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

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**Abstract**

This paper addresses how changing the admission and financial aid rules at colleges affects future earnings. I estimate a structural model of the following decisions by individuals: where to submit applications, which school to attend, and what field to study. The model also includes decisions by schools as to which students to accept and how much financial aid to offer. Simulating how the educational choices of blacks would change were they to face the white admission and aid rules shows that race-based advantages had little effect on earnings. However, removing race-based advantages does affect black educational outcomes. In particular, removing advantages in admissions substantially decreases the number of black students at top-tier schools while removing advantages in financial aid causes a decrease in the number of blacks who attend college.

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

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# 1 Introduction

Since 1996, the use of race in the admissions decisions of public colleges and universities has been challenged through court cases in Michigan, Georgia, and Texas, through ballot initiatives in California and Washington, and through the governor's office in Florida. In addition to admissions policies, race-specific financial aid has also come under fire. Scholarships provided by the University of Maryland that were restricted to blacks alone were ruled to be unconstitutional in court.[1] Despite the considerable public debate on race-based advantages in higher education, there is little understanding of how these programs affect the future outcomes of their intended beneficiaries. This paper seeks to estimate the effects of removing race-based advantages in both admissions and financial aid on black earnings and educational choices.

To accomplish this, I estimate a structural model 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 in and what major to study. These educational decisions are then linked to future earnings. I also estimate the decisions by schools as to whether to admit a student and, conditional on admitting, how much financial aid to offer.

There are a number of complications with estimating the effect of affirmative action in higher education on earnings. The first arises from affirmative action in higher education not having a direct effect on earnings, but only an indirect effect through the college decision-making process. Affirmative action affects whether individuals are admitted or how much aid they are offered. Adjusting these admissions and financial aid rules indirectly affects future earnings by influencing where individuals apply to college and therefore where they attend college. Without understanding the process by which individuals decide where to apply, it is impossible to quantify the effects of affirmative action. For example, if blacks were subjected to the same admissions rules as whites, would they undo the effects of removing affirmative action by applying to a larger number of elite schools or would they decide not to apply to college at all? This paper is the first to structurally estimate how individuals decide where to submit applications by explicitly modeling individuals' expectations on admittance, financial aid, and future earnings.

The second complication comes from the self-selection inherent in the educational process. This self-selection may take many forms. First, the returns to college may differ across the abilities of individuals with those who have the highest returns the most likely to take part

[1] See `http://chronicle.com/indepth/affirm/court.htm` for a review of recent court cases on affirmative action.

in the 'treatment' of attending college (see Card (2001), Heckman and Vytlacil (1998) and Heckman, Tobias, and Vytlacil (2000)). Second, the choices individuals make while in college may affect the treatment of attending college. For example, attending college and choosing to major in the natural sciences may result in higher earnings than choosing to major in the humanities. Finally, higher ability individuals may find college less difficult and therefore may be more likely to attend college, even if the returns to ability do not depend on whether one has a college degree.[2] I capture all of these sources of heterogeneous treatment effects through explicitly modeling the choice of major and allowing the monetary returns to different majors to vary with college quality and observed and unobserved ability. This is particularly important in evaluating affirmative action programs as the marginal individual who attends college may have very different expected returns than the average individual who attends college.

By estimating the structural model and appropriately accounting for selection, the admissions and financial aid rules are linked to where individuals submit applications, which school to attend, and what field to study. It is then possible to track how these decisions would change given a change in the admissions and financial aid rules. Earnings expectations under the different rules can then be calculated before individuals submit applications by assigning probabilities of applying and attending particular schools under different rules and calculating the associated expected earnings for each of the possible education paths.

Simulating the effects of removing preferential treatment for blacks in admissions and in financial aid shows surprisingly little effect on black male earnings despite blacks enjoying much larger premiums for attending college than their white counterparts. The small effects on expected earnings from removing black advantages in financial aid occur because those individuals who are at the margin of attending are also the ones who have the lowest treatment effect; their abilities are relatively better suited to the non-college market and they are likely to choose majors with low premiums. On the admissions side, preferential treatment for blacks only occurs at top-tier schools. Removing the preferential treatment in admissions has little effect on earnings because the return to college quality is small and those blacks affected by the policy are most likely to attend college regardless of whether affirmative action is in place.

While the effects of affirmative action in higher education on expected earnings is small, removing affirmative action programs would have effects on the distribution of blacks at top-tier schools and the percentage of blacks attending college. Although removing affirmative action in admissions has a very small effect on the overall college attendance rate, I find

[2]Many of these points are discussed in Altonji (1993).

that the percentage of black students falls dramatically at top-tier schools. For example, the percentage of black males attending colleges with average SAT scores above 1200 falls by over forty percent. In contrast, removing advantages in financial aid does not affect the distribution of blacks at the top schools as much as removing admissions advantages, but does have a larger effect on the college attendance rates. Even when controlling for unobserved ability, the parameter estimates imply an over five percent drop in the college attendance rates of black males had they faced the white financial aid rules.

With the study of the returns to college having a rich history in labor economics, it is important to understand how this paper builds on the previous literature. Although this is the first study to quantify the effects of affirmative action in higher education by structurally modeling all aspects of the college decision-making process, many papers have estimated different parts of the full model. Three papers in particular have reduced form versions of many parts of the education process. Manski and Wise's 1983 book *College Choice in America* provides a series of chapters on college application,[3] admissions, financial aid, and enrollment. Bowen and Bok (1998) contains perhaps the most comprehensive description of the correlations between race and education in top-tier schools. Most relevant to the work here is their documentation of the black advantage in admissions at top-tier schools and the finding that higher earnings are correlated with attending higher quality colleges. Brewer, Eide, and Goldhaber (1999) estimate reduced form application, admissions, and enrollment rules. They document a larger role of affirmative action in the early seventies than in the early nineties. None of these papers model the links between the various parts of the college decision-making process. For example, estimation of advantages in admissions are not tied to expected future earnings or the choice of college. Further, these papers do not control for selection on unobservables.

While the works discussed above have examined the general trends across a variety of college education decisions, many papers have focused on one aspect of the market for higher education. On the supply side, while the literature is sparse, Kane (1998) documents black advantages in admissions at top-tier schools while Kane and Spizman (1994) document similar advantages in financial aid across all schools. On the demand side, Fuller, Manski, and Wise (1982) and Brewer and Ehrenberg (1999) estimate multinomial logit models of the choice of college, with the latter also estimating the returns to college type and controlling for selection using the methodology developed in Lee (1983). Light and Strayer (2002) examine the decision to enroll and graduate from colleges of different qualities. They pay particular attention to

[3]See Venti and Wise (1982) for the first paper on college application choice.

race and find that, conditional on the same observed and unobserved characteristics, blacks are more likely to attend colleges of all quality levels. Both Berger (1988) and Arcidiacono (forthcoming) model the choice of major and find large earnings differences for particular majors even after controlling for selection.[4] Many studies have estimated the returns to college quality, with mixed evidence on how important college quality is to future earnings.[5] This paper links much of the above literature by explicitly modeling each of the relevant decisions which then makes policy analysis possible.

In addition to the detailed work on specific aspects of college education, there has been a vast literature on the returns to years of schooling.[6] Most relevant to the work here are the dynamic, structural models of Cameron and Heckman (1998, 2001) and (1999) and Keane and Wolpin (1997, 2000, 2001). These papers look at much longer time horizons, trading off the details of the college education process for a more explicit modeling of the year by year decisions as to whether to further one's education. The latter three papers estimate expectations of future utility, taking into account the option values of each of the possible decisions. In calculating these expectations, researchers face a tradeoff between the correlation structure of the unobservable preferences and having closed forms expressions for the expectations of future utility. One of the advantages of assuming a generalized extreme value (GEV) distribution for unobservable preferences is that, under certain conditions on the evolution of the state space,[7] closed form expressions exist for the expectations of future utility. The tradeoff is the very restrictive correlation structure of the unobserved preferences where the unobservable preferences usually take on either a multinomial logit or a nested logit form. With the nested logit, unobservable preferences within a nest share a common component but there is no correlation across nests. This paper applies a GEV framework developed in the industrial organization literature, Bresnahan, Stern, and Tratjenberg (1997), which allows the unobservable preferences to be correlated across multiple nests. Unobservable preferences are then correlated across both schools and majors while still having closed form expressions on the expectations of future utility.

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

[4]Grogger and Eide (1995), James et. al (1989), and Loury and Garman (1995) also document substantial earnings differences across majors.

[5]Daniel, Black, and Smith (1997), James et. al (1989), and Loury and Garman (1995), find strong positive effects of college quality. Dale and Krueger (2002) find much smaller effects when using information about what schools individuals were rejected at to control for unobserved ability.

[6]See Card (1999) for a review.

[7]See Rust (1986, 1994).

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 college (conditional on being accepted) and what field to study. The model has four stages 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.

There are two types of parameters for dynamic discrete choice models: transition parameters ($\gamma$'s), which affect the probability of being in particular states, and preference parameters ($\alpha$'s), which affect the utility of particular choices at particular states. Since transition or preference parameters appear in each stage of the model, in order to avoid confusion I subscript parameters and variables for each stage. Namely, parameters and variables for the labor market are subscripted by $w$, for the choice of college and major by $c$, for admissions by $a$, for financial aid by $f$, and for applications by $s$. Individual subscripts are suppressed.

Throughout, the discussion will be as though all the errors in the various stages are independent of one another and hence each stage could be estimated separately— essentially assuming away the selection problem. This assumption will be relaxed later in the paper through the use of mixture distributions. Mixture distributions allow for the various stages to be connected through an individual's unobserved 'type', controlling for the dynamic selection that occurs in the model. These unobserved types then affect an individual's productivity in the labor market, their probability of admission and financial aide, and there preferences for particular schooling combinations. The use of the mixture distribution is discussed in more detail in section 2.6.

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

Once individuals enter the workforce they make no other educational decisions: the labor market is an absorbing state. Individuals then receive utility only through earnings.[8] Earnings are a function of ability, $A$, where $A$ is individual specific. I assume that the human capital gains for attending the $j$th 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. Heterogeneity in these earnings differentials may also exist as the amount of human capital accumulation an individual obtains in a particular major may depend upon their ability. Log earnings $t$ years after high school are then given by:

$$\ln(W_{jkt}) = \gamma_{wk1} + \gamma_{wk2}A + \gamma_{wk3}\overline{A_j} + \gamma_{wk4}X_w + g_{wkt} + \epsilon_{wt} \tag{1}$$

where $X_w$ is a vector of other characteristics which may affect earnings, $k$ indicates major, and $g_{wkt}$ represents how earnings grow over time. Should the individual not choose one of the college options, $j = k = 0$ and the variables characterizing the college are set to zero. The shocks (the $\epsilon_{wt}$'s) are assumed to be distributed $N(0, \sigma_w^2)$.

Note that this model explicitly incorporates comparative advantage. Particular majors may have low wage intercepts but high returns to ability. Similarly other majors or the no-college option may have high intercepts but low returns to ability.[9]

The data set I use to estimate the model is a short panel of high school graduates from a particular cohort. Accurately estimating growth rates for particular majors far out into the life cycle is not possible. Instead, I estimate the log earnings equation with year indicator variables interacted with sex and whether or not the individual choose one of the college options. The corresponding growth rates are then only calculated for years in which we actually have wage observations.

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

$$u_{wjk} = \alpha_w \log\left(E_w\left[\sum_{t=t'}^{T} \beta^{t-t'} P_{kt} W_{jkt}\right]\right) \tag{2}$$

[8]Nonmonetary benefits in the workforce for particular schooling paths will not be separately identified from the utility of those paths while in college. Hence, for ease of exposition I speak of these only in terms of the utility in college.

