A Structural Equilibrium Model of the Market for Higher Education: Assessing the Impact of Eliminating Affirmative Action

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Abstract

This paper examines the determinants of the match between graduating high school seniors and postsecondary institutions in the United States using an equilibrium framework. I jointly model the behavior of these individuals and institutions by allowing individuals' application and matriculation choices to be functions of perceived institutional policies and permitting colleges' admissions rules to depend on expected individual behavior. I estimate the parameters of a structural model with maximum simulated likelihood using data on individuals' postsecondary choices from the National Education Longitudinal Study of 1988 (NELS) and institutional information from the Integrated Postsecondary Education Data System (IPEDS). Predicted individual and institutional behavior is used to examine how the equilibrium match between individuals and colleges is affected by mandated race-neutral admission policies at public institutions. The model's predictions are also used to calculate the welfare gains or losses accrued by various demographic groups following widespread affirmative action bans in the market for higher education.

Keywords: Higher Education, Affirmative Action, College Choice, Human Capital, Simultaneous Search, Matching

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1 Introduction

This year an estimated 2.8 million students will graduate from high school in the United States and grapple with the decision about whether and where to go to college; approximately 30 percent of these students are minorities. The postsecondary opportunities available to these minority graduates are related, in part, to the existence of affirmative action policies at U.S. colleges and universities. Although most selective institutions of higher education actively seek and encourage diversity, for an increasing number of colleges the explicit consideration of race in the allocation of admission and financial aid offers is prohibited. Legal decisions and political initiatives in Texas, California, Washington, and Florida during the latter half of the 1990s may reveal a trend toward mandated race-neutral admission and financial aid policies at public colleges and universities.[1] Declining enrollments by underrepresented minorities at the affected institutions in these states have inflamed an already passionate debate about college access and the future of affirmative action in higher education.[2] Although the sharp declines in minority admission rates resulting from these policy changes receive most of the attention in the popular press, there is also evidence that college application behavior is affected by the elimination of affirmative action.[3] Additionally, rapid shifts in minority applications, admissions, and enrollments from more selective to less selective institutions within tiered systems, like the University of California, make it clear that careful empirical research on the impact of eliminating race-sensitive policies is warranted.

Although the observed changes in student and college choices in these states are very informative, it is difficult to extrapolate from the outcomes in this small sample of states/colleges to a broader scale. This research seeks to answer the following question. How would a widespread mandate for race-neutral policies in the U.S. higher education market affect the educational investment decisions of individuals and the admissions and financial aid policies of institutions? While the proliferation of lawsuits regarding the use of race by colleges does not necessarily indi-

[1] The explicit consideration of race by postsecondary institutions was banned at Texas colleges and universities with the 1996 *Hopwood* decision. Initiatives prohibiting race-sensitive policies in the public sector were passed by voters in California (*Proposition 209*, 1996), Washington (*Initiative 200*, 1998), and Florida (*One Florida Initiative*, 1999).

[2] See Tables 6 and 7 for enrollment trends in selective Texas and California colleges.

[3] See Figures 3 and 4 for trends in application and enrollment at various University of California campuses.

cate that affirmative action will disappear from higher education entirely, the increasing pressure on the U.S. Supreme Court to examine this important issue provides justification for considering the consequences of such a development.

In order to address the specific question posed above as well as a broader set of issues regarding college-going behavior, this research examines the determinants of the match between graduating high school seniors and postsecondary institutions in the United States. The two-sided matching process has important consequences for the distribution of wages and income in the economy, the quality of the pool of labor available to firms, and differential access and attainment by various racial and socioeconomic groups. The decisions of individuals and institutions are inherently intertwined; individuals consider probabilities of admission and financial aid receipt prior to submitting applications and universities form expectations about how their policies affect applicant pools and yield rates. Any change in public policy that alters the choices available to one of these two groups of economic agents necessarily modifies the behavior of the other. The equilibrium model presented in this paper incorporates the decisions of both individuals and institutions in order to avoid the potential selection bias associated with modeling only a portion of the matching process.[4] The approach employed here also captures the secondary, or equilibrium, effects that are essential for conducting meaningful policy analysis.

