Affirmative Action in Higher Education: How do Admission and Financial Aid Rules Affect Future Earnings?

Peter Arcidiacono*

May 2, 2001

Abstract

This paper addresses how changing the admission and financial aid rules at colleges affect future earnings. In order to complete this task, I estimate a model which includes decisions by individuals as to where to submit applications, which school to attend, and what field to study as well as decisions by schools as to which students to accept and how much financial aid to offer. Throughout, individuals have rational expectations and maximize the present value of lifetime utility, recognizing the dependence of future utility on choices made today. By estimating the whole process it is possible to see how the decision-making behavior, and the corresponding future earnings associated with these decisions, would be affected by changing the admission and financial aid rules.

Key Words: Dynamic Discrete Choice, Returns to Education, Human Capital, Schooling Decisions.

1 Introduction

Affirmative action in higher education has received much attention in the popular press due to decisions in California, Texas, and Florida to ban racial preferences in college admissions. The decisions have been met with much protest and there are few issues (perhaps abortion

*Department of Economics, Duke University. Email: psarcidi@econ.duke.edu. Preliminary and incomplete. Comments welcome.

or same sex unions) which stir up more emotion than these practices. Yet there has been no work which is able to pin down the effect these practices have on future earnings of the intended beneficiaries.

The reason this effect has not been quantified is that the process by which affirmative action affects future earnings is complicated: affirmative action affects the admission rules of the schools, not earnings directly. In order to understand the effect changing admission rules has on future earnings, we must first understand how individuals decide where to submit applications and then, conditional on the acceptance set, which school to attend. Once the admission rules have been linked to the decisions of students as to where to submit applications and where to attend, it is possible to track how these decisions would change given a change in the admissions rules. We can then form earnings expectations for students at the beginning of the process by assigning probabilities of applying and attending particular schools under different admissions rules and calculating the associated expected earnings for each of the possible education paths.

While this is the first study to tie admissions rules to future earnings, others have documented the relationship between college quality and earnings. College quality, measured by anything from expenditures per student to average test scores to independent rankings, has generally been found to have a weak, but positive, effect on earnings. Brewer and Ehrenberg (1999) classify colleges into six categories and estimate a multinomial logit on how students select into various categories. They then estimate a log wage regression controlling for selection using the methodology developed in Lee (1983). Daniel, Black, and Smith (1997) and Loury and Garman (1995) both estimate log wage regressions with the hopes of mitigating the effects of selection by controlling for observable measures of ability. Using a 'quality index' the former find large effects of college quality on earnings, while the latter use average SAT scores of the school and find modest effects for whites and large effects for blacks. Dale and Krueger (1999) use information about what schools individuals were rejected at to control for unobserved ability. They find a positive, but very weak, relationship between college quality and earnings.

College quality may have effects on other variables which in turn affect future earnings. Others have shown that the choice of major may be as important, if not more important, than the choice of college to one's future purchasing power.[1] James et. al (1989) state that ".. while sending your child to Harvard appears to be a good investment, sending him to your local state university to major in Engineering, to take lots of math, and preferably to attain a high GPA, is an even better private investment." (page 252). Hence, it may be important to understand how college quality affects future earnings indirectly through channels such as choice of major, grade point average, and the probability of dropping out.

This paper attempts to estimate the key features of the college decision making process. In particular, I estimate a model of how individuals decide where to submit applications, and conditional on being accepted, which college to enroll and what major to study. I also estimate the decisions by schools as to whether to admit a student and, conditional on admitting, how much financial aid to offer. All stages of the estimation are linked by using mixture distributions.

With the estimates of the full model, I conduct three policy simulations. In the first, one is guaranteed to be admitted to all schools. The second waives the monetary costs of the school while the third combines the previous two. Large predicted increases in the probability of choosing a schooling option result from the policy simulations. Comparing men who come from low income families to those who are at the bottom half of the SAT math distribution, a financial aid program helps the former group relatively more than a guaranteed admission program. In fact, monetary gains for men from the admissions program are higher for those who do not come from low income families while the monetary gains from any program which includes full financial aid are higher for those who do come from low income families.

The rest of the paper proceeds as follows. Section 2 presents the model and estimation strategy. Section 3 discusses the data. Results are presented in section 4 with a discussion of how well the model matches the data given in section 5. Policy simulations are examined in section 6. Section 7 provides some concluding remarks as well as ideas for future research.

2 The Model and Estimation Strategy

In this section I present a model of how individuals decide where to submit applications, where to attend (conditional on being accepted) and what field to study. The model has four stages

[1] Arcidiacono (1999), Grogger and Eide (1995), James et. al (1989), and Loury and Garman (1995).

which are outlined below.

Stage 1 Individuals choose where to submit applications.

Stage 2 Schools make admissions and financial aid decisions.

Stage 3 Conditional on the offered financial aid and acceptance set, individuals decide which school to attend and what field to study. Individuals may also choose to opt out of school altogether and enter the labor market.

Stage 4 All individuals enter the labor market.

Since decisions made in stage 1 are conditional on expectations of what will happen in the future, the discussion of the model begins with stage 4 and works backward to stage 1.

2.1 Stage 4: The Labor Market and the Utility of Working

Once individuals enter the workforce they make no other decisions: the labor market is an absorbing state. Individuals then receive utility only through earnings. Earnings are a function of ability, A, where A is individual specific. I assume that the human capital gains for attending the jth college operate through the average ability of the students at the college, $\overline{A_j}$. In some majors individuals may acquire more human capital than in other majors, leading to earnings differentials across majors. I assume that log earnings for a particular year are given by:

$$\ln(W_{ijkt}) = \gamma_{1k} + \gamma_{2k}A_i + \gamma_{3k}\overline{A_j} + \gamma_{4k}X_{wi} + g_{itk} + \epsilon_{it} \tag{1}$$

where X_{wi} is a vector of other characteristics which may affect earnings, k indicates major, and g_{ikt} is the growth rate on earnings. The shocks (the ϵ_{it}'s) are assumed to be distributed $N(0, \sigma^2)$.

Utility of being in the workforce is given by the expected present value of the log of lifetime earnings:

$$u_{wijk} = E\left(\log\left[\sum_{t=t'}^{T} \beta^{t-t'} W_{ijkt}\right]\right) \tag{2}$$

where T is the retirement date and t' is the year the individual enters the workforce. This expression can be rewritten as :

$$u_{wijk} = \gamma_{1k} + \gamma_{2k}A_i + \gamma_{3k}\overline{A_j} + \gamma_{4k}X_{wi} + E\left(\log\left[\sum_{t=t'}^{T} \exp(g_{ikt} + \epsilon_{it})\right]\right). \tag{3}$$

2.2 Stage 3: Choice of College and Major

At stage 3, individuals may choose a school from a set J_a which includes all the schools that accepted the individual. The colleges themselves are not important; it is only the characteristics of the colleges that are relevant to the model. That is, one does not receive utility from attending Harvard but from attending a school that has faculty and students with particular characteristics. Those who decide to attend college must also choose a major from the set K. The same set of majors exist at all colleges. When making the college and major decisions, individuals take into account the repercussions these decisions have on future earnings.

