollment Rate, Ages 18-19		$E_{it} \geq 16$ by Age 38
	4-year	2-year	
Baseline	.1398	.0420	.2881
Single-period recession at age 21	.1398	.0420	.2895
Ten-period recession beginning at age 21	.1398	.0420	.2890

Chapter 6

Conclusion

I find effects of tuition and labor market conditions on college enrollment that are measurable but modest. For example, my simulation indicates a 6% increase in the number of individuals who attain 16 years of schooling attendant on a reduction in tuition of $1000. By contrast, I find that a policy that fully subsidizes postsecondary education provided an individual has worked full-time for one year, will raise the number of persons with a stock of 16 years of education by only 2.4%. Finally, I also find that the bulk of any voluntary reduction in full-time work resulting from increased unemployment rates (and the wage losses implied by it) is spent on activities other than schooling.

The relatively modest sizes of the simulated effects point to the importance of nonpecuniary factors in the decision to enter or leave schooling, particularly the high psychic costs of returning to school after a long absence. It is also possible that the small policy effects are the result of enrollment limits, and of eligibility and selection rules employed by higher quality colleges. Thus the insensitivity to tuition and other factors may be an indication of restrictions on the total number of slots available at colleges. This remains an important topic for future research to assess.

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