I allow colleges' admission rules to depend on expected individual behavior and permit individuals' application and matriculation choices to be functions of perceived institutional policies. Individuals in the model choose whether and to which colleges they apply and, ultimately, whether/where to enroll. In the application stage of the process, individuals search nonsequentially for the portfolio of college applications that maximizes their expected utility. Individuals then receive admissions and financial aid offers and learn additional information about the colleges before making a final enrollment decision. Entering the labor force or enrolling in a community college are options available to individuals at any stage of the decision-making process. Each postsecondary institution in the model chooses a threshold admission rule that is a function of observable applicant characteristics and an unobservable (to the econometrician and applicant) match value. I assume that a college's choice of admission rule is motivated by fac-

[4] See Willis and Rosen (1979), Manski and Wise (1983), and Becker (1990) for discussions of the consequences of incorrect exogeneity assumptions in models of postsecondary decision-making.

tors affecting the institution's reputation or prestige and constrained by an exogenous budgetary constraint.

The model parameters are estimated with maximum simulated likelihood using data on individuals' postsecondary choices from the National Education Longitudinal Study of 1988 (NELS) and institutional information from the Integrated Postsecondary Education Data System (IPEDS) and Barron's *Profiles of American Colleges*. Because the parameters of the model are structural, they represent the true underlying preferences of individuals and universities if the model is correctly specified. Structural parameters are invariant to changes in public policy and, as a result, can be used to analyze policy changes that have not already been implemented, have been implemented on only a small scale, or are not captured by available datasets. In the present study, predicted individual and institutional behavior is used to examine how the equilibrium match between individuals and colleges is affected by mandated race-neutral admissions policies at public institutions, and how these effects vary with demographic characteristics. Although the model permits colleges to re-weight applicant characteristics following a simulated affirmative action ban (perhaps placing greater weight on attributes that are correlated with race), I also examine the effect of several policies that could potentially replace affirmative action in higher education. For example, I simulate a policy guaranteeing a certain percentage of each high school's graduating class admission to at least one state college, which is known as an *x% program* or a *class-rank rule*. Additionally, I simulate the effect of increasing college recruitment efforts at high schools with large minority populations. Both of these policies have been implemented following affirmative action bans in California, Texas, and Florida in an attempt to counteract the resulting reduction in campus diversity.

In the next section, I summarize the literature that is relevant to explaining the postsecondary choices of individuals and the decision-making processes of colleges and universities. Sections 3 and 4 describe the theoretical models of student and university behavior, respectively, and equilibrium is discussed in Section 5. The dataset employed and summary statistics are discussed in Section 6, while Section 7 of the paper describes the estimation and simulation procedures. General estimation results are given in Section 8 and a discussion of affirmative action policy and various policy simulations are presented in Section 9. Section 10 concludes.

2 Literature

Early empirical studies of the demand for a college education, like those of Campbell and Siegel (1967) and Galper and Dunn (1969), use linear regression techniques to estimate the effect of changes in income and college cost on aggregate enrollment patterns. Though these studies elucidate the financial sensitivity of college enrollees, a great deal of information is lost in the process of aggregating individual-level data. Information about the determinants of college choice can be obtained from the preferences that students reveal when they choose college over the labor force or one postsecondary institution over another. Revealed preference and random utility studies typically compare the utility generated by the various college options available to students. Radner and Miller (1975) is the first empirical application of this type of model to the college choice decision, as well as the first to extend the number of postsecondary alternatives beyond two (college and work) through the use of a multinomial logit model (see McFadden (1978)).[5] Radner and Miller point out a potential flaw in their study and, in doing so, encourage a series of refinements attempting to simultaneously model individual and institutional behaviors. Manski and Wise (1983) is probably the most well known of these refinements. Their study addresses the application, admission, financial aid, enrollment, and completion stages of the postsecondary choice process, stressing the importance of unobservable characteristics that influence multiple stages of the matching process. Subsets of the individual and college choices are estimated jointly, however, the full set of decisions made in the matching process are not modeled together. As the authors acknowledge, treating various portions of the two-sided matching process as though they are exogenous, when in fact they are determined simultaneously *within* the decision system, may bias parameter estimates.