Define the flow utility u_{1ijk} as the utility received while actually attending college j in major k for individual i. This flow utility includes the effort demanded in major k at school j as well as any compensating differentials which may take place (such as college quality being a consumption good). Each of the majors then vary in their demands upon the students. Let v_{1ijk} be the corresponding expected present discounted value of indirect utility:

$$v_{1ijk} = u_{1ijk} + \beta E_1(u_{wijk}) \tag{4}$$

where β is the discount rate. Individuals then choose the option which yields the highest present value of lifetime utility.

Individuals also have the option to not attend college, with the utility given by:

$$v_{1io} = u_{wio} \tag{5}$$

where the o subscript indicates that the individual chose the outside option of working immediately.

I now specify in more detail the components of u_{1ijk}. Embedded in this flow utility is the effort required to accumulate human capital in college. I assume that each major requires a fixed amount of work which varies by the individual's ability, A_i, ability of one's peers, $\overline{A}_j$, and the major chosen, k. Hence, individuals with identical characteristics, attending schools with peers of similar abilities, and in the same major will have identical effort levels. This cost of effort is given by c_{1ijk}. The flow utility for pursuing a particular college option is then:

$$u_{1ijk} = \alpha_{c1} X_{1ijk} - c_{1ijk} + \epsilon_{1ijk} \tag{6}$$

where X_{1ijk} is a vector of individual, school, and major variables which affect how attractive particular education paths are. These include such things as the cost of the school, college quality as a consumption good, and whether particular sexes have preferences for particular majors. The individual's unobserved preference for particular schooling options is given by ϵ_{1ijk}. I assume that ϵ_{1ijk} is distributed i.i.d. extreme value. The probability of choosing a particular schooling option then takes a multinomial logit form.

I assume the following functional form for the cost of effort:

$$c_{1ijk} = \alpha_{c2k}(A_i - \overline{A}_j) - \alpha_{c3}(A_i - \overline{A}_j)^2 \tag{7}$$

Note that the psychic cost function allows the costs to majoring in particular fields to vary by relative ability in the linear term, but not in the squared term. While I will be able to identify α_{c3}, I will not be able to separately identify α_{c2k} because college quality can serve as a consumption good. This cost of effort may lead to optimal qualities that are on the interior: even if an individual was allowed to attend all colleges, the individual may choose to not attend the highest quality college because of the effort required. With different levels of effort required by different majors, optimal college qualities may vary by major. Individuals are then trading off the cost of obtaining the human capital with the future benefits.

2.3 Stage 2: Admissions and Financial Aid

Given a set of applicants, schools decide who is admitted and how much financial aid will be given to each student. Entering into the school's utility function is the average ability of their students, $\overline{A}$, the sum of tuition payments net of any scholarships, and a school's unobserved preference for a particular student. I assume that the admission rules resulting from the school's maximization problem yield logit probabilities. The probability of being admitted to school j is then given below, with X_{aij} including such things as the quality level of the school and the individual's own ability and γ_a being a vector of coefficients to be estimated.

$$Pr_i(j \in J_a | j \in J) = \frac{\exp[\gamma_a X_{aij}]}{\exp[\gamma_a X_{aij}] + 1}$$

I assume that the stochastic part of these probabilities is independent across schools. Hence, the probability that an individual who applies to the set of schools J has the choice set J_a is given by:

$$Pr_i(J_a|J) = \prod_{j}^{\#J} \left(\frac{\exp[\gamma_a X_{aij}]}{\exp[\gamma_a X_{aij}] + 1} \right)^{j \in J_a} \left(\frac{1}{\exp[\gamma_a X_{aij}] + 1} \right)^{j \notin J_a} \tag{8}$$

I now turn toward the financial aid decision. Write the bill paid by the student, t_{ij}, as $s_{ij}t_j$ where t_j is the actual cost of attending school j and s_{ij} is the share of that actual cost. I assume that the optimal financial aid rule follows a tobit with s_{ij} as the dependent variable. In particular, we have:

$$
\begin{aligned}
s^*_{ij} &= \gamma_s X_{sij} + \epsilon_{sij} && && (9)\\
s_{ij} &= 0 && \text{if } s^*_{ij} \leq 0 && (10)\\
s_{ij} &= 1 && \text{if } s^*_{ij} \geq 0 && (11)\\
s_{ij} &= s^*_{ij} && \text{if } 0 < s^*_{ij} < 1 && (12)
\end{aligned}
$$

with ϵ_{sij} being drawn from a normal distribution and is completely unknown to the student.

2.4 Stage 1: Applying to College

Let there be a set of $\mathbb{J}$ colleges where an individual may submit an application. There is a cost (c_{0i}) to applying to colleges which is increasing in the number of applications. The expected utility of applying to all of the schools in $J \subset \mathbb{J}$ for individual i is then given by v_{0iJ}. Let $\#\mathbb{J}$ indicate the total number of colleges. The individual then has $2^{\#\mathbb{J}}$ options regarding which subset of schools he will submit an application.

The probability of being accepted to a college is zero if no application is submitted. If an application is submitted, the probability of acceptance is given by $E_0(a_j(A_i, F_{ij}))$ where the expectation occurs because the individual does not know how the university will perceive the fit of the student. Since each school may accept or reject the student, the number of possible outcomes for applying to all the schools in subset J is $2^{\#J}$, where $\#J$ is the number of schools in subset J. Let J_a indicate the subset of schools at which the individual was accepted and let $Pr(J_a)$ be the corresponding probability of this outcome occurring. Individuals make their application decisions based upon their expectations on the probability of acceptance, the expected financial aid conditional on acceptance, and an expectation of how well they will like attending a particular college and major. I assume that the present value of lifetime utility at the time the individual is making the application decisions is given by:[2]

[2]Note that the β that preceded the expected value of future utility in section 2 has been replaced by an α_{a1}. $\alpha_{a1} = \frac{\beta\mu_m}{\mu_a}$ where μ_m and μ_a are the variance scale parameters for the choice of school and major stage and

$$v_{0iJ} = \alpha_{a1} \sum_{a=1}^{2^{\#J}} E_0(V_{1i}|J_a)Pr_i(J_a) - \alpha_{a2}X_{aiJ} + \epsilon_{0iJ} \tag{13}$$

where X_{aiJ} represent the variables which affect the cost of applying to set J for individual i.