[9]As will be discussed in the section on unobserved heterogeneity, comparative advantage across schooling options will also be present as certain 'types' of individuals will see higher returns in one major but lower returns in another.

where $T$ is the retirement date, $t'$ is the year the individual enters the workforce, and $\beta$ is the discount factor. The probability of working in a particular year is given by $P_{kt}$. The expectation is then taken with respect to future labor force participation and shocks to earnings. I assume that conditional on sex and major all individuals have the same expectations regarding future labor force participation.[10] Under these assumptions, equation (2) can be rewritten as:

$$u_{wjk} = \alpha_w(\gamma_{wk1} + \gamma_{wk2}A + \gamma_{wk3}\overline{A_j} + \gamma_{wk4}X_w) + \alpha_w \log\left(E_w\left[\sum_{t=t'}^{T}\beta^{t-t'}P_{kt}\exp(g_{wkt} + \epsilon_{wt})\right]\right) \tag{3}$$

Whether utility of working is given by the expected value of the log of lifetime earnings, the log of the expected value of lifetime earnings, or the expected value of the sum of the log of yearly earnings does not affect the empirical specification. In all of these cases, utility can be written as a linear term plus a function of the trend in earnings over time. It is only this latter function which is different across the three specifications. Since I do not have good information on earnings growth rates across years and majors, I assume that the expected growth rates are common across individuals of the same gender and major.[11] Hence, this last term, which includes both the growth dates and future participation decisions, is captured by sex interacted with a major-specific constant.[12] Note further that no assumptions need to be made on the discount factor as it too is absorbed into the major-specific intercept.

## 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, utility from attending Harvard can be captured by the characteristics of Harvard. 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, $u_{cjk}$, as the utility received while actually attending college $j$ in major $k$. This flow utility includes the effort demanded in major $k$ at school $j$ as well as any

[10] The number of blacks in the data set is small. Thus, blacks are allowed to have different preferences for attending college, but not for particular majors. Differences in unemployment rates for blacks are embedded in this model as long as they are proportional to the employment rates for whites conditional on attending or not attending college.

[11] See Arcidiacono (forthcoming) for a similar specification.

[12] Since the utility of attending college also has a major-specific constant, these two constant terms will not be separately identified.

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 $v_{cjk}$ be the corresponding expected present discounted value of indirect utility:

$$v_{cjk} = u_{cjk} + u_{wjk} \tag{4}$$

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:

$$v_{co} = u_{wo} \tag{5}$$

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

I now specify in more detail the components of $u_{cjk}$. 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, $A$, 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 $c_{jk}$. The flow utility for pursuing a particular college option is then:

$$u_{cjk} = \alpha_{c1} X_{cjk} - c_{jk} + \epsilon_{cjk} \tag{6}$$

where $X_{cjk}$ is a vector of individual, school, and major variables which affect how attractive particular education paths are. These include such factors as the monetary cost of the school net of financial aid, college quality as a consumption good, and whether particular sexes have preferences for particular majors. $X_{cjk}$ also includes major-specific intercepts.[13] The individual's unobserved preference for particular schooling options is given by $\epsilon_{cjk}$.

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

$$c_{jk} = \alpha_{c2k}(A - \overline{A}_j) + \alpha_{c3}(A - \overline{A}_j)^2 \tag{7}$$

Note that the cost of effort 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 $\alpha_{c3}$, I will not be able to separately identify $\alpha_{c2k}$ because college quality can serve as a consumption good and high ability individuals may have preferences for particular majors independent of effort costs; college quality and abilities of the students may enter the utility of majoring in a particular field through $X_{cjk}$ as well. 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

[13] When the mixture distribution is added, these major-specific intercepts will be allowed to vary by type.

individual may not choose to 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.[14]

Note also that many of the variables that affect the utility of college also affected the utility of working. In order to identify $\alpha_w$, the coefficient on the log of the expected value of lifetime earnings, an exclusion restriction will be necessary. This is discussed in more detail in the data and identification sections.

I assume that $\epsilon_{cjk}$'s follow a generalized extreme value distribution. Special cases of the generalized extreme value distribution lead to multinomial logit and nested logit models. With nested logit models, errors in one nest cannot be correlated with errors in another nest. For example, if we nested the choice of school, then it would not be possible to also nest the choice of major. However, a paper in the industrial organization literature, Bresnahan, Stern, and Trajtenberg (1997) (henceforth BST), shows that, consistent with McFadden's (1978) framework,[15] another special case of the generalized extreme value distribution allows for errors to be correlated across multiple nests while still being consistent with random utility maximization. I use this specification to allow errors to have a component that is common across all majors at a particular school and a component that is common across all school choices involving the same choice of major. In particular, it is possible to have $\epsilon_c$'s which are correlated across both schools and majors using the following $G$ function:

$$G(e^{v'_c}) = a_{c1}\sum_j\left(\sum_k \exp(v'_{cjk}/\rho_{c1})\right)^{\rho_{c1}} + a_{c2}\sum_k\left(\sum_j \exp(v'_{cjk}/\rho_{c2})\right)^{\rho_{c2}} + \exp(v'_{co}) \quad (8)$$

where $\rho_{c1}, \rho_{c2} \in [0,1]$, $a_{c1} + a_{c2} = 1$, and $v'_{cjk} = v_{cjk} - \epsilon_{cjk}$ (the indirect utility net of the

[14]See Arcidiacono (forthcoming) for a more detailed discussion of the identification of effort costs.

[15]McFadden's (1978) framework is as follows. Let $r = 1, ..., R$ index all possible choices. Define a function $G(y_1, ..., y_R)$ on $y_r \geq 0$ for all $r$. If $G$ is nonnegative, homogeneous of degree one, approaches $+\infty$ as one of its arguments approaches $+\infty$, has nonnegative $n$th cross-partial derivatives for odd $n$ and nonpositive cross-partial derivatives for even $n$, then McFadden (1978) showed that:

$$F(\epsilon_1, ..., \epsilon_R) = \exp\{-G(e^{-\epsilon_1}, ..., e^{-\epsilon_R})\}$$

is the cumulative distribution function for a multivariate extreme value distribution. Further, the probability of choosing the $r$th alternative conditional on the observed characteristics of the individual is given by:

$$P(r) = \frac{y_r G_r(y_1, ..., y_R)}{G(y_1, ..., y_R)},$$

where $G_r$ is the partial derivative of $G$ with respect to the $r$th argument.

unobservable preference). The $a_{c1}$ and $a_{c2}$ terms are defined as follows:

$$\begin{aligned} a_{c1} &= (1-\rho_{c1})/(2-\rho_{c1}-\rho_{c2}) \\ a_{c2} &= (1-\rho_{c2})/(2-\rho_{c1}-\rho_{c2}). \end{aligned}$$

Note that as $\rho_{c1}$ ($\rho_{c2}$) approaches one, $a_{c1}$ ($a_{c2}$) approaches zero and the $G$ function reverts to the one used to derive a nested logit with errors only correlated within majors (schools). While the $\epsilon_c$'s are known to the individual, they are not observed by the econometrician. Hence, from the econometrician's perspective, the probability of choosing the $k$th major at the $j$th school is then given by:

$$P(j,k) = \frac{a_{c1}\exp(v'_{cjk}/\rho_{c1})\left(\sum_k \exp(v'_{cjk}/\rho_{c1})\right)^{\rho_{c1}-1} + a_{c2}\exp(v'_{cjk}/\rho_{c2})\left(\sum_j \exp(v'_{cjk}/\rho_{c2})\right)^{\rho_{c2}-1}}{G(e^{v'_c})}. \tag{9}$$

## 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 its students, $\overline{A}$, the sum of tuition payments net of any scholarships, and a school's unobserved preference for a particular student. The school side does not fall directly out of a well-specified optimization problem for the schools themselves. However, I am not interested in how schools respond to changes in the application pool, but in how changing the school admission and financial rules affect student behavior. Hence, it is not crucial that I estimate parameters on the school side which are policy invariant as it is exactly these policies that I am interested in varying.

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 $X_{aj}$ including such factors as the quality level of the school and the individual's own ability and $\gamma_a$ being a vector of coefficients to be estimated.

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

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:

$$P(J_a|J) = \prod_{j}^{\#J} \left(\frac{\exp[\gamma_a X_{aj}]}{\exp[\gamma_a X_{aj}]+1}\right)^{j\in J_a} \left(\frac{1}{\exp[\gamma_a X_{aj}]+1}\right)^{j\notin J_a}, \tag{10}$$

the product of the logit probabilities of the individual outcomes.

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

$$\begin{aligned} s_j^* &= \gamma_f X_{fj} + \epsilon_{fj} && (11)\\ s_j &= 0 && \text{if } s_j^* \leq 0\\ s_j &= 1 && \text{if } s_j^* \geq 1\\ s_j &= s_j^* && \text{if } 0 < s_j^* < 1 \end{aligned}$$

where $X_{fj}$ is a vector of individual and institutional characteristics affecting financial aid outcome. Hence, the share of the bill paid will have mass points at no aid and full aid which is consistent with the data. The forecast error, $\epsilon_{sj}$, is independent of $X_{fj}$, independent across schools, and is unknown to the student until after the application decision has been made.[16]

## 2.4 Stage 1: Applying to College

Let there be a set of $\mathbb{J}$ colleges where an individual may submit an application. Since each school may accept or reject the student, the number of possible outcomes for applying to all the schools in $J \subset \mathbb{J}$ 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 particular college and major combinations in the future.[17] I assume that the expected utility of applying to the set $J$, $v_{sJ}$, is given by:

$$v_{sJ} = \alpha_{s1} E_s(V_c|J) + u_{sJ} + \epsilon_{sJ}$$

where $V_c$ is the value of the best alternative at the college and major choice stage, $u_{sJ}$ is the flow utility (application cost) of applying to the set $J$, and $\epsilon_{sJ}$ is the unobserved preference for applying to the set $J$.[18] By assuming a particular functional form on the application costs

[16]Both this assumption as well as the assumption of independent errors in admissions is relaxed later in the paper as the intercept terms in both equations are allowed to vary by type. Hence, highly productive people may see higher earnings as well as higher probabilities of admittance and financial aid at all colleges.

[17]Note that at this stage the individual knows the gross costs of attending each school. However, he only has expectations regarding how much of those gross costs he will actually have to pay as financial aid is uncertain.

[18]Note that even though $E_s(V_c|J)$ is already denominated in utils, there is still a coefficient on the variable. $\alpha_{s1} = \frac{\mu_c}{\mu_s}$ where $\mu_c$ and $\mu_s$ are the variance scale parameters for the choice of school and major stage and the

and taking into account the probability of being admitted into each school in the set, the expression becomes:

$$v_{sJ} = \alpha_{s1} \sum_{a=1}^{2^{\#J}} E_s(V_c|J_a)P(J_a|J) - \alpha_{s2}X_{sJ} + \epsilon_{sJ} \tag{12}$$

where $X_{sJ}$ represent the variables which affect the cost of applying to set $J$.

I assume that unobservable tastes for particular schools and majors, the $\epsilon_c$'s, are independent from the $\epsilon_s$'s. All individuals then have the same expectations with regard to the realizations of the $\epsilon_c$'s. I need this assumption to make the expectations on future utility of applying to a particular set of schools $J$ tractable.[19] Integrating out and discretizing the financial aid realizations into $L$ categories, Rust (1987) showed that the conditional expectations have a closed form solution. With these assumptions, equation (12) can be rewritten as:

$$\begin{aligned} v_{sJ} = \quad & \alpha_{s1} \textstyle\sum_{a=1}^{2^{\#J}} \Bigg( \displaystyle\sum_{l=1}^{L} \ln \Bigg[ a_{c1} \sum_{j} \Bigg( \sum_{k} \exp(v'_{cjk}/\rho_{c1}) \Bigg)^{\rho_{c1}} \\ & \qquad + a_{c2} \sum_{k} \Bigg( \sum_{j} \exp(v'_{cjk}/\rho_{c2}) \Bigg)^{\rho_{c2}} + \exp(v'_{co}) \Bigg] \pi(s_{al}|X_{fJ}) ds_a \Bigg) P(J_a|X_{aJ}) \\ -\alpha_{s2}X_{sJ} + \quad & \epsilon_{sJ} \end{aligned} \tag{13}$$

where $\pi$ discretized pdf of $s_a$, the financial aid decisions at each of the schools in the acceptance set.