I assume that unobservable tastes for particular schools and majors are such that ϵ_{0ij} is uncorrelated with ϵ_{1ij}. All individuals then have the same expectations with regard to the realizations of ϵ_{1ij}. I need this assumption to make the expectations on future utility of applying to a particular set of schools J tractable.[3] With the further assumption that the ϵ_{0ij}'s are distributed i.i.d. extreme value across application sets, multinomial logit probabilities result.

With these assumptions and integrating out the financial aid realizations, the conditional expectations have a closed form solution.[4] Specifically, the present discounted value of lifetime utility of applying to the set of schools J is given by:

$$v_{0iJ} = \beta \sum_{a=1}^{2^{\#J}} \left[\int \ln \left(\sum_{j=1}^{\#J_a+1} \sum_{k=0}^{K} \exp[v_{1ijk}] \right) \pi(s_a|A_i, \overline{A}_{J_a}) ds_a \right] Pr_i(J_a) - \alpha_{a2}X_{aiJ} + \epsilon_{0iJ} \tag{14}$$

where $\overline{A}_{J_a}$ is the vector of average school qualities in the acceptance set J_a and π is the pdf of s_a, the financial aid decisions at each of the schools in the acceptance set. After discretizing the possible values that s_a can take on into L states, the following results:[5]

$$v_{0iJ} = \beta \sum_{a=1}^{2^{\#J}} \left[\sum_{l}^{L} \ln \left(\sum_{j=1}^{\#J_a+1} \sum_{k=0}^{K} \exp[v_{1ijk}] \right) p(s_{am}|A_i, \overline{A}_{J_a}) \right] Pr_i(J_a) - \alpha_{a2}X_{aiJ} + \epsilon_{0iJ} \tag{15}$$

where p is the discretized version of π.

2.5 The Estimation Strategy

With independent errors across the stages, the log likelihood function can now be divided into five pieces:

---

the application stage, respectively. Typically with multinomial logits these scale parameters are assumed to be one in order to identify the parameters of the utility function. Since we have, in a sense, two multinomial logits on two very different decisions (applying versus attending) that are connected by the expected utility term, we can only identify one variance term relative to the other given a set value for β.

[3] This assumption is made more palatable later in the paper.

[4] See McFadden (1981) for the result.

[5] That consistent estimates are obtained here is due to Rust (1987).

$L_1(\gamma_m)$- the log likelihood contribution of earnings.

$L_2(\gamma_a)$- the log likelihood contribution of admissions decisions.

$L_3(\gamma_s)$- the log likelihood contribution of financial aid.

$L_4(\alpha_c, \gamma_w)$- the log likelihood contribution of college and major decisions conditional on the acceptance set.

$L_5(\alpha_a, \alpha_c, \gamma_w, \gamma_a, \gamma_s)$- the log likelihood contribution of the application decision.

where the total log likelihood function is then just $L = L_1 + L_2 + L_3 + L_4 + L_5$.

Note that consistent estimates of γ_m, γ_a, and γ_s can be found from maximizing L_1, L_2, and L_3 separately.[6] With the estimates of γ_m, consistent estimates of α_c can be obtained from maximizing L_4. All of these estimates can then be used in L_5 to find consistent estimates of α_a.

The computational savings from employing this method are quite large. The expectation on the value of applying to any reasonable number of schools is very expensive to calculate, let alone calculate the derivative. This method minimizes the number of times this expectation needs to be calculated. The maximization then reduces to ordinary least squares for the earnings estimates, a logit at each school for the admissions estimates, a tobit for the financial aid estimates, and two multinomial logits for the college and major decision and the application decision.

2.6 Serial Correlation of Preferences and Unobserved Ability

One of the assumptions which seems particularly unreasonable is that the unobservable preferences parameters are uncorrelated over time. That is, if one has a strong unobservable preference for engineering initially, he is just as likely as someone who has a strong unobservable preference for education initially to have an unobservable preference for education when it comes time to choose a college and a major. We would suspect that this is not the case. Further, it is unreasonable to assume that there is no unobserved (to the econometrician) ability which is known to the individual.[7]

[6] See Rust and Phelan (1997) and Rothwell and Rust (1997).

[7] See Willis and Rosen (1979) for the importance of selection in education.

One method of dealing with this problem is to assume that there are R types of people with π_r being the proportion of the rth type in the population.[8] Types remain the same throughout all stages, individuals know their type, and preferences for particular fields and college quality may then vary across types. An example would be if the parameters of the utility function do not vary across types except for the constant term. This would be the same as having a fixed effect which is common across everyone of a particular type. The likelihood function being maximized then follows a mixture distribution, with the following log likelihood resulting for the special case of the types only affecting the preference parameters and the probability of acceptance.

$$L(\alpha_a, \alpha_c, \gamma_w, \gamma_a, \gamma_s) = \sum_{i=1}^{I} \ln \left(\sum_{r=1}^{R} \pi_r \mathcal{L}_{1ir} \mathcal{L}_{2ir} \mathcal{L}_{3ir} \mathcal{L}_{4ir} \mathcal{L}_{5ir} \right) \tag{16}$$

Here, the α's and γ_S's can vary by type and $\mathcal{L}$ refers to the likelihood (as opposed to the log likelihood).

Now the parts of the log likelihood function are no longer additively separable. If they were, a similar technique could be used as in the case of complete information: estimate the model in stages with the parameters of previous stages being taken as given when estimating the parameters of subsequent stages. Using the EM algorithm,[9] I am able to separate the problem out.

Note that the conditional probability of being a particular type is given by:

$$Pr_i(r|\mathbf{X_i}, \alpha, \gamma, \pi) = \frac{\pi_r \mathcal{L}_{1ir} \mathcal{L}_{2ir} \mathcal{L}_{3ir} \mathcal{L}_{4ir} \mathcal{L}_{5ir}}{\sum_{r=1}^{R} \pi_r \mathcal{L}_{1ir} \mathcal{L}_{2ir} \mathcal{L}_{3ir} \mathcal{L}_{4ir} \mathcal{L}_{5ir}} \tag{17}$$

where $\mathbf{X_i}$ refers to the data on the decisions and the characteristics of the individual.

The EM algorithm has two steps: first calculate the expected log likelihood function given the conditional probabilities at the current parameter estimates, second maximize the expected likelihood function holding the conditional probabilities fixed. This process is repeated until convergence is obtained. But the expected log likelihood function here is now additively

[8]See Keane and Wolpin (1997) for another example of using mixture distributions to control for unobserved heterogeneity in a dynamic discrete choice model.

[9]See Dempster, Laird, and Rubin (1977)

separable.

$$\sum_{i=1}^{I}\sum_{r=1}^{R} Pr_i(r|\mathbf{X_i},\alpha,\gamma,\pi)\left(L_{1ir}(\gamma_m)+L_{2ir}(\gamma_a)+L_{3ir}(\gamma_s)+L_{4ir}(\alpha_c,\gamma_m)+L_{5ir}(\alpha_a,\alpha_c,\gamma_m,\gamma_a,\gamma_s)\right) \tag{18}$$

Taking the conditional probabilities as given, I can get estimates of γ_m from maximizing L_{1r} times the conditional probabilities. Similarly, estimate γ_a and γ_s from maximizing the conditional probabilities times L_{2i} and L_{3i}, respectively. I then only use L_4 to find estimates of α_c— not needing L_4 to obtain estimates of γ_w. These estimates are then used when finding α_a from L_5. Note that all of the parts of the likelihood are still linked through the conditional probabilities where the conditional probabilities are updated at each iteration of the EM algorithm. Arcidiacono and Jones (2000) show this method produces consistent estimates of the parameters with large computational savings.

3 Data

I use the National Longitudinal Study of the Class of 1972 (NLS72) as the primary data source. The NLS72 is a stratified random sample which tracks individuals who were seniors in high school in 1972. Individuals were interviewed in 1972, 1973, 1974, 1976, 1979, and 1986. The NLS72 has individual level data on test scores and earnings.

Using the same data set, Arcidiacono (1999) established the following results:

1. The lucrative majors draw the high math SAT score students at each school.

2. At schools with high average SAT scores, a greater percentage of the students choose the more lucrative majors.

3. The SAT English score has little or no impact of future earnings.

As a consequence of that analysis, I define ability of the student as their SAT math score. Further, the quality of the college is defined as the average math ability of the students at the college.

Also motivated by the work in Arcidiacono (1999), majors are aggregated into four groups: engineering, physical sciences, and biological sciences in group 1, business and economics in group 2, social sciences, other, and humanities in group 3, and education in group 4. The maximum number of choices available is then thirteen: four majors for each of three schools and a work option.

The NLS72 has data on the top three schooling choices of the individual in 1972 and on whether or not the individual was accepted to each of these schools. J_a is then defined as the up to three schools which the individual listed as accepting him. Unfortunately, the NLS72 does not have data on whether an individual was considering any other four year institutions. Hence, I may only be partially observing J_a. I use data on decisions made in 1975 as to whether to attend college. This should roughly correspond to the senior year for the students. The data for those who choose a schooling option is then restricted to students who were attending a college in their original choice set: transferring schools is not modeled.

The NLS72 also has data on the costs and financial aid packages offered at each school. Costs are calculated as tuition plus books plus room and board. Individuals list their general scholarships as well as school-specific scholarships. The only measure of financial aid I use is this scholarship data. There is much censoring, as over 68% of individuals receive no financial aid from scholarships.

Some restrictions must be made given the data constraints and to keep the problem tractable. First, a student can only apply to at most three schools. I only have data on at most three schools. This turns out to be not very restrictive as the percentage of people who actually apply to three schools is small. Second, I need to restrict the number of schools where the individual can submit an application. I restrict the set of schools to eight, with individuals being able to apply to any combination of up to three schools from these eight. This leaves ninety-two possible sets the individual may apply to. I further restrict the data such that the only individuals who are in the data set have applied to at least one school. Hence, one application is free. The policy simulations will then be for those individuals who planned on applying to college in the old regime.

The NLS72 has good data on yearly earnings for 1973 through 1979 and also for 1986. However, surveys conducted when the respondents were older would be necessary to obtain accurate experience profiles late into the life cycle. In the log earnings regression I control for experience with year dummies interacted with sex. I then use data from the Current Population Survey for 1976 (CPS) to obtain the expected lifetime earnings profiles. I use the same restrictions placed on the NLS72 sample with regards to hours worked and yearly earnings and then regress CPS log yearly earnings on a quartic function of experience for each sector and sex. With the parameter estimates, experience profiles are then generated. Here, I am assuming that experience is uncorrelated with the other variables.

This is, at best, an ad hoc measure of constructing experience profiles. However, as long as the experience profiles are only a function of gender and major the choice of the utility function[10] leads miscalculations of the growth rates to be put directly into the constant term for the major or the term that has gender interacted with major.

In order to identify the coefficient on the expected present value of the log of lifetime earnings, we need a variable which affects choice of school and major only through earnings. I use state differences in the college premium from 1973-1975 for workers aged 22-35 as a variable which affects choice of school and major only through earnings. This variable is calculated from the CPS. Some small states are aggregated in the CPS, leading to differences in the college premia across twenty-two regions. Descriptive statistics for all variables are given in the Appendix.

Retirement dates are at ages 64 and 62 for college graduates and high school graduates respectively. These correspond to the ages in the 1976 Current Population Survey after which the percentage of full-time male workers falls below fifty percent. Individuals who choose a college option enter the workforce at age 22, while those who do not attend college enter at age 18.

4 Results (Preliminary)

In this section, I present the results of the estimation of the model. I begin with the school side, admissions and financial aid, before proceeding with the student side. Throughout, two models are presented. One does not place any controls for unobserved heterogeneity, only one 'type' of person. The other allows for two types, where one's type affects all aspects of the problem from the application decision to expected earnings.

[10] Having utility be a function of the expected present value of the log of lifetime earnings gets the result. However, the result is actually more general as the specification here could also come from the log of the expected value of life time earnings or the expected value of the sum of the logs of yearly earnings. All three of these specifications lead errors in growth rates to be put into the constant terms.

4.1 Admissions

Table 1 presents the estimates of the admissions logit. In both models, increasing one's own SAT math score as well as one's high school class rank both increase the probability of being accepted. However, increasing both one's own SAT math score and that of the school where the individual is applying results in decreasing the probability of being accepted. Admissions to colleges is not particularly competitive until high levels of college quality are reached.[11] Neither the individual's gender nor whether the school was private had a significant effect on the probability of being admitted. Adding an additional type had virtually no effect on the parameter estimates as shown in column 2.