With the calculation of the expected value of lifetime utility in hand, I now specify the distribution of the taste parameters, the $\epsilon_s$'s. Similar to the college and major choice stage, it is reasonable to assume that unobserved preferences for application bundles where some of the schools overlap should be correlated. I specify a distribution where each school has its own nest. Hence, the nest for the first school in $\mathbb{J}$ includes all $J$'s which have as one of its elements the first school. An application of BST's framework once again applies. Namely, order the schools in $\mathbb{J}$ from $1, ..., N$. Order the possible combinations of schools from $1, ..., R$ and let $J_r$

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. Any discounting across stages will not be separately identified but will instead be incorporated into this parameter.

[19] When unobserved heterogeneity is added through the use of mixture distributions, the expectations on the values of particular application sets will vary with type. That is, high unobserved ability individuals will have higher expectations regarding the value of all application sets.

denote the set of schools in the $r$th combination. The $G$ function I use is then given by:

$$G(v'_s) = \sum_{n=1}^{N} \frac{1}{M} \left( \sum_{r=1}^{R} (n \in J_r) \exp(v'_{sr}/\rho_s) \right)^{\rho_s} + \sum_{r=1}^{R} \left( 1 - \sum_{n=1}^{N} \frac{(n \in J_r)}{M} \right) \exp(v'_{sr}) + \exp(v'_{so}) \tag{14}$$

where $v'_{sr} = v_{sr} - \epsilon_{sr}$, $M$ is the maximum number of schools one can apply to, and $\rho_s \in [0, 1]$ is the nesting parameter. The last term allows the individual to not apply to any schools, while the second to last term adjusts the $G$ function for the fact that some combinations of schools have smaller numbers of schools than others. That the $\rho_s$ is common across schooling nests restricts the correlation within each school's nest to be the same.

This $G$ function then leads to the probability of choosing the application set $J_r$ being given by:

$$P(J_r) = \frac{\sum_{n=1}^{N} \frac{1}{M} \left( \sum_{r'=1}^{R} (n \in J_r)(n \in J_{r'}) \exp(v'_{sr'}/\rho_s) \right)^{\rho_s - 1} \exp(v'_{sr}/\rho_s) + \left( 1 - \sum_{n=1}^{N} \frac{(n \in J_r)}{M} \right) \exp(v'_{sr})}{G(v'_s)}. \tag{15}$$

Note that if the number of schools in $J_r$ equals $M$, then the second term disappears. As in the college and major choice stage, as $\rho_s$ approaches one the model reverts to a multinomial logit.

### 2.5 The Estimation Strategy

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

$L_1(\gamma_w)$- the log likelihood contribution of earnings;

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

$L_3(\gamma_f)$- the log likelihood contribution of financial aid;

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

$L_5(\alpha_s, \alpha_c, \alpha_w, \gamma_a, \gamma_f, \gamma_w)$- the log likelihood contribution of the application decision.

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

Note that consistent estimates of $\gamma_w$, $\gamma_a$, and $\gamma_f$ can be found from maximizing $L_1$, $L_2$, and $L_3$ separately.[20] With the estimates of $\gamma_w$, consistent estimates of $\alpha_c$ and $\alpha_w$ can be

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

obtained from maximizing $L_4$. All of these estimates can then be used in $L_5$ to find consistent estimates of $\alpha_s$.[21]

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 preference 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.[22]

One method of dealing with this problem is to assume that there are $R$ types of people with $\pi_r$ being the proportion of the $r$th type in the population.[23] Types remain the same throughout all stages, individuals know their type, and preferences and abilities may vary across type.[24] The log likelihood for a particular individual then follows the mixture distribution:

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

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

[21] The standard errors, however, are not consistent. I take one Newton step on the full likelihood function to obtain consistent estimates of the standard errors.

[22] See Willis and Rosen (1979) for the importance of controlling for selection when estimating the returns to education.

[23] See Keane and Wolpin (1997), Eckstein and Wolpin (1999), and Cameron and Heckman (1998, 2001) for other examples of using mixture distributions to control for unobserved heterogeneity in a dynamic education models.

[24] 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 random effect which is common across everyone of a particular type.

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. Arcidiacono and Jones (2003) show that the Expectation-Maximization (EM) algorithm[25] restores the additive separability at the maximization step.

In particular, note that the conditional probability of being the $r$th type is given by:

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

where $\mathbf{X}$ 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 for a particular observation is now additively separable:

$$\sum_{r=1}^{R} P(r|\mathbf{X}, \alpha, \gamma, \pi) \left( L_{1r}(\gamma_w) + L_{2r}(\gamma_a) + L_{3r}(\gamma_f) + L_{4r}(\alpha_c, \alpha_w, \gamma_w) + L_{5r}(\alpha_a, \alpha_c, \alpha_w, \gamma_a, \gamma_f, \gamma_w) \right). \tag{18}$$

Taking the conditional probabilities of being a particular type as given, I can obtain estimates of $\gamma_w$ from maximizing the $L_{1r}$'s times the conditional probabilities of being a particular type. Similarly, estimates of $\gamma_a$ and $\gamma_f$ come from maximizing the conditional probabilities times the $L_{2r}$'s and $L_{3r}$'s, respectively. I then only use the $L_{4r}$'s and the conditional probabilities to find estimates of $\alpha_c$ and $\alpha_w$— not needing $L_{4r}$ to obtain estimates of $\gamma_w$. These estimates are taken as given and the $L_{5r}$'s are used only to find the $\alpha_s$'s. 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 (2003) show this method produces consistent estimates of the parameters with large computational savings.

Note also the the population probabilities of being a particular type, the $\pi_r$'s, can depend upon characteristics of the individual. Here, type is allowed to depend upon whether one comes from a high or low income family.[26] Allowing income to affect type probabilities in this way does not affect the sequential EM algorithm. Rather than updating the unconditional probability of being a particular type using the whole sample, the unconditional probabilities now vary by income and are updated individually using the sample of high and low income households respectively.

[25] See Dempster, Laird, and Rubin (1977) for the seminal paper on the EM algorithm.

[26] The definition of high and low income are given in the data section below.

# 3 Data

The National Longitudinal Study of the Class of 1972 (NLS72) is the primary data source for estimating the model. 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. Table 1 provides descriptive statistics for the whole sample, those who applied to college, and those who attended college. All statistics are disaggregated by race.[27]

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 $J_a$. However, this turns out to be not very restrictive as the percentage of students who report applying to three schools is small, with approximately ten percent of those who apply to college submitting three applications.

In order to keep the model computationally tractable, I need to restrict the number of schools where the individual can submit an application. It not possible to estimate a model where an individual may apply to all combinations of schools in the United States. 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. Schools were assigned randomly with seventy percent of the draws coming from schools in the same state as the student. All colleges where an individual actually submitted an application were included in the choice set. This leaves ninety-two possible application sets.

The first four rows in Table 1 then show how the probability of applying, being admitted, and attending vary by race. Blacks and whites were equally likely to submit any applications and the average number of applications conditional on applying was 1.4 for both groups. The unconditional probability of being admitted is higher for whites, with blacks being over fifty percent more likely to be rejected.

I use data on decisions made in 1974 as to whether to attend college. This should roughly

[27]The sample was selected as follows. In order to be in the final data set, survey respondents must have participated in the first follow-up study as well has have valid test score information either from taking the SAT or the standardized test given to the NLS72 participants in the first year. Of these, 6,940 did not apply to a four-year college in their senior year of high school. Of the 7,877 who did apply, 4,645 had a valid schooling option. Of the 4,645, 3,670 had valid information on major choice and did not transfer schools. This last set of attrition resulted in a reduction of 24% of the sample of those who submitted an application. I therefore reduced (randomly) the sample of those who did not apply by 24% as well, leaving the sample of non-applicants at 5,244. This attrition had no effect on the ratio of men to women or blacks to whites.

correspond to the junior year of college. 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. If an individual attends college but drops out before the junior year, they are treated as not having attended college. With this measure, Table 1 shows that the college attendance rates conditional on applying are twenty-five percent higher for whites.

The next set of rows show the characteristics of the schools applied to and attended as well as how much aid was offered. The schools' math and verbal SAT scores, as reported by the schools themselves, are used as my measures of school quality.[28] James et. al (1989) find that the only measure of college quality which significantly affects earnings is student quality. This does not necessarily imply peer effects as student quality may be driven by the quality of the instruction which is not easily measured. Costs are calculated as tuition plus books plus room and board. Both the college quality and the cost data are taken from the schools themselves. Individuals list their general scholarships as well as school-specific scholarships. The only measure of financial aid I use is this scholarship data. Scholarships are constrained to be less than the total cost of the school. There is much censoring, as over 60% of individuals receive no financial aid from scholarships.

The table shows that whites apply to and attend colleges with much higher SAT math and verbal scores than their black counterparts. Cost may have something to do with this as blacks applied to college which were on average less expensive and also received more aid than whites. Although the out of pocket expenses were on average lower for blacks who chose to attend, this was not the case for whites. A possible explanation is that there are more high income whites and this group may have received poor financial aid packages yet still planned on attending college.

With blacks applying to worse schools and being admitted at lower rates, the role of affirmative action may seem limited. However, Brewer, Eide, and Goldhaber (1999) document that affirmative action in college during this time period (early seventies) was actually much stronger than in later years. These facts may be reconciled by examining the third set of rows which points towards large differences in backgrounds of the white and black populations.

The difference in SAT scores is particularly striking. Columns (1) and (6) show that blacks who attended college performed over fifty points worse on both the math and verbal sections of the SAT[29] than whites in the population at large. These gaps increase to over 150 points

[28]These data, as well as the tuition and various other costs of attending the school, are found in The Basic Institutional Source File. This file has information from the 1973-74 Higher Education Directory, the 1973-74 Tripariate Application Data file, the 1972-73 HEGIS Finance Survey and the 1972 ACE Institutional Characteristics File, all of which are surveys of colleges.

[29]Many individuals, particularly those who did not apply to college, did not take the SAT. However, partici-

and 130 points for the math and verbal scores when comparing white and black attendees. For both groups, SAT scores are higher for those who attended than those who just applied, and higher for those who applied than those who did not.

Large differences also exist in both high school class rank[30] and in the percent of families that are low income, where low income is defined as being below the median family income in the data for those who report a family income.[31] In both cases and in all groupings, blacks have lower high school class ranks and are more likely to come from low income families than whites. Consistent with the results on SAT math score, both higher incomes and class ranks are found as we move from the full sample to the sample that attended college. Black females were more likely to attend college than their male counterparts, but this is not the case for whites.[32]

In order to identify the coefficient on future earnings, I need a variable that affects choice of school and major only through earnings; $X_w$ must have an element not contained in $X_c$. I use state differences in the log 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 March Current Population Survey (CPS). Some small states are aggregated in the CPS, leading to differences in the college premiums across twenty-two regions. The descriptive statistics indicate this may be a good choice as for both blacks and whites the highest college premiums are found for those who attended college, with higher values for those who applied than in the population at large. It is interesting to note that blacks were more likely to live in states where the college premium was high.

Motivated by the work in Arcidiacono (forthcoming), majors are aggregated into four groups: engineering, physical sciences, and biological sciences in group 1, business and economics in group 2, social sciences, humanities, and other in group 3, and education in group 4.

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pants in the NLS72 took both a math and a verbal test in the base year of the survey. For those who did take the SAT, I regressed SAT math and SAT verbal on the score of the math and the verbal tests, respectively. These results were then used to forecast SAT math and verbal scores for those who did not take the SAT. Those who neither took the SAT or the NLS72 test were removed from the sample. Some individuals did not take this standardized test. These individuals were slightly more likely to be black (18% compared to the final sample of 12%) but were equally likely to be female. Individuals in this group were much more likely to not to have responded to the other survey questions.