Table 1: Admission Estimates

	One Type		Two Types	
	Coefficient	Standard Error	Coefficient	Standard Error
Female	-0.0718	0.0895	-0.0710	0.0880
SAT Math (000's)	3.4575	0.5143	3.4960	0.5090
HS Class Rank	1.7565	0.2019	1.7568	0.2023
Don't Know Rank	0.9893	0.1667	0.9910	0.1674
School Quality (000's)	-13.3923	0.6854	-13.5410	0.6770
Private	-0.0164	0.0862	-0.0139	0.0857
Type 1	6.6140	0.3168	6.7362	0.3156
Type 2			6.6403	0.3165

4.2 Financial Aid

Table 2 gives the estimates of the financial aid tobit. Similar to the admissions results, those who have high SAT math scores and class ranks increase the probability of receiving good aid packages. College quality reverses here as high quality colleges appear to be more generous in offering to pay for a percentage of the total costs. Private schools also offer larger financial aid packages. As expected, low income students receive better packages than those who are

[11] Venti and Wise (1982) found a similar result.

not low income. Gender was again insignificant.

Table 2: Financial Aid Estimates

	One Type		Two Types	
	Coefficient	Standard Error	Coefficient	Standard Error
Female	0.0192	0.0151	0.0207	0.0151
SAT Math (000's)	0.3117	0.0816	0.3169	0.0820
HS Class Rank	0.3797	0.0395	0.3796	0.0398
Don't Know Rank	0.2951	0.0342	0.2953	0.0344
Low Income	0.3015	0.0152	0.3012	0.0153
School Quality (000's)	0.5800	0.1235	0.5725	0.1242
Private	0.1744	0.0173	0.1741	0.0174
Type 1	-1.1550	0.0627	-1.1368	0.0630
Type 2			-1.1662	0.0650
Variance	0.4795	0.0204	0.4795	0.0204

4.3 Earnings

Estimates of the earnings parameters are given in Table 3. 1986 earnings are used as the base year, with the coefficients on the year dummies and the year dummies interacted with sex omitted. The state college premium, which is our one variable which affects schooling choices only through earnings, is positive and significant. In the college regression without unobserved heterogeneity, own ability is positive for all majors and for those who do not attend college. Business majors see the highest return on ability and, given the point estimates, engineers receive the second lowest return on own ability. Point estimates of the coefficients on school quality are positive except for those choosing education. Those choosing one of the Hard Science options see the highest return on quality.

The coefficient estimates make it possible to calculate what the highest paying option is. Choosing business leads to the highest earnings at low school quality levels while choosing Hard Science yields the highest earnings at high quality levels. In particular, for a male student with an SAT math score of 500, school quality levels below 482 ensure business as the highest paying field while school quality levels above 482 make engineering the highest paying field. If the student's SAT score was instead 600, the cutoff school quality would increase to 570. This does not hold when the mixture distribution is added. Namely, those choosing math see the highest returns on ability and the second highest returns on college quality. However, although the returns on ability and college quality are higher for math, the highest paying field for men across all interior SAT math scores and school qualities is business. For both Hard Science and Business, adding a second type led to large decreases in the point estimates of the coefficient on college quality.

The type interactions were all very large and significant. Type 2's have a comparative advantage in Hard Science, Business, and Social Science/ Humanities, but are at a disadvantage when not choosing college or choosing education as a field.

4.4 College and Major Choice

I now use the estimates of the earnings regression in the calculation of the parameters of the utility for attending a particular college in a particular major. These estimates are reported in Table 4.

Large differences across gender exist in the choice of major. Women prefer to stay away from engineering/math and business relative to men. The monetary cost of attending college is significantly negative and more negative for those who come from low income families. Private schools and schools in the same state both make choosing a schooling more attractive, all else equal. The coefficient on the expected log of the present value of earnings was positive and significant.

The coefficients on individual SAT math scores also look similar across the two models, revealing strong differences in preferences for fields based upon math ability. High SAT math scores are associated with a preference for engineering over business and social science, and business and social science over education. Business moves ahead of social science when we move to the model with two types.

The college quality coefficients, with the exception of education, are positive in both models. The coefficient for Business majors is always smaller than both the coefficient for Hard Science and for Social Science/Humanities. Increasing college quality then makes Business

Table 3: Earnings Estimates

		One Type		Two Types	
		Coefficient	Standard Error	Coefficient	Standard Error
	State College Premium	0.2838	0.1424	0.2282	0.0622
SAT Math Interactions (000's)	Hard Science	0.3079	0.0430	0.4120	0.1630
	Business	0.6002	0.0616	0.4020	0.2830
	Soc/Hum	0.2161	0.0501	0.2620	0.1470
	Education	0.3577	0.3572	0.3500	0.2760
	No College	0.3596	0.0358	0.3780	0.0720
School Quality Interactions (000's)	Hard Science	0.6262	0.0678	0.2210	0.2990
	Business	0.2934	0.0900	0.1480	0.4080
	Soc/Hum	0.5311	0.0826	0.5550	0.2860
	Education	-0.3100	0.7549	-0.3450	0.3880
Female Interactions	Hard Science	-0.2259	0.2074	-0.2601	0.0510
	Business	-0.2049	0.2280	-0.1960	0.0593
	Soc/Hum	-0.2730	0.2149	-0.3029	0.0420
	Education	-0.2132	0.8770	-0.1668	0.0666
	No College	-0.2693	0.4850	-0.2283	0.0456
Constant	Hard Science	6.7033	1.3037	7.0056	0.5790
	Business	6.7175	1.3410	7.1668	0.5811
	Soc/Hum	6.6721	1.3163	6.8362	0.5684
	Education	6.9612	4.0663	7.5508	0.5694
	No College	6.8612	1.2810	7.6049	0.5383
Type 2 Interactions	Hard Science			0.5418	0.0298
	Business			0.4526	0.0347
	Soc/Hum			0.4666	0.0291
	Education			-0.3987	0.0548
	No College			-0.4571	0.0115

Table 4: Utility Estimates

		One Type		Two Types	
		Coefficient	Standard Error	Coefficient	Standard Error
Female Interactions	Hard Science	-0.1617	0.1573	0.1286	0.0947
	Business	-1.1239	0.2632	-0.9804	0.1365
	Soc/Hum	0.3707	0.1351	0.6839	0.0771
	Education	1.0842	0.1406	1.1662	0.1413
SAT Math Interactions (000's)	Hard Science	8.0429	0.8278	7.7056	0.5130
	Business	2.5135	1.1407	3.2733	0.6350
	Soc/Hum	2.7114	0.7789	2.7051	0.4430
	Education	0.3118	0.7882	0.4782	0.6620
School Quality Interactions (000's)	Hard Science	3.7179	1.0490	4.9127	0.6630
	Business	1.1155	1.4148	1.6552	0.9070
	Soc/Hum	4.0675	0.9893	3.4934	0.6040
	Education	0.4062	0.7620	0.7773	0.6460
Coefficients Common Across Majors	Net Cost	-1.6780	0.1675	-1.6391	0.1586
	Low Income*Net Cost	-1.3496	0.2060	-1.3644	0.2024
	Private	0.3150	0.0287	0.3090	0.0270
	School in State	0.1076	0.0142	0.1119	0.0141
	$(\text{SAT-Quality})^2$	-8.9399	1.4026	-8.8900	1.2600
	Log Earnings	3.5553	1.2967	4.3633	1.6236
Type 1 Interactions	Hard Science	-8.1783	0.5973	-7.7605	0.4168
	Business	-4.0123	0.7769	-3.4768	0.5183
	Soc/Hum	-5.0548	0.5021	-4.4801	0.3391
	Education	-2.3997	0.4015	-1.5753	0.3792
Type 2 Interactions	Hard Science			-9.2703	0.4162
	Business			-5.4327	0.5534
	Soc/Hum			-6.1401	0.3473
	Education			-3.3792	0.4895
	Prob. Type 1			0.3846	0.0181

more attractive than education, but both Hard Science and Social Science/ Humanities more attractive than business. The relative ability squared term is negative and significant suggesting the possibility of interior optimal school qualities. The effect of college quality on earnings through the choice of major is not clear. While education is a low paying specialty, business is either the highest paying or the second highest paying field.

Large differences exist across types. While Type 2's have much larger returns to choosing Hard Science, Business, or Social Science/Humanities, they would prefer not to attend relative to their Type 1 counterparts. This makes sense: college is made up of two groups, one where the returns are high but the individual prefers not to be at college, and the other where the returns are low but the individual enjoys college. It is difficult to see how type affects major choice from the parameter estimates. Calculating the proportion choosing each field conditional type showed type 1's twice as likely to choose business and over three times as likely to choose education. Fifty-six percent of Type 1's attended college while forty-six percent of Type 2's.

4.5 Application Stage

Using estimates from the previous four regressions, I now estimate the parameters of the utility function for applying to college. Table 5 presents these estimates. The coefficient on the present value of future utility is both positive and significant. Since we believe that individual's discount rates are less than one and the coefficient is much greater than one, this suggests that the variance of the unobservable preferences at the application stage is smaller than at the college and major choice stage. Increasing the number of applications submitted is costly. There is no significant difference between the application costs of low income applicants and regular applicants. Adding unobserved heterogeneity to the model does not affect the parameter estimates.

5 Model Fit

Given the parameter estimates, it is possible to see how the model matches key features of the data. In particular, I consider how the model matches for males, both in how individuals sort themselves across majors but across schools as well.

Table 5: Application Estimates

	One Type		Two Types	
	Coefficient	Standard Error	Coefficient	Standard Error
PV of Future Utility	6.1513	0.4230	6.1893	0.3706
Application>1	-4.6394	0.1670	-4.6537	0.1523
Application=3	-3.1070	0.1450	-3.1302	0.1348
Low Income*(Application>1)	0.2214	0.0975	0.2251	0.0973
Low Income*(Application=3)	-0.1318	0.1411	-0.1401	0.1417

Table 6 presents the model predictions for the distribution of majors as well as the distribution of SAT math scores across majors. These distributions are calculated for males, low income males, and males with SAT math scores below the mean. The actual data is listed in the first column, with the second two columns containing the prediction with and without controls for unobserved heterogeneity. One noticeable feature from the table is that the models with and without unobserved heterogeneity have predictions that are virtually identical. These predictions are also very close to the actual results when considering males alone, except that the predicted college attendance rates are slightly lower than the actual rate. High SAT math students tend to choose hard science over business and the social sciences, while choosing business and the social sciences over education. The model also matches the general trends of lower college attendance for low income students and low SAT math students, though the gap between the predicted and actual does increase. However, this may be due to low cell counts in the actuals.

Table 7 gives the predictions as to where individuals attend school. In particular, it shows the school qualities (given by the average SAT math score of the school) by major across males, low income males, and low SAT math males. It also shows actual and predicted school costs across the three groups conditional on attending college. The school quality predictions for males by major are quite close to the actuals. The general trends are correct for the other two groups, though the spread across majors is not as large in the predicted values as it is in the actuals. The cost data seems more suspect as the predicted values are always around

Table 6: Individual Predictions

Variable	Group	Major	Actual	One Type	Two Types
Percent Choosing	Males	Hard Science	0.1729	0.1620	0.1616
		Business	0.1204	0.1160	0.1156
		Social Science	0.1681	0.1560	0.1557
		Education	0.0375	0.0367	0.0366
	Low Income Males	Hard Science	0.1395	0.1297	0.1287
		Business	0.0870	0.1036	0.1033
		Social Science	0.1588	0.1380	0.1372
		Education	0.0525	0.0354	0.0349
	SAT Math < Mean	Hard Science	0.0497	0.0600	0.0597
		Business	0.0968	0.0909	0.0910
		Social Science	0.1414	0.1271	0.1265
		Education	0.0548	0.0419	0.0427
SAT Math (000's)	Males	Hard Science	0.5890	0.5838	0.5839
		Business	0.5206	0.5260	0.5259
		Social Science	0.5199	0.5234	0.5235
		Education	0.4648	0.4855	0.4840
	Low Income Males	Hard Science	0.5773	0.5677	0.5674
		Business	0.5129	0.5086	0.5102
		Social Science	0.4880	0.5044	0.5043
		Education	0.4394	0.4667	0.4702
	SAT Math < Mean	Hard Science	0.4127	0.4219	0.4220
		Business	0.4220	0.4083	0.4081
		Social Science	0.4009	0.4071	0.4071
		Education	0.3963	0.3970	0.3964

ten percent higher than the actual values. This may be due to how the application sets are created.[12] The predictions due match the actuals in that low income students and low SAT math students choose lower cost schools.

Table 7: School Predictions

Variable	Group	Major	Actual	One Type	Two Types
		Hard Science	0.5578	0.5480	0.5481
		Business	0.5312	0.5207	0.5208
	Males	Social Science	0.5374	0.5315	0.5317
		Education	0.4962	0.5031	0.5017
		Cost†	0.2843	0.3002	0.3001
		Hard Science	0.5466	0.5376	0.5375
School	Low Income	Business	0.5165	0.5128	0.5135
Quality	Males	Social Science	0.5201	0.5230	0.5231
(000's)		Education	0.4889	0.4956	0.4959
		Cost	0.2633	0.2848	0.2844
		Hard Science	0.5200	0.5077	0.5078
	SAT Math	Business	0.5157	0.4953	0.4954
	< Mean	Social Science	0.5082	0.5050	0.5052
		Education	0.4787	0.4845	0.4834
		Cost	0.2575	0.2777	0.2774

† Costs are in tens of thousands of dollars.