[30]This variable is taken from the high schools themselves and is on a percentage basis where a one indicates the student was at the top of the class.

[31]About one-third of the sample does not report a family income. Based upon their behavior, these individuals look like they come from high income families and are coded as such.

[32]Note that the percentage female is much higher for blacks in the full sample than for whites. This is true in the survey itself and is not a result of the selection rules used to obtain the sample.

Table 1: Sample Means

| | Full Sample | | Applied | | Attended | |
|---|---|---|---|---|---|---|
| | White | Black | White | Black | White | Black |
| Prob. of Applying | 0.4115 | 0.4133 | | | | |
| Prob. of Attending | 0.2114 | 0.1667 | 0.5137 | 0.4033 | | |
| Prob. of Admission | | | 0.9121 | 0.8609 | | |
| Number of Applications | 0.5924 | 0.5809 | 1.4397 | 1.4006 | 1.5772 | 1.5491 |
| | (0.8312) | (0.8066) | (0.6777) | (0.6503) | (0.7443) | (0.7246) |
| Math School Quality | | | 535.6 | 460.3 | 538.2 | 466.5 |
| | | | (55.2) | (100.2) | (51.2) | (104.5) |
| Verbal School Quality | | | 508.2 | 438.8 | 509.6 | 446.1 |
| | | | (52.8) | (97.5) | (48.9) | (101.8) |
| School Cost† | | | 11,505 | 10,596 | 11,403 | 10,632 |
| | | | (4192) | (3843) | (4003) | (4124) |
| Financial Aid | | | 1,250 | 2,180 | 1,456 | 3,195 |
| | | | (2736) | (3796) | (2930) | (4594) |
| State College Premium†† | 0.2684 | 0.2949 | 0.2705 | 0.2959 | 0.2722 | 0.2999 |
| | (0.0621) | (0.0566) | (0.0623) | (0.0586) | (0.0621) | (0.0600) |
| SAT Math | 442.1 | 334.3 | 500.3 | 360.9 | 529.8 | 378.9 |
| | (104.2) | (70.0) | (105.9) | (82.1) | (101.2) | (85.6) |
| SAT Verbal | 410.3 | 305.5 | 465.4 | 332.4 | 489.8 | 356.9 |
| | (100.7) | (67.5) | (102.8) | (79.5) | (99.5) | (87.5) |
| HS Class Rank | 0.5589 | 0.4677 | 0.6983 | 0.5710 | 0.7633 | 0.6212 |
| | (0.2780) | (0.2749) | (0.2351) | (0.2629) | (0.2032) | (0.2546) |
| Unknown HS Class Rank | 0.1143 | 0.2322 | 0.1373 | 0.2634 | 0.1249 | 0.2486 |
| Low Income‡ | 0.4410 | 0.7139 | 0.3508 | 0.6737 | 0.3169 | 0.6416 |
| Female | 0.4950 | 0.5732 | 0.4736 | 0.6107 | 0.4757 | 0.6358 |
| Natural Science | | | | | 0.2246 | 0.1329 |
| Business | | | | | 0.1628 | 0.1734 |
| Social Science | | | | | 0.4450 | 0.4855 |
| Education | | | | | 0.1676 | 0.2081 |
| Observations | 7876 | 1038 | 3241 | 429 | 1665 | 173 |

†Costs and aid are in 1999 dollars and is defined as Tuition+Books+Room and Board. Financial aid is scholarships only. Both costs and financial aid are for all schools applied to in the second column and the only the school attended in the third column.

‡ Defined as family's before tax income being less than $36,000 (1999 dollars).

††Taken from the 1973-1975 March Current Population Surveys.

The maximum number of choices available at the college decision stage is then thirteen: four majors for each of three schools and a work option. Differences in major choice exist across the races, with blacks being substantially less likely to choose natural science majors.

The final row gives the number of observations in each category. Note that the number of blacks is quite small, with only 173 attending college. This limits what race effects can be identified in the model. At the earnings stage, I allow earnings by blacks to differ from those of whites and allow this difference to vary based upon whether the individual attended college. At the college stage, I allow blacks to have a preference for attending (or not attending) college. In both the earnings and college choice stages, the limited observations make it impossible to estimate major-specific wage premiums or preferences for particular majors that differ by race. At both the admissions and financial aid stage, race is taken into account in the intercept term, in an interaction with college quality, and an interaction with low income. The interaction with college quality is implemented because past research (see Bowen and Bok (1997), Brewer, Eide, and Goldhaber (1999), and Kane (1998)) has found that racial preferences are only present at top tier colleges. The black effect on admissions and aid is also constrained to be positive. Hence, blacks may face the white rules up to a particular college quality level and receive advantages after that point. This issue is discussed in more detail in the results section.

I also place restrictions on the effects of math and verbal college quality and math and verbal ability. Arcidiacono (forthcoming) found that math ability and college quality were much more important than their verbal counterparts in major selection and future earnings. Hence, I restrict the effect of ability and college quality to only operate through the math channel. However, for admissions and aid, the total SAT score is used. In the earnings regression I further restrict the effect of both math ability and college quality to be weakly positive. These restrictions are made as the college quality and ability measures are all highly collinear.

## 4 Identification

As discussed in the model section, with the schooling decisions being choices it is important to control for selection at all stages of the model. All characteristics of the individuals themselves are taken as exogenous including such things as test scores and parental income. When the errors are assumed to be uncorrelated across the various stages of the model, selection into schools and majors is only controlled for by these exogenous characteristics.

However, there are surely some unobserved features of the individual that affect both educational decisions and future earnings. As stated in section 2.6, a mixture distribution is used which allows the errors to be correlated across the various stages of the model through an individual's 'type.' An individual's type is unobserved and integrated out of the likelihood function. As is standard in the dynamic discrete choice literature, the assumption is that once type is controlled for there is no selection problem: controlling for type removes the correlation between the residual in the log earnings regression and the choice of college and major. I now discuss what features of the data are used to identify an individual's type.[33]

Particularly important to the identification strategy is the use of the dynamics of the model. Information from the following outcomes are used to identify the selection into colleges and majors:

- Schools where the individual did and did not submit applications.
- Admissions realizations from the schools.[34]
- Financial aid realizations at all schools where the individual was admitted.

We would expect none of these realizations to directly affect earnings, yet all would be expected to be correlated with unobserved ability. A person with high unobserved ability may apply to many schools, be admitted to many schools, and receive outstanding financial aid packages. Those who receive higher than expected (by the econometrician) realizations on financial aid, admissions, and number and quality of applications may have higher unobserved ability regardless of whether or not they attended college or chose a particular major. These realizations then enter into the log earnings regression through an individual's type which is accounted for by the use of the mixture distribution.

Exclusion restrictions from the characteristics of the individuals themselves also are used to identify the unobserved types. In particular, I use the following characteristics of the individuals as exclusion restrictions in various parts of the model:

- Parental income affects admissions and financial aid decisions, but not earnings directly.
- Similarly, SAT verbal scores and high school class rank have no direct effect on earnings.
- The premium workers receive for a college education in particular states affects the choice of college and major only through earnings.

[33]Functional form invariably helps to identify types as well, though we would like to identify the types by more than functional form.

[34]Dale and Krueger (2002) use similar variation to identify the labor market returns to college quality. They use information on the schools that rejected the student to control for selection into higher quality colleges.

Absent a story of job contacts, parental income affects earnings only through the student's ability to pay for college and also through unobserved ability. Also, total SAT scores affect financial aid and admissions but only SAT math scores affect earnings. Arcidiacono (forthcoming) shows no return to verbal ability. However, SAT verbal scores will dictate whether some individuals go to college and others do not due to the opportunity to get into better colleges and receive better aid packages. Hence, at the margin, high unobserved ability and high verbal ability may serve as substitutes. Finally, the premium college graduates receive in particular states is assumed to affect the choice of college and major only through earnings. In states where the college premium is higher, those with lower unobserved ability may be induced to choose a college option. These individuals know they will have to work harder in college than their high unobserved ability counterparts, but are willing to do so for the higher wages.

# 5 Results

In this section, I present the estimation results. 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; there is only one 'type' of person. This model has correlations in the errors within the application and college and major choice stages but has no correlation across the stages of the model. The other allows for two types, where one's type affects all aspects of the problem from the application decision to expected earnings through a dummy term.[35] These types work as random effects and link all stages of the model. The population probability of being a particular type is allowed to vary with income level.[36]

## 5.1 Admissions

Table 2 presents the estimates of the admissions logit with and without controls for unobserved heterogeneity. Comparing the two models shows that, while Type 2's have a higher probability

[35] Models with more types were also estimated. The standard errors on these models blew up and yielded nonsensical results. The reason for the difficulty is that we observe only one college and major decision. Identifying additional preference parameters for that particular stage requires additional structure. A three type model where the effect of type in the college and major choice stage was constrained to be proportional to the effect of type on earnings yielded similar results to the two type model.

[36] Keane and Wolpin (1997, 2000, 2001) also allow the population type probabilities to depend upon income level through a logit specification. In this paper income level affects the population type probabilities through means that differ across high and low income individuals.

Table 2: Logit Admission Probabilities†

| | One Type | | Two Types | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| Female | -0.0925 | 0.0847 | -0.1162 | 0.0863 |
| Black | -4.2959 | 1.2933 | -4.2597 | 5.7867 |
| SAT (000's) | 2.6531 | 0.2484 | 2.7415 | 0.2502 |
| HS Class Rank | 1.5728 | 0.2166 | 1.4754 | 0.2167 |
| Don't Know Rank | 0.8740 | 0.1749 | 0.8079 | 0.1731 |
| Low Income | -0.0134 | 0.0908 | 0.0224 | 0.0924 |
| Black×Low Income | 0.2782 | 0.5265 | 0.2756 | 0.8465 |
| School Quality (000's) | -8.2513 | 0.2398 | -8.3561 | 0.2996 |
| Black×School Quality | 3.8633 | 1.0452 | 3.8272 | 4.7509 |
| Private | 0.0579 | 0.0910 | 0.0404 | 0.0923 |
| Type 1 | 7.3661 | 0.2104 | 7.1922 | 0.2229 |
| Type 2 | | | 7.6635 | 0.2317 |

†5269 observations are used in this stage from 3670 individuals.

of being admitted,[37] the coefficient estimates of the rest of the parameters are similar across the two specifications. Increasing one's own SAT score as well as one's high school class rank both increase the probability of being accepted. However, increasing both one's own SAT score and the average SAT score of the school where the individual is applying by the same amount results in decreasing the probability of being accepted. College admissions are not particularly competitive until high levels of college quality are reached.[38] Neither the individual's gender nor whether the school was private had a significant effect on the probability of being admitted.

Recall that the black effect is constrained to be positive. Hence, if particular levels of school quality would imply a negative effect of being black, the white admissions rule is used. The black variable and the corresponding interactions with low income and school quality show large differences from the coefficients for whites. Low income black students are given a small advantage over other black students. The overall effect of being black on the probability of admission depends upon the quality of the school. The estimates for both models show advantages for high (low) income blacks beginning at college quality levels above 1100 (1040).

Figure 1 displays the admissions probabilities as a function of college quality for five representative agents: two white high income males, with SAT scores of 800 and 1200 respectively, two high income black males, again with SAT scores of 800 and 1200, and one low income black male with an SAT score of 800. From the graph, it is clear that the advantages blacks have in admissions only occur at very high levels of college quality. Further, these advantages have little to do with the income level of the black student: an increase in SAT score of 400 points yields a much higher increase in the probability of admission than being low income.

## 5.2 Financial Aid

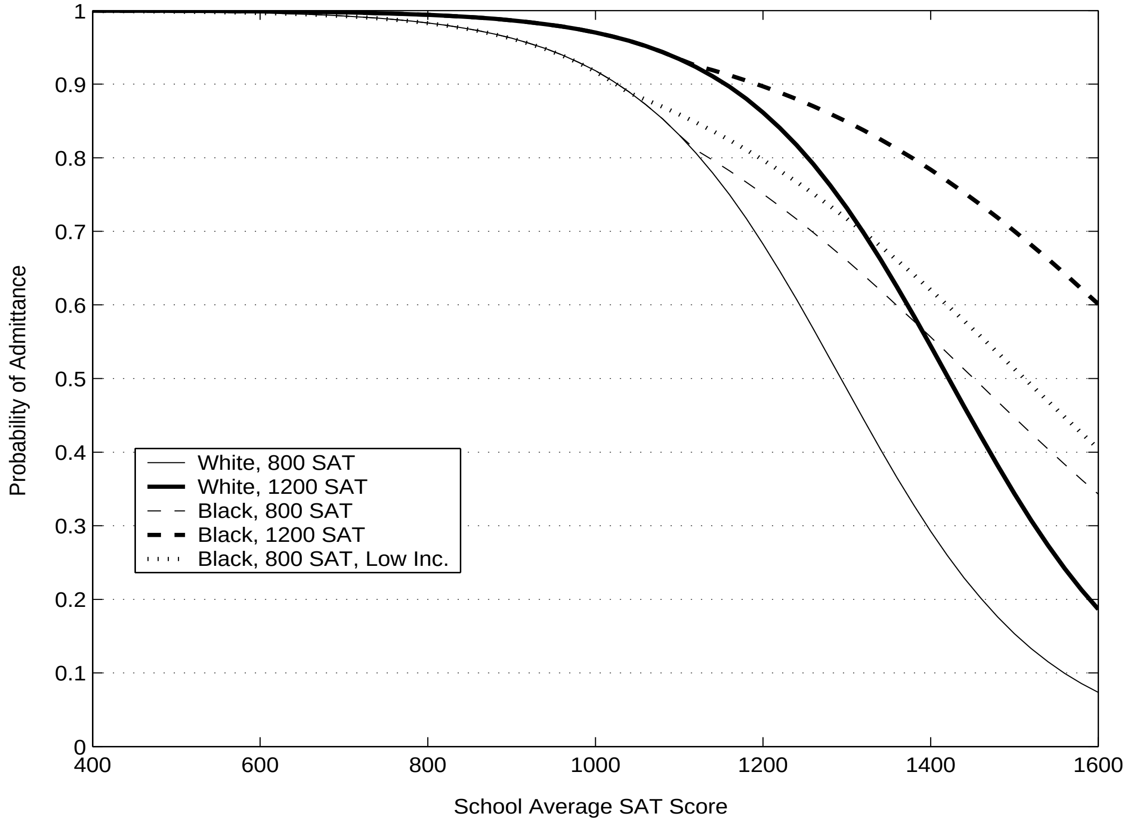
Table 3 gives the estimates of the financial aid tobit. Similar to the admissions results, while Type 2's receive more aid, adding controls for unobserved heterogeneity did not significantly affect the other parameter estimates. Those who have high SAT math scores and class ranks have higher probabilities 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 not low income. Gender was again insignificant.

In addition to admissions, black students also face different financial aid rules. The black

[37]A white male with a 1200 SAT score, at the ninetieth percentile for high school class rank and applying to a college with a 1200 average SAT score would be admitted 86% of the time if he was Type 1, but 91% of the time if Type 2.

[38]Venti and Wise (1982), Bowen and Bok (1997) and Kane (1998) found similar results.

Figure 1: Admissions as a Function of Race, School Quality, and Ability†




†High school class rank is held at the the seventy-fifth percentile. Graph is for estimates without controls for unobserved heterogeneity.

coefficient is positive and significant. However, the interaction between black and low income is negative. The interaction of black and college quality is positive but insignificant.

To get a sense of the magnitude of the black advantage in financial aid, I calculate the probability of receiving aid for a male with an 800 SAT score, a 0.8 high school class rank, who applies to a public school with school quality equal to 800 for the model without controls for unobserved heterogeneity.[39] The probability of receiving aid given the preceding characteristics is 47.2% for a low income black student, 42.9% for a high income black student, and 40.7% for a low income white student. Conditional on receiving some aid, but not full aid, a school with an 800 average SAT score pays an additional 16.4% and 5.6% of the total bill for low income and high income black students than a similar low income white student.

[39]Similar results hold when the controls for heterogeneity are implemented.

Table 3: Tobit Estimates of the Share of Costs Paid By the School[†]

| | One Type | | Two Types | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| Female | 0.0115 | 0.0140 | 0.0045 | 0.0143 |
| Black | 0.3218 | 0.0876 | 0.3081 | 0.1052 |
| SAT (000's) | 0.3236 | 0.0428 | 0.3450 | 0.0445 |
| HS Class Rank | 0.4066 | 0.0377 | 0.3840 | 0.0390 |
| Don't Know Rank | 0.2950 | 0.0326 | 0.2780 | 0.0337 |
| Low Income | 0.3491 | 0.0158 | 0.3569 | 0.0162 |
| Black×Low Income | -0.2413 | 0.0372 | -0.2410 | 0.0382 |
| School Quality (000's) | 0.3737 | 0.1060 | 0.3413 | 0.1266 |
| Black×School Quality | 0.1046 | 0.1682 | 0.1182 | 0.2057 |
| Private | 0.1789 | 0.0169 | 0.1743 | 0.0173 |
| Type 1 | -1.4676 | 0.0604 | -1.5162 | 0.0693 |
| Type 2 | | | -1.3902 | 0.0681 |
| Variance | 0.5150 | 0.0103 | 0.5122 | 0.0104 |

[†]4710 observations are used in this stage from 3459 individuals.

## 5.3 Earnings

Estimates of the earnings parameters are given in Table 4. 1986 earnings are used as the base year, with the coefficients on the year dummies and the year dummies interacted with sex omitted. Log mean state earnings conditional on education,[40] which is our one variable which affects schooling choices only through earnings, is positive and significant in both specifications. Math ability is positive for all majors and for those who do not attend college regardless of controls for unobserved heterogeneity.

The constraint that math college quality has a positive effect on earnings binds for education and business, though for business the constraint only holds when controls for unobserved heterogeneity are implemented. Controlling for unobserved heterogeneity substantially reduces the return to math college quality for natural science and business majors.

The black coefficient is negative and significant: conditional on the controls, blacks earn less than whites without a college degree. This is not true for blacks who obtain a college degree as the coefficient on black interacted with college is positive and larger than the black intercept. Affirmative action in the workplace may account for the result. With employers valuing diversity, and since the number of blacks graduating from college is small, this leads to higher earnings for blacks conditional on having a degree. It also suggests that blacks may be liquidity constrained and therefore unable to take advantage of the higher premiums from attending college.

The coefficient on black interacted with college almost doubles when controls for unobserved heterogeneity are implemented. All else equal, college-educated blacks earn over seven percent more than their white counterparts. Affirmative action in college may contribute to the coefficient increasing once we account for selection. By introducing advantages for blacks in the admissions and aid processes, schools may attract black students whose academic backgrounds, both observed and unobserved, are weaker at the margin.

Similar to the admissions and aid estimates, Type 2's receive higher earnings. This is true particularly for the natural science and social sciences/humanites. However, in all cases Type 2's have a comparative advantage over Type 1's in the college market, all else equal.

With the returns to abilities and type varying across majors, heterogeneous treatment effects exist. Table 5 calculates the earnings premiums for males by race and major. To see the difference in treatment effects, these premiums are calculated using the average characteristics by race for three groups: those who did not apply to college, those who applied but did not

[40]Recall that this variable is calculated from the March Current Population Survey and is conditional on whether an individual attended college for more than two years.

Table 4: Log Earnings Estimates†

| | | One Type | | Two Types | |
|---|---|---|---|---|---|
| | | Coefficient | Standard Error | Coefficient | Standard Error |
| | Log Mean State Earnings | 0.4313 | 0.0077 | 0.2886 | 0.0165 |
| | Black | -0.0588 | 0.0026 | -0.0676 | 0.0058 |
| | Black×College | 0.0852 | 0.0081 | 0.1418 | 0.0150 |
| SAT Math Interactions (000's) | Natural Science | 0.5414 | 0.0427 | 0.4559 | 0.0915 |
| | Business | 0.6656 | 0.0535 | 1.0602 | 0.1115 |
| | Soc/Hum | 0.2570 | 0.0298 | 0.5133 | 0.0516 |
| | Education | 0.2942 | 0.0591 | 0.3338 | 0.1040 |
| | No College | 0.3361 | 0.0086 | 0.4088 | 0.0186 |
| Math School Quality Interactions (000's) | Natural Science | 0.5848 | 0.0723 | 0.3900 | 0.1466 |
| | Business | 0.2153 | 0.0836 | 0.0000 | — |
| | Soc/Hum | 0.4271 | 0.0577 | 0.5002 | 0.1024 |
| | Education | 0.0000 | — | 0.0000 | — |
| Female Interactions | Natural Science | -0.2873 | 0.0150 | -0.2901 | 0.0254 |
| | Business | -0.2057 | 0.0155 | -0.2019 | 0.0266 |
| | Soc/Hum | -0.2255 | 0.0126 | -0.2205 | 0.0180 |
| | Education | -0.2147 | 0.0184 | -0.1922 | 0.0292 |
| | No College | -0.3575 | 0.0077 | -0.3354 | 0.0107 |
| Constant Interactions | Natural Science | | | 6.3193 | 0.1669 |
| | Business | | | 6.2952 | 0.1616 |
| | Soc/Hum | | | 6.0523 | 0.1568 |
| | Education | | | 6.3503 | 0.1605 |
| | No College | | | 6.5886 | 0.1440 |
| Type 2 Interactions | Natural Science | | | 0.5583 | 0.0174 |
| | Business | | | 0.4572 | 0.0180 |
| | Soc/Hum | | | 0.5450 | 0.0145 |
| | Education | | | 0.4623 | 0.0330 |
| | No College | | | 0.4568 | 0.0029 |

†Intercepts, year effects and sex times year effects are also included. All year and sex year effects are interacted with college. 1986 is the base year. 31,616 observations are used in this stage from 7859 individuals.

attend, and those who attended college.

Regardless of the groupings, premiums are always highest for natural science and business and lowest for education. Without controls for unobserved heterogeneity, the differences in premiums for the three groups is small both for blacks and whites. Adding unobserved heterogeneity leads to larger differences across the three groups, with those who attend college having the highest premiums and those who apply but did not attend having higher premiums than those who did not apply.[41] Adding unobserved heterogeneity leads to lower premiums in all majors for both whites and blacks, though the drop is much larger for whites. This again suggests that, perhaps due to affirmative action, college works as a better sorting device for whites than for blacks. Since premiums still differ dramatically across majors, other factors, such as compensating differentials or the effort required in the major, must be leading individuals to choose majors with lower premiums.

These premiums are much smaller than those reported in the literature. Typically estimates of this type are presented holding experience constant. However, the premiums calculated here are at a particular point in time: fourteen years after graduation. Hence, there is a tradeoff between the college premium and the lost years of experience. The returns to experience are higher if one has a college degree. However, even with these higher returns to experience, education majors still have not made up for the lost experience even after ten years. Adjusting for this experience effect yields college premia that are quite similar to the previous literature.[42]

## 5.4 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 6.

The first set of rows show the coefficients which are common across majors. Both with and without unobserved heterogeneity, 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 option more attractive, all else equal.

Important to the specification is allowing for the relative math ability squared to affect the decision as to which college to attend and whether to attend college at all. The negative coefficient on this variable implies that, even if the very best schools were free and allowed

[41] The one exception to this is education where the premiums are virtually identical across the groupings.

[42] See, for example, Keane and Wolpin (2000).