6 Policy Simulations

With the model doing a reasonable job of predicting the trends in the data, I now proceed with the policy simulations. In particular, I use the estimates of the earnings process, financial aid and admission rules, and the parameters of the utility function, to simulate how changes

[12] To get the eight schools where the individual is considering submitting applications, schools were randomly drawn. This may lead to more small, costly private schools entering the application set. One remedy would be to weight the draws on the schools by the enrollments of the schools.

in the financial aid and admission rules affect college decision-making and, in turn, future earnings. I perform three policy simulations: guaranteeing admission to all schools, waiving the monetary cost of attending school, and a combination of the previous two. All policy simulations are under a partial equilibrium setting. Hence, they should be interpreted as what would happen if we changed the rules for a random person as opposed to changing the rules for the population or a large portion of the population.[13]

In order to complete the simulations, I need growth rates for earnings. I use the cross-sectional growth rates taken from the Current Population Survey in 1976, four years after they graduate from high school. Different growth rates are calculated for men and women with at least college degree and for men and women who just completed high school. Hence, growth rates do not vary by major.[14] These growth rates come from regressing log earnings on a quartic function of experience.[15]

Results for men are given in Tables 8 and 9, with Table 9 having controls for unobserved heterogeneity. All the policies lead to large increases in the average probability of completing college. Under a guaranteed admission policy, the increase in the proportion of people attending college is almost seven percent. These gains hold when the sample is restricted to those who come from low income families or have SAT math scores below the sample mean. Under the policy of one hundred percent financial aid, the increase in the proportion of men attending college is close to thirteen percent. These gains, however, are not distributed evenly across the population. Not surprisingly, those coming from low income families see the largest increases at around 16%. This is a pattern in all the results: similar gains for low income and low SAT math people under guaranteed admission, much larger gains for low income people under one hundred percent financial aid. Also, the reason the gains are always higher under the financial aid simulation is that individuals have high probabilities of being accepted to colleges that are not at the top of the SAT math distribution but have very low probabilities of receiving large financial aid packages in the form of scholarships.

[13]See Heckman, Lochner, and Taber (1998) for an analysis of the general equilibrium effects of a tuition subsidy program.

[14]Some have pointed out that engineers tend to have flatter earnings profiles. I believe (but cannot substantiate) that this is true for those who stay as engineers: top engineers have moved on to management later in the life cycle.

[15]The implicit assumption is that growth rates are uncorrelated with the other variables.

On the earnings side, men see about a $12,000 increase in the present value of lifetime earnings under the guaranteed admission plan. These simulations are sensitive to the growth rates calculated from the CPS sample and the discount rate. More work is needed to see how robust the results are to alternative assumptions on the growth rates and discount rates. The guaranteed admission programs raise earnings most for the population as a whole and least for those at the bottom of the SAT math distribution. Under the hundred percent aid simulation, earnings gains for the population are around $17,000 for the population but $21,000 for low income families. Both numbers, and the gap between them, increase if we add types. Adding types slightly lowers the returns to the admissions program while slightly increasing the returns to the financial aid program for all but those at the bottom of the SAT math distribution. Moving from the admission program to the financial aid program helps low income students much more than those at the bottom of the SAT math distribution.

Table 8: Policy Simulations: One Type

		Guaranteed Admission	100% Financial Aid	Guaranteed Admission + %100 Financial Aid
Population	PV Gain in Earnings	$12,590	$17,480	$35,487
	Increased Prob. Of College	0.068	0.129	0.222
Low Income	PV Gain in Earnings	$9,604	$21,257	$37,507
	Increased Prob. Of College	0.056	0.166	0.255
SAT Math<Mean	PV Gain in Earnings	$7,818	$14,874	$28,870
	Increased Prob. Of College	0.059	0.139	0.234

There are a number of reasons we may be suspicious of these simulations. The present value of lifetime earnings calculations assume that everyone works every year after graduation from high school or college. To the extent that labor force participation rates matter, the simulations results would change. In addition, those who did not choose one of the schooling options are assumed to have worked for four years in the labor market. Yet, some of these individuals may have attended school for a portion of that time. This would lead to higher

Table 9: Policy Simulations: Two Types

		Guaranteed Admission	100% Financial Aid	Guaranteed Admission + %100 Financial Aid
Population	PV Gain in Earnings	$11,917	$17,831	$35,194
	Increased in Prob. Of College	0.068	0.127	0.219
Low Income	PV Gain in Earnings	$8,960	$22,077	$38,444
	Increased in Prob. Of College	0.056	0.163	0.252
SAT Math¡Mean	PV Gain in Earnings	$6,646	$13,966	$27,230
	Increased in Prob. Of College	0.058	0.135	0.229

earnings estimates from the yearly log earnings regressions which would then translate into much higher present value of lifetime earnings. Underreporting rejections by schools would also lead to lower estimates for the first and third policy simulations. Individuals report that they were accepted to over ninety percent of the schools where they submitted applications. The policy simulations may be too high if the multinomial logit framework is wrong. Ackerberg and Rysman (2000) show that the multinomial logit model is very restrictive in how it handles adding options. By allowing the college options to 'fill up' in the unobservable dimension, the policies would not be as effective at increasing college enrollment rates.

7 Conclusion

Affirmative action in higher education is a very controversial topic. Yet, little is known about how these programs affect the earnings of their intended beneficiaries. The reason for this is that the path by which earnings are affected is complicated: affirmative action affects admissions rules, not earnings directly. This paper provides a first step at understanding how both admissions and financial aid rules affect expected future earnings.

On the school side, I model the admissions and financial aid decisions. On the student side, I model the choice as to where to submit applications, where to attend and what major to choose conditional on the acceptance set, and the relationship between these choices and earnings. With the estimates of all the parts of the model, I simulate how changes in admissions and financial rules affect future earnings.

Not surprisingly, large increases in the number of people who choose college result from either guaranteeing admission to all schools or granting one hundred percent financial aid. What is interesting is how the results break down by whether the student is from a low income family or is at the bottom of the SAT math distribution. While the gains for the two groups are similar under the guaranteed admission program, the gains are much larger for the low income group under the one hundred percent aid program.