Table 5: Male Earnings Premiums By Race and Major†

| | | One Type | | | | Two Types‡ | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Natural Science | Business | Soc Sci/ Humanities | Education | Natural Science | Business | Soc Sci/ Humanities | Education |
| Whites | Did not apply | 19.4% | 18.7% | 12.4% | 4.0% | 6.4% | 5.4% | -12.9% | -19.0% |
| | Apply, did not attend | 20.1% | 21.1% | 12.0% | 3.8% | 6.9% | 10.0% | -12.0% | -19.4% |
| | Attend College | 22.4% | 23.4% | 11.5% | 3.6% | 10.8% | 10.5% | -8.5% | -19.7% |
| Blacks | Did not apply | 27.2% | 25.3% | 22.9% | 14.1% | 20.3% | 14.2% | 0.5% | -3.3% |
| | Apply, did not attend | 28.2% | 26.8% | 22.8% | 14.1% | 20.7% | 16.8% | 1.2% | -3.5% |
| | Attend College | 28.8% | 27.9% | 22.5% | 14.0% | 24.7% | 19.0% | 4.8% | -3.5% |
| Change in Premium | +100 SAT Math | 2.1% | 3.3% | -0.8% | -0.4% | 0.5% | 6.5% | 1.0% | -0.8% |
| | +100 Math Quality | 5.8% | 2.2% | 4.3% | 0.0% | 3.9% | 0.0% | 5.0% | 0.0% |

†Premiums are relative to No College and are calculated 14 years after high school graduation using the average characteristics by race conditional on not applying, applying and attending, and attending and using the average SAT math score over all schools.

‡For the two type model, the average probability of being a particular type conditional on the cell (e.g. white male, did not apply) is used.

Table 6: Utility Estimates†

| | | One Type | | Two Types | |
|---|---|---|---|---|---|
| | | Coefficient | Standard Error | Coefficient | Standard Error |
| Coefficients Common Across Majors | Black×College | 0.2457 | 0.0625 | -0.4543 | 0.0778 |
| | Net Cost | -1.5127 | 0.1735 | -1.4137 | 0.2109 |
| | Low Income×Net Cost | -1.5561 | 0.2352 | -1.3793 | 0.2547 |
| | Private School | 0.2701 | 0.0253 | 0.2144 | 0.0309 |
| | School in State | 0.0976 | 0.0215 | 0.0937 | 0.0284 |
| | (SAT Math-Quality)$^2$ | -8.9823 | 1.1471 | -8.5836 | 1.3382 |
| | Expected Log Earnings | 2.3429 | 0.4790 | 6.2231 | 1.066 |
| SAT Math Interactions (000's) | Natural Science | 7.6766 | 0.6984 | 8.8538 | 0.7540 |
| | Business | 3.0954 | 0.4935 | 0.2465 | 0.5651 |
| | Soc/Hum | 3.4154 | 0.3322 | 3.1956 | 0.3879 |
| | Education | 1.6333 | 0.5042 | 2.5549 | 0.5878 |
| Math School Quality Interactions (000's) | Natural Science | 5.1813 | 0.6758 | 3.6310 | 0.7226 |
| | Business | 2.6140 | 0.7815 | 2.6767 | 0.8352 |
| | Soc/Hum | 3.9808 | 0.5026 | 1.3850 | 0.5399 |
| | Education | 0.9296 | 0.7504 | 0.0645 | 0.8569 |
| Type 1 Interactions | Natural Science | -8.6664 | 0.6086 | -9.9144 | 0.6380 |
| | Business | -4.5538 | 0.4438 | -5.3511 | 0.4937 |
| | Soc/Hum | -4.9208 | 0.3113 | -6.2336 | 0.3606 |
| | Education | -3.1011 | 0.3632 | -4.5652 | 0.4520 |
| Type 2 Interactions | Natural Science | | | -9.3054 | 0.6301 |
| | Business | | | -4.4014 | 0.4689 |
| | Soc/Hum | | | -5.1635 | 0.3145 |
| | Education | | | -2.6477 | 0.4071 |
| Nesting Parameters | $\rho_{c1}$ (School) | 0.5040 | 0.1280 | 0.5467 | 0.1515 |
| | $\rho_{c2}$ (Major) | 0.6676 | 0.0837 | 0.5346 | 0.0816 |

†Also includes sex indicator variables interacted with major choice. 3670 observations are used in this stage.

everyone to attend, some students would find it optimal to attend schools that were better suited to their own abilities.[43]

Unobserved heterogeneity does, however, substantially affect both the black coefficient and the coefficient on expected log earnings. Without controls for unobserved heterogeneity, blacks have a preference for attending college. However, with controls for unobserved heterogeneity, the sign reverses with blacks actually preferring not to attend college, all else equal. This is in part driven by the higher monetary returns to education for blacks when controls for unobserved heterogeneity are included. These increased returns are also magnified by the increase in the effect expected log earnings has on the probability of choosing a particular schooling combination. This coefficient more than doubles in the model with unobserved heterogeneity. Blacks are more likely to choose college conditional on their characteristics, but do so because of the high college premium, not due to preferences.

The next two sets of rows show how the individual's SAT math score and the average SAT math score of the school affect the choice of school and major. Higher SAT math scores make college in general attractive and in particular the natural sciences. The same pattern is observed for the effect of the average SAT math score for the school, but this effect is dampened once unobserved heterogeneity is added to the model.

Differences in preferences for particular school-major combinations also exist across types. In addition to enjoying a comparative advantage in earnings from going to college, Type 2's also have a preference for college relative to Type 1's. This preference differential is particularly strong in the social sciences and education.

The last two rows show the estimates of the nesting parameters. Both the estimates of the nesting parameters are significantly less than one whether or not controls for unobserved heterogeneity are implemented, suggesting that unobservable preferences have a component that is correlated across school and another component that is correlated across major.

Recall that the treatment effect of attending college on earnings depended upon the choice of major, with higher premiums in the natural science and business majors. Table 7 then shows which of the treatments individuals are likely to select into conditional on attending colleges.[44] That is, what major would we expect individuals to choose had they been forced into the treatment of attending college?

The first set of rows simulates the probabilities conditional on attending for whites. Those who did not apply to college would be most likely to choose a major with a lower premium

[43] See Arcidiacono (forthcoming) for a similar result.

[44] This exercise is done by simulating the choices of the full model, including the application stage, and dividing by the simulated probability of choosing one of the college options.

had they attended, while those who attended were also most likely to choose one of the more lucrative majors conditional on attending. Regardless of controls for unobserved heterogeneity, moving down the rows shows decreases in the probabilities of choosing majors except in the natural sciences, with correspondingly large increases in choosing one of the natural sciences. Adding controls for unobserved heterogeneity actually increases the predicted probability of choosing a lucrative major, shifting the expected treatment for those who did not attend college from the social sciences and education into business.

The results for blacks are not as straight forward. Moving down the rows again shows an increase in the number of natural science majors and a decrease in the number of business majors. However, the results for social science and education majors are ambiguous. As with whites, adding unobserved hetereogeneity shifts the predicted decisions of blacks who did not attend college from social science and education into business.

### 5.5 Application Stage

Using estimates from the previous four regressions, I now estimate the parameters of the utility function for applying to college. Table 8 presents these estimates. The coefficient on the present value of future utility is both strongly 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. Further, since the coefficient falls when controls for unobserved heterogeneity are implemented, adding unobserved heterogeneity leads to a larger decrease in the variance of the college choice stage than in the application stage. Increasing the number of applications submitted is costly with a falling marginal cost. Application cost are no higher for low income students until unobserved heterogeneity is added.

Also shown in Table 8 are the log likelihoods for the two models as well as the population probabilities of being a particular type conditional on high and low income. Adding the mixture distribution to control for unobserved heterogeneity substantially increases the likelihood. Recall that Type 2's had higher admissions probabilities, were more likely to obtain lucrative financial aid packages, and also had a comparative advantage in the college sectors. The results indicate that they are also more likely to come from high income families.[45]

[45]High income is defined as having parents who earn more that $36,000 a year in 1999 dollars.

Table 7: Expected Major Choices Conditional on Attending College[†]

| | | One Type | | | | Two Types | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Natural Science | Business | Soc Sci/ Humanities | Education | Natural Science | Business | Soc Sci/ Humanities | Education |
| Whites | Did not apply | 14.1% | 29.1% | 43.7% | 13.1% | 14.5% | 32.7% | 41.4% | 11.4% |
| | Apply, did not attend | 22.2% | 27.2% | 40.5% | 10.2% | 22.5% | 30.3% | 38.2% | 8.9% |
| | Attend College | 30.8% | 23.2% | 37.7% | 8.3% | 30.6% | 23.3% | 37.8% | 8.3% |
| Blacks | Did not apply | 7.1% | 30.0% | 45.1% | 17.8% | 7.2% | 34.8% | 42.7% | 15.3% |
| | Apply, did not attend | 10.5% | 29.6% | 43.6% | 16.3% | 10.7% | 34.3% | 41.1% | 13.9% |
| | Attend College | 12.6% | 26.6% | 44.5% | 16.2% | 12.5% | 27.1% | 44.0% | 16.4% |

[†]Estimates are calculated from simulating the probabilities of choosing particular educational paths divided by the probability of attending college.

Table 8: Application Estimates†

| | One Type | | Two Types | |
|---|---|---|---|---|
| | Coefficient | Standard Error | Coefficient | Standard Error |
| PV of Future Utility | 4.1636 | 0.2316 | 2.7809 | 0.1433 |
| Application≥1 | -4.7757 | 0.1387 | -3.9501 | 0.0828 |
| Application≥2 | -3.1387 | 0.1827 | -2.3995 | 0.1274 |
| Application=3 | -1.5650 | 0.2299 | -0.8052 | 0.1734 |
| Low Income×(Application≥1) | 0.0574 | 0.0890 | -0.1146 | 0.0723 |
| Low Income×(Application≥2) | 0.0852 | 0.0800 | 0.0116 | 0.0729 |
| Low Income×(Application=3) | -0.0956 | 0.1076 | -0.0911 | 0.0922 |
| $\rho_s$ (nesting parameter) | 0.6671 | 0.0744 | 0.5102 | 0.0574 |
| | | | | |
| Prob. Type 1 \| Low Income | | | 0.6012 | 0.0099 |
| Prob. Type 1 \| High Income | | | 0.4965 | 0.0099 |
| Log likelihood for full model | -44,978 | | -38,094 | |

† 8914 observations are used in this stage. Each individual has 92 application sets to choose from.

# 6 Model Fit

Given the parameter estimates, it is possible to see how the model matches key features of the data from Table 1. Table 9 displays the actual data and the predictions of the model both for whites and blacks and with and without unobserved heterogeneity. Throughout, the general trends in the data are matched quite well, with the model with unobserved heterogeneity matching particularly well for blacks.

The first set of rows shows how the model matches the application and attendance decisions of the full sample. For whites, both models match the trends in the data. For blacks, both models underpredict the probability of applying and the number of applications, though the model with unobserved heterogeneity is much closer to the actual data.

The second set of rows are for those who applied to college, where the models' predictions are not for the subsample that actually applied to college but for who the models predict will apply to college. Again, for both models, the predicted probabilities of attending and the number of applications for whites is very similar to what is observed in the data. As will be the case throughout the rest of the section, the model without unobserved heterogeneity overpredicts the number of females choosing to apply. However, the model without unobserved heterogeneity more closely matches the SAT distribution of those who applied. For blacks, the probability of attending conditional on applying is too high. This must be the case since the model with unobserved heterogeneity underpredicted the probability of applying and the number of applications submitted yet matched the mean probability of attending for the full sample. With the exception of overpredicting the number of females applying in the model without unobserved heterogeneity, both models predict the other trends for blacks well.

The final set of rows compares the data on those who attended college with those who were predicted to attend. Both models underpredict school quality for whites and overpredict for blacks. This overprediction for blacks is much stronger for the model without unobserved heterogeneity. That the school qualities are overpredicted for blacks means that we may be overpredicting the losses due to removing affirmative action policies as advantages are much greater for blacks at higher quality schools.

Table 10 examines how well the two models predict the admissions and financial aid decisions of the schools. For admissions, I examine the overall admit rate by race as well as looking at those individuals with SAT scores above the mean. For financial aid, Table 10 focuses on the share of total cost paid by the school with separate results by race and by whether the individual came from a low income family. Both models do very well at predicting the admissions decisions regardless of whether the predictions are conditional on SAT scores. However, the model with unobserved heterogeneity does a better job of predicting the share of costs paid by the school for both the full sample and for those who come from low income families. For both whites and blacks, the model without unobserved heterogeneity over-predicts financial aid.

# 7 Policy Simulations

With the model predicting the trends in the data reasonably well, 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 in the financial aid and admission rules affect college decision-making and, in turn, future earnings. My measure of future earnings will be predicted earnings ten years after college. I perform three policy simulations all related to the removal of affirmative action: giving blacks the same financial aid rules as whites, giving blacks the same admissions rules as whites, and giving blacks both the same admissions and financial aid rules. 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

Table 9: Comparing Model Predictions of Individual Choices with the Data†

| Group | Variable | Whites | | | Blacks | | |
|---|---|---|---|---|---|---|---|
| | | Actual | One Type | Two Types | Actual | One Type | Two Types |
| Full Sample | Prob. of Applying | 0.4115 | 0.4194 | 0.4146 | 0.4133 | 0.3532 | 0.3599 |
| | Prob. of Attending | 0.2114 | 0.2085 | 0.2044 | 0.1667 | 0.1536 | 0.1562 |
| | Number of Applications | 0.5924 | 0.6039 | 0.5970 | 0.5809 | 0.4912 | 0.5037 |
| Applied to College | Prob. of Attending | 0.5137 | 0.4972 | 0.4930 | 0.4033 | 0.4350 | 0.4339 |
| | Number of Applications | 1.4397 | 1.4401 | 1.4398 | 1.4006 | 1.3908 | 1.3994 |
| | Low Income | 0.3508 | 0.3593 | 0.3554 | 0.6737 | 0.6551 | 0.6487 |
| | Female | 0.4736 | 0.5045 | 0.4880 | 0.6107 | 0.6366 | 0.6231 |
| | SAT Math | 500.3 | 496.1 | 481.0 | 360.9 | 367.3 | 356.3 |
| | SAT Verbal | 465.4 | 452.2 | 441.2 | 332.4 | 328.5 | 321.6 |
| Attended College | Number of Applications | 1.5772 | 1.6631 | 1.5702 | 1.5491 | 1.5231 | 1.5332 |
| | Low Income | 0.3169 | 0.3107 | 0.3001 | 0.6416 | 0.6643 | 0.5993 |
| | Female | 0.4757 | 0.5001 | 0.4866 | 0.6358 | 0.6643 | 0.6663 |
| | SAT Math | 529.8 | 527.7 | 514.8 | 378.9 | 393.1 | 379.6 |
| | SAT Verbal | 489.8 | 476.7 | 468.0 | 356.9 | 345.8 | 338.4 |
| | Math School Quality | 538.2 | 524.2 | 518.1 | 466.5 | 501.3 | 484.6 |
| | Verbal School Quality | 509.6 | 501.3 | 495.9 | 446.1 | 472.5 | 465.5 |

†Estimates are calculated from simulating the probabilities of choosing particular educational paths divided by the probability of attending college.

Table 10: Comparing Model Predictions of Admissions and Financial Aid with the Data†

| | | Data | One Type | Two Type |
|---|---|---|---|---|
| Whites | Prob. of Admit | 0.8978 | 0.8991 | 0.8940 |
| | Prob. of Admit \| SAT>Mean | 0.9110 | 0.9243 | 0.9198 |
| | Share of Costs‡ | 0.1036 | 0.1051 | 0.0997 |
| | Share of Costs \| Low Income | 0.1653 | 0.1812 | 0.1742 |
| Blacks | Prob. of Admit | 0.8640 | 0.8650 | 0.8591 |
| | Prob. of Admit \| SAT>Mean | 0.8830 | 0.9084 | 0.9176 |
| | Share of Costs | 0.1906 | 0.1948 | 0.1877 |
| | Share of Costs \| Low Income | 0.1948 | 0.2098 | 0.2036 |

†Estimates are calculated from summing over the probability of applying and being admitted and receiving aid and then dividing by the sum of the probabilities of applying.

‡Share of costs covered is given by $\frac{Scholarships}{TotalCost}$.

a large portion of the population.[46] However, as we will see shortly, affirmative action affects such a small percentage of the population that any general equilibrium effects are expected to be very small.[47]

Table 11 gives losses in expected earnings fourteen years after high school graduation for black males from switching blacks to the white admissions and/or financial aid rules at various quantiles. The first set of rows does not control for unobserved heterogeneity while the second set of rows does. To assess the effect the application decision has on the gains and losses associated with affirmative action, the first set of columns allows the individuals to change their application decisions based upon the change in admissions or aid rules. The second set of columns, however, restricts the application decision to be the same as before the policy change. Adding the application decisions leads to losses which are roughly one and a half to three times as large as the losses when individuals cannot adjust their application decision. Hence, rather than applying to more high quality colleges when affirmative action is removed, and thereby undoing some of the negative effects of the policy change, the effect of the policy change on earnings is reenforced by individuals choosing to either apply to lower quality colleges or not

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

[47]The estimated effects would be smaller still if schools responded to the removal of affirmative action by weighting characteristics correlated with race more heavily.

apply at all.

Adding controls for unobserved heterogeneity generally reduced the expected losses by over forty percent; controlling for selection leads to reduced losses from removing affirmative action programs. However, regardless of controls for selection or adjustments in the application decision, the expected losses in earnings are quite small. At the ninetieth percentile of losses, for example, removing both affirmative action in financial aid and in admissions reduces yearly earnings ten years after college by $410 without unobserved heterogeneity and $191 with unobserved heterogeneity. To put these numbers in perspective, the gap between black male expected earnings for the 50th percentile versus the 60th percentile is $2900. It is only at the ninety-ninth percentile that significant earnings changes occur; with largest losses at $1633 without unobserved heterogeneity and $1163 with unobserved heterogeneity.

Similar small effects of financial aid have been found in Keane and Wolpin (1999, 2000, 2001). Their studies found very little effect from tuition subsidy programs. These results are confirmed here using an entirely different methodology– allowing individuals to attend different types of schools and choosing different majors at the expense of modelling decisions far out into the life-cycle. What is noticeable about the results in Table 11 is the particularly small effect of changes in admissions rules– the effect of financial aid is always larger except sometimes at the 99th percentile.

It should be noted that the results in Table 11 are expectations. As these decisions play out, some students will make the exact same decisions as they made without affirmative action. The students who are at the margin and therefore do change their decisions based upon the rules may have much higher (or lower) future earnings than those predicted here. Table 12 looks at the expected distribution of earnings after individuals have already made their college decisions.[48] Not surprisingly, the model with unobserved heterogeneity yields a much larger spread on earnings across the quantiles. Similar to Table 11, losses are much smaller when controls for unobserved heterogeneity are implemented.

One interesting feature of Table 12 is what part of the black distribution of earnings is affected by the affirmative action policies in the model without unobserved heterogeneity. In particular, both the largest changes and the largest standard errors are found at the 90th

[48]Calculating the ex post losses from the policies would require sampling from the GEV distributions assigned for the unobervable preferences. While the GEV distribution lends itself well to obtaining probabilities of particular actions, drawing from the distribution is very difficult. Cardell (1997) shows how to take advantage of the independence assumptions to draw from a nested logit specification. No similar results are available for the BST specification. Metropolis-Hastings is also not computationally possible as the number of terms in the joint pdf increases exponentially with the number of alternatives.

Table 11: Ex Ante Expected Earnings Losses Ten Years After College for Black Males From Switching to White Admission and Financial Aid Rules †

| | | Adjustment in Application Decision | | | No Adjustment in Application Decision | | |
|---|---|---|---|---|---|---|---|
| Admission Rules | | Black | White | White | Black | White | White |
| Aid Rules | Quantile | White | Black | White | White | Black | White |
| One Type | 25th | $23 | $1 | $28 | $11 | $1 | $15 |
| | | (10) | (20) | (20) | (5) | (10) | (10) |
| | 50th | $60 | $9 | $70 | $24 | $6 | $29 |
| | | (26) | (34) | (35) | (10) | (16) | (15) |
| | 75th | $126 | $27 | $146 | $46 | $16 | $59 |
| | | (55) | (60) | (68) | (20) | (27) | (27) |
| | 90th | $330 | $86 | $410 | $101 | $46 | $145 |
| | | (140) | (117) | (143) | (43) | (53) | (57) |
| | 95th | $507 | $195 | $606 | $161 | $107 | $213 |
| | | (217) | (183) | (203) | (72) | (90) | (89) |
| | 99th | $827 | $506 | $1,320 | $281 | $330 | $610 |
| | | (362) | (317) | (393) | (120) | (184) | (170) |
| Two Types | 25th | $4 | $0 | $5 | $2 | $0 | $3 |
| | | (4) | (5) | (5) | (2) | (4) | (4) |
| | 50th | $13 | $2 | $17 | $7 | $2 | $10 |
| | | (8) | (18) | (19) | (4) | (11) | (11) |
| | 75th | $45 | $11 | $58 | $19 | $8 | $27 |
| | | (24) | (47) | (49) | (11) | (26) | (26) |
| | 90th | $134 | $36 | $181 | $52 | $22 | $79 |
| | | (68) | (96) | (99) | (27) | (53) | (51) |
| | 95th | $218 | $99 | $297 | $80 | $69 | $130 |
| | | (107) | (132) | (132) | (41) | (75) | (73) |
| | 99th | $476 | $344 | $702 | $175 | $221 | $379 |
| | | (213) | (245) | (222) | (82) | (188) | (154) |

†Calculations are for black males before making any college decisions and are relative to expected earnings given current affirmative action policies. Earnings are in 1999 dollars. Standard errors in parentheses.

percentile. Individuals at or above the 95th percentile are relatively unaffected by affirmative action policies as they are likely to attend college with or without the programs. Individuals significantly below the 90th percentile are unlikely to attend college regardless of what policies are in place.

Affirmative action may have effects in the labor market even if the channel is not through earnings. For example, attending college may lead to lower unemployment rates. Analyzing the present value of lifetime earnings requires making assumption about growth rates on earnings, the discount factor, and unemployment rates both with and without a college education. Because of the assumptions entailed, I discuss this analysis in the Appendix. I show there that only under the most extreme assumptions is there any economically significant effect of affirmative action on the present value of lifetime earnings.

If affirmative action in higher education has little effect on the labor market, what does it affect? Tables 13 addresses this question by examining the effect of different admissions and financial aid rules on the educational decisions of blacks. Without unobserved heterogeneity, removing the black advantage in financial aid results in a 9.5% drop in the number of blacks attending college. This drop is smaller when unobserved heterogeneity is added at 6.1%. That the enrollment effects are larger than the effects on earnings points to the largest decreases in the probabilities of college attendance coming from those individuals whose expected earnings would increase the least from attending college.

Removing the black advantage in admissions has a much smaller effect on the number of blacks attending college with drops of 2.3% and 1.5% for the models without and with unobserved heterogeneity respectively. While the effect of removing financial aid advantages is fairly uniform across majors, removing admissions advantages disproportionately lowers the number of majors in the natural sciences.

While removing affirmative action in admissions thus does not have a large effect on the college attendance rates for blacks, it has a dramatic effect on the number of blacks attending high quality colleges. In particular, both models predict an over forty percent drop in the number of black males attending colleges with average SAT scores greater than or equal to 1200. While this drop is large, it is counteracted by the increase in the number of blacks attending colleges where the average SAT score is below 1100.