There are two extensions of the model which would be interesting to pursue. The first is gains to diversity. That is, if blacks would prefer to attend schools with other blacks, an affirmative action program may have a reenforcing effect where letting in one black student encourages another black student to attend. This is currently not taken into account in the policy simulations, and significantly adds to the complexity of the model. Now, not only do we have to keep track of each individual's education decisions, but also how those decisions aggregate up into distributions of minorities at each school.

One criticism of affirmative action in higher education is that it leads minorities into environments where they cannot succeed. The only way that this can be consistent with rational expectations is if individuals receive information in the admissions and financial aid decisions of the schools. Individuals who are considering attending top colleges are used to succeeding. They may, however, have incomplete information as to how well their abilities match up with those attending top colleges. Individuals then use information from college admissions and financial aid to update their expectations on their own abilities. Affirmative action programs then provide a trade off between larger choice sets and less information. While the first extension would most likely lead to increases in the gains of affirmative action, this latter extension would not.

Appendix

Table 10: Descriptive Statistics

	Mean	Standard Deviation
Female	0.4896	0.5000
SAT Math (000's)	0.4810	0.1133
Low Income Family	0.3891	0.4876
1st Choice Quality	0.5210	0.0639
Net Cost 1st Choice(0000's)	0.2292	0.1172
Private School	0.3123	0.4635
School in State	0.7836	0.4118
State College Premium	0.2736	0.0624
Hard Science	0.1451	0.3522
Business	0.0822	0.2748
Soc/Hum	0.1872	0.3901
Education	0.0858	0.2801
Number of Applications	1.4350	0.6747
Number of Acceptances	1.2831	0.668
Observations	3660	

References

[1] **Ackerberg, Daniel and Marc Rysman.** "Unobserved Product Differentiation in Discrete Choice Models: Estimating Price Elasticities and Welfare Effects." working paper, 2000.

[2] **Arcidiacono, Peter.** "Option Values, College Quality, and Earnings: Results from a Dynamic Model of College and Major Choice." working paper, 1999.

[3] **Arcidiacono, Peter.** "Affirmative Action in Higher Education: How do Admission and Aid Rules Affect Future Earnings?" working paper, 2000.

[4] **Arcidiacono, Peter and John B. Jones.** "Finite Mixture Distributions, Sequential Likelihood, and the EM Algorithm." working paper, 2000.

[5] **Attiyeh, Gregory and Richard Attiyeh.** "Testing for Bias in Graduate School Admissions." *Journal of Human Resources*, 32 (3:1997).

[6] **Berger, Mark.** "Predicted Future Earnings and Choice of College Major." *Industrial and Labor Relations Review*, 41 (3:1988).

[7] **Bowen, William G. and Derek Bok.** *The Shape of the River: Long-Term Consequences of Considering Race in College and University Admissions.* (Princeton, NJ: Princeton University Press, 1998).

[8] **Brewer, Dominic; Eide, Eric; Ronald Ehrenberg.** "Does it Pay to Attend an Elite Private College? Cross-Cohort Evidence on the Effects of College Type on Earnings." *Journal of Human Resources*, 34 (1:1999).

[9] **Dale, Stacy Berg and Alan B. Krueger.** "Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables." Working Paper #409, Princeton University, December, 1998.

[10] **Daniel, Kermit; Black, Dan; and Smith, Jeffrey.** "College Quality and the Wages of Young Men." Working Paper, 1997.

[11] **Daymont, Thomas and Paul Andrisani.** "Job Preferences, College Major, and the Gender Gap in Earnings." *Journal of Human Resources*, 19 (1984).

[12] **Eckstein, Zvi and Kenneth Wolpin.** "The Specification and Estimation of Dynamic Stochastic Discrete Choice Models: A Survey." *Journal of Human Resources*, 24 (4:1999).

[13] **Fuller, David; Manski, Charles and David Wise.** "New Evidence on the Economic Determinants of Postsecondary Schooling Choices." *Journal of Human Resources*, 17 (1982).

[14] **Grogger, Jeff and Eric Eide.** "Changes in College Skills and the Rise in the College Wage Premium." *Journal of Human Resources*, 30 (2:1995).

[15] **Heckman, James J.; Lochner, Lance and Christopher Taber.** "General-Equilibrium Treatment Effects: A Study of Tuition Policy." *American Economic Review*, 88 (2:1998).

[16] **Heckman, J. and B. Singer.** "A Method for Minizimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." *Econometrica*, 52 (2:1984).

[17] **James, Esteller; Nabeel, Alsalam; Conaty, Joseph and Duc-Le To.** "College Quality and Future Earnings: Where Should You Send Your Child to College?" *American Economic Review: Papers and Proceedings*, 79 (May 1989).

[18] **Keane, Michael P. and Kenneth I. Wolpin.** "The Career Decisions of Young Men." *Journal of Political Economy*, 105 (3:1997).

[19] **Loury, Linda Datcher and David Garman.** "College Selectivity and Earnings." *Journal of Labor Economics*, 13 (2:1995).

[20] **McFadden, Daniel.** "Econometric Models of Probabilistic Choice." *Structural Analysis of Discrete Data with Econometric Applications*, (Edited by Manski, Charles and Daniel McFadden). (1981).

[21] **McFadden, Daniel.** "Modelling the choice of Residential Location" in *Spatial Interaction Theory and Planning Models* (Edited by Karlqvist, Anders; Lundqvist, Lars; Snikcars, Folke; and Jorgen Weibull.) (New York, NY: North-Holland Publishing Company, 1978).

[22] **Mroz, Thomas.** "Discrete Factor Approximations in Simultaneous Equation Models: Estimating the Impact of a Dummy Endogenous Variable on a Continuous Outcome." working paper, October 1997.

[23] **Rothwell, Geoffrey and John Rust.** "On the Optimal Lifetime of Nuclear Power Plants." *Journal of Business and Economic Statistics,* 15 (2:1997).

[24] **Rust, John.** "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher." *Econometrica*, 55 (5:1987).

[25] **Rust, John.** "Structural Estimation of Markov Decision Processes." *Handbook of Econometrics, Volume 4,* (1994).

[26] **Rust, John.** "Numerical Dynamic Programming in Econometrics." *Handbook of Computational Economics,* (1996).

[27] **Rust, John and Christopher Phelan.** "How Social Security and Medicare Affect Retirement Behavior in a World of Incomplete Markets." *Econometrica*, 65 (4:1997).

[28] **Venti, Stephen and David Wise.** "Test Scores, Educational Opportunities, and Individual Choice." *Journal of Public Economics*, 18 (1982).

[29] **Willis, Robert and Sherwin Rosen.** "Education and Self-Selection." *Journal of Political Economy* 87 (5:1979).