## 8 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

Table 12: Ex Post Expected Earnings Losses Ten Years After College for Black Males From Switching to White Admission and Financial Aid Rules †

| | | Base | Adjustment in Application Decision | | | No Adjustment in Application Decision | | |
|---|---|---|---|---|---|---|---|---|
| Admission Rules<br>Aid Rules | Quantile | Black<br>Black | Black<br>White | White<br>Black | White<br>White | Black<br>White | White<br>Black | White<br>White |
| One Type | 25th | $35,227 | $35,227 | $35,227 | $35,227 | $35,227 | $35,227 | $35,227 |
| | | (223) | (224) | (223) | (225) | (222) | (223) | (222) |
| | 50th | $36,440 | $36,409 | $36,440 | $36,409 | $36,440 | $36,440 | $36,409 |
| | | (235) | (234) | (239) | (236) | (238) | (235) | (234) |
| | 75th | $38,352 | $38,289 | $38,333 | $38,264 | $38,333 | $38,352 | $38,330 |
| | | (263) | (272) | (264) | (266) | (267) | (264) | (268) |
| | 90th | $43,359 | $41,917 | $43,020 | $41,546 | $42,856 | $43,146 | $42,614 |
| | | (1278) | (1509) | (1225) | (1281) | (1383) | (1251) | (1327) |
| | 95th | $48,480 | $47,889 | $48,235 | $47,644 | $48,323 | $48,339 | $48,122 |
| | | (825) | (948) | (755) | (852) | (854) | (789) | (812) |
| | 99th | $56,333 | $56,091 | $56,003 | $55,459 | $56,311 | $56,214 | $55,956 |
| | | (706) | (802) | (686) | (798) | (724) | (688) | (708) |
| Two Types | 25th | $29,421 | $29,421 | $29,421 | $29,421 | $29,421 | $29,421 | $29,421 |
| | | (245) | (245) | (245) | (245) | (245) | (245) | (245) |
| | 50th | $30,898 | $30,898 | $30,898 | $30,898 | $30,898 | $30,898 | $30,898 |
| | | (259) | (257) | (258) | (255) | (258) | (257) | (257) |
| | 75th | $46,478 | $46,443 | $46,443 | $46,443 | $46,443 | $46,446 | $46,443 |
| | | (378) | (378) | (379) | (376) | (379) | (379) | (379) |
| | 90th | $49,537 | $49,323 | $49,537 | $49,320 | $49,537 | $49,537 | $49,505 |
| | | (445) | (434) | (408) | (400) | (439) | (431) | (416) |
| | 95th | $53,677 | $53,177 | $53,513 | $53,035 | $53,513 | $53,554 | $53,431 |
| | | (948) | (944) | (872) | (838) | (946) | (887) | (882) |
| | 99th | $67,546 | $67,263 | $67,200 | $67,065 | $67,512 | $67,348 | $67,210 |
| | | (1260) | (1252) | (1194) | (1225) | (1232) | (1202) | (1208) |

†Simulated earnings are after making all college decisions. Earnings are in 1999 dollars. Standard errors in parentheses.

Table 13: Black Male Choices Under Different Admissions and Aid Rules[†]

| | One Type | | | | Two Types | | | |
|---|---|---|---|---|---|---|---|---|
| Admission Rules | Black | Black | White | White | Black | Black | White | White |
| Aid Rules | Black | White | Black | White | Black | White | Black | White |
| Natural Science | 1.94% | 1.77% | 1.86% | 1.69% | 1.82% | 1.71% | 1.76% | 1.66% |
| | (0.18%) | (0.18%) | (0.16%) | (0.16%) | (0.22%) | (0.22%) | (0.21%) | (0.20%) |
| Business | 3.31% | 3.01% | 3.27% | 2.97% | 3.39% | 3.19% | 3.36% | 3.16% |
| | (0.46%) | (0.43%) | (0.45%) | (0.41%) | (0.49%) | (0.46%) | (0.48%) | (0.44%) |
| Soc/Hum | 5.16% | 4.66% | 5.03% | 4.55% | 5.51% | 5.16% | 5.42% | 5.08% |
| | (0.57%) | (0.61%) | (0.56%) | (0.57%) | (0.63%) | (0.66%) | (0.61%) | (0.61%) |
| Education | 1.62% | 1.48% | 1.61% | 1.47% | 1.87% | 1.76% | 1.86% | 1.76% |
| | (0.36%) | (0.34%) | (0.34%) | (0.32%) | (0.39%) | (0.37%) | (0.37%) | (0.35%) |
| College | 12.03% | 10.91% | 11.76% | 10.68% | 12.59% | 11.82% | 12.40% | 11.66% |
| | (1.15%) | (1.14%) | (1.12%) | (1.06%) | (1.26%) | (1.25%) | (1.22%) | (1.16%) |
| School Avg. SAT Score≥1100 | 1.93% | 1.62% | 1.49% | 1.26% | 1.78% | 1.57% | 1.43% | 1.28% |
| | (0.19%) | (0.22%) | (0.17%) | (0.11%) | (0.20%) | (0.22%) | (0.17%) | (0.11%) |
| School Avg. SAT Score≥1200 | 0.67% | 0.54% | 0.38% | 0.32% | 0.61% | 0.52% | 0.38% | 0.33% |
| | (0.13%) | (0.14%) | (0.06%) | (0.03%) | (0.13%) | (0.13%) | (0.06%) | (0.03%) |

[†]Standard errors in parentheses

is that the path by which earnings are affected is complicated: affirmative action affects admissions and financial aid rules, not earnings directly. Individuals can undo or reenforce the effect of changes in admissions and financial aid rules on earnings through their application behavior. 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 and where to attend and what major to choose conditional on the acceptance set. I also model the relationship between these choices and earnings. With the estimates of all the parts of the model, I simulate how constraining the admissions and financial rules blacks face to be the same as the rules for whites affects future earnings and college decisions of blacks.

Simulating the effects of removing black advantages in admission and in financial aid showed surprisingly little effect on black male earnings, despite blacks enjoying much larger premiums to attending college than their white counterparts. The small effects on expected earnings from removing black advantages in financial aid occur because those individuals who are at the margin of attending are also the ones who have the lowest treatment effect; their abilities are relatively more rewarded in the non-college market and they are the ones who are most likely to chose majors with low premiums. On the admissions side, black advantages only occur at high quality schools. Removing black advantages in admissions have little effect on earnings because the return to college quality is small and those blacks affected by the policy are most likely to attend college regardless of whether affirmative action is in place.

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.

The second extension deals with the issue of 'fit.' 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.

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## Appendix

In this appendix I make the necessary assumptions such that it is possible to compare discounted present value of lifetime earnings across different admissions and financial aid rules. In particular, it is necessary to specify the growth rate on earnings for college and no college workers across the life-cycle. The NLS72 does not track individuals far enough out to obtain these growth rates. Instead, I take individuals 19-65 in 1976 and regress earnings on a quartic function of experience with experience measured as age minus years of education minus six and perform this regression on college and no college individuals separately.[49] I further assume that individuals who pursue the no college option start working at age 19 while those who pursue the college option start working at 22. The same restrictions on earnings and hours for the NLS72 sample were used here as well.

Using the calculated growth rates, Table 14 gives the losses in the expected present value of lifetime earnings due to the removal of various parts of affirmative action under different assumptions about the discount factor and unemployment rates across the college and no college sectors. The calculations are made only for the model that accounts for unobserved heterogeneity. The first set of columns uses a discount factor of 0.95 while the second uses a discount factor of 0.98. Results are for the 90th, 95th, and 99th quantiles of earnings losses.

[49]The specification for college graduates for the experience portion yielded: $0.1512 \times EXPER - 0.00777 \times EXPER^2 + 0.000189 \times EXPER^3 + (1.845x10e^{-6}) \times EXPER^4$. The results I used for the no college sector were: $0.1283 \times EXPER - 0.00575 \times EXPER^2 + 0.000118 \times EXPER^3 + (0.966x10e^{-6}) \times EXPER^4$.

With no employment and a discount factor of 0.95, the present value of the 99th percentile of losses from removing black advantages in financial aid is a $5,211. This increases to $9,172 when both admissions and financial aid rules are removed. This latter drop is less than a 0.8% drop in the present value of lifetime earnings. Removing all advantages in admissions and financial aid yields a $21,607 drop in earnings at the 99th percentile of losses, which translates into a 1.1% drop in the present value of lifetime earnings. As with the previous tables, the results are much smaller at the 90th or even the 95th percentile of losses.

The next set of rows displays the earnings losses under different assumptions about the unemployment rates in the college and no college sectors. The largest earnings losses occur when the unemployment rate is set at zero in the college sector and ten percent in the no college sector. Earnings losses then rise as high as $27,842 at the 99th percentile when the discount factor is set at 0.98. In terms of percentage decrease in lifetime earnings, the maximum loss occurs when the unemployment rate in the college sector is set at 5% and the no college unemployment rate is set at 15%. Here, the expected present value losses at the 99th percentile are still less that 1.8%. Only under the most extreme assumptions on the discount factors and unemployment rates do we see any economically significant effects of the removal of affirmative action.

Table 14: Simulated Present Value of Lifetime Earnings Under Different Assumptions on Unemployment Rates and Discount Factors†

| | | | Discount Factor=0.95 | | | Discount Factor=0.98 | | |
|---|---|---|---|---|---|---|---|---|
| | Admission Rules<br>Aid Rules | Quantile | Black<br>White | White<br>Black | White<br>White | Black<br>White | White<br>Black | White<br>White |
| College UR=0% | No College UR=0% | 90th | $972 | $354 | $1359 | $3935 | $1072 | $5227 |
| | | | (554) | (774) | (916) | (1957) | (2796) | (2881) |
| | | 95th | $1990 | $1169 | $2881 | $6310 | $3023 | $8812 |
| | | | (978) | (1398) | (1477) | (3117) | (3901) | (3975) |
| | | 99th | $5211 | $4395 | $9172 | $14140 | $10594 | $21607 |
| | | | (2259) | (3275) | (2876) | (6395) | (7455) | (6784) |
| College UR=0% | No College UR=10% | 90th | $2588 | $685 | $3548 | $6774 | $1667 | $8794 |
| | | | (1330) | (1888) | (1960) | (3428) | (4966) | (5014) |
| | | 95th | $ 4237 | $1781 | $5529 | $10254 | $4145 | $13231 |
| | | | (1994) | (2461) | (2464) | (4872) | (5978) | (5830) |
| | | 99th | $8866 | $5921 | $12193 | $19384 | $12225 | $27842 |
| | | | (3905) | (4387) | (3866) | (9109) | (9927) | (8581) |
| College UR=5% | No College UR=10% | 90th | $1811 | $514 | $2407 | $5025 | $1315 | $6799 |
| | | | (898) | (1284) | (1323) | (2588) | (3680) | (3804) |
| | | 95th | $2902 | $1445 | $4112 | $8110 | $3382 | $10544 |
| | | | (1447) | (1846) | (1893) | (3809) | (4690) | (4691) |
| | | 99th | $6666 | $5098 | $10566 | $16789 | $10898 | $22540 |
| | | | (3017) | (3626) | (3264) | (7401) | (8253) | (7191) |
| College UR=5% | No College UR=15% | 90th | $2535 | $668 | $3454 | $6593 | $1615 | $8519 |
| | | | (1304) | (1853) | (1925) | (3332) | (4829) | (4881) |
| | | 95th | $4125 | $1728 | $5375 | $9941 | $3990 | $12798 |
| | | | (1937) | (2391) | (2388) | (4728) | (5797) | (5641) |
| | | 99th | $8613 | $5669 | $11697 | $18596 | $11693 | $26885 |
| | | | (3786) | (4242) | (3716) | (8821) | (9583) | (8240) |

†Experience effects estimated from the 1976 Current Population Survey using a quartic on wages for males aged 19-65. No College workers enter the workforce at age 19, College workers at 22. UR refers to the unemployment rate. Earnings are in 1999 dollars. Standard errors in parentheses.