Research on the supply side of the higher education market struggles with the fact that most colleges and universities only loosely resemble profit maximizing firms or other nonprofit institutions that charge a price for services rendered (like hospitals). Colleges have enough unique attributes and constraints on their behavior that they are often placed into a category by them-

[5] The alternatives in early applications of the multinomial logit model were not specific institutions, but rather *types* of colleges like two-year, public four-year, private four-year colleges, and so on.

selves.[6] With no universally accepted theory of the firm to readily apply when the firms are colleges, a number of studies examine the choices made by a particular institution as a starting point for understanding college decision-making. Miller (1981) examines the supply behavior of elite private universities using data from Stanford's admissions and financial aid offices. University decision-makers maximize institutional welfare subject to a budget constraint by choosing how many of each applicant-type to admit and the composition of financial aid packages for each type. Ehrenberg and Sherman (1984) perform a similar analysis for Cornell University, where the university chooses what fraction of students' total college bill to cover rather than the composition of the aid package. Both of these institution-specific studies utilize more detailed data than is available for a nationally representative sample of colleges and, although informative, the results are not easily extended to other colleges or on a broader scale. Other research posits that colleges maximize profits subject to a zero-profit resource constraint. Rothschild and White (1995) take this approach, specifying the technology for producing different types of human capital from different types of student-inputs. Price charged, or net tuition, has the natural interpretation as the difference between human capital outputs and "wages" paid to different types of student-inputs. The institutions in this model take individual behavior as exogenous, so there is no uncertainty regarding student application or enrollment behavior. As with college demand studies, unrealistic exogeneity assumptions may result in biased parameters estimates of university decision making.

Arcidiacono (2001) models each stage of interaction between individuals and colleges, as well as choice of college major and the impact it has on future earnings. Arcidiacono's paper is the most similar to the current study, primarily because it is a structural model of behavior, so points of departure from the current model and estimation strategy are discussed throughout the paper. The most prominent differences are with regard to error structure, restrictiveness of assumptions imposed on individual behavior, dataset employed, estimation strategy, and policy simulations.

[6] See Winston (1997) for an informative and humorous discussion of colleges as unique firms.

3 Theoretical Model of Individual Behavior

At some point prior to high school graduation, an individual collects information about his postsecondary options by talking to family, friends, teachers, and guidance counselors about jobs, vocational schools, community colleges, and/or four-year colleges.[7] Based on this initial information and his expectations about wages (current and future), probabilities of admission, and financial aid packages, he ranks the alternatives and chooses a portfolio of colleges that maximizes his expected indirect utility. After submitting applications to this portfolio of schools, he learns additional information about the alternatives, such as the actual admissions and financial aid decisions of the colleges, and also how his preferences may have been altered by campus visits, more discussion with family and friends, or other less-quantifiable factors. The incorporation of this additional information is followed by a matriculation decision, which may be going to work, attending community college, or enrolling in one of the four-year colleges to which he is offered admission. As with application decisions, expected utility maximization drives his enrollment choice. The straightforward series of decisions described above is presented as an economic model of individual college-going behavior below.

High school seniors face $J+2$ postsecondary alternatives, which include the labor force, community college, and J four-year degree-granting colleges and universities.[8] Let U_{ij} be the indirect utility that individual i derives from choosing to purchase a college education from institution j. Utility is a function of observable benefits and costs associated with j, which are measured by interactions of individual characteristics and college attributes, X_{ij}. Individual characteristics contributing to utility include academic ability, race, family income, and characteristics of the individual's high school. These characteristics are permitted to interact with important attributes of colleges such as the quality and diversity of the student body, student-faculty ratio, tuition, and financial aid generosity. Additional variables in X_{ij} that vary with each potential individual/college pair are distance between i's high school and college j and the value of individual i's expected future income stream conditional on attending college j. An individual's unobserved

[7] Attempts to use gender-neutral pronouns were distracting and reduced clarity, thus, the male pronoun is used throughout.

[8] The terms college and university are used interchangably in this paper to refer to any four-year degree-granting postsecondary institution in the United States.

taste for a college education, regardless of the specific institution it comes from, is represented by an individual-specific fixed effect, μ_i. U_{ij} also may be influenced by the postsecondary decisions of friends or some other aspect of i's taste for alternative j that is known only to individual i, denoted by ξ_{ij}. These two components of utility, μ_i and ξ_{ij}, are known to individual i prior to applying or enrolling at any postsecondary institution, but are not observed by the econometrician (or colleges) during any stage of the process. For simplicity, I assume that indirect utility is a linear function of observed and unobserved benefits and costs and that values of a random disturbance term, ε_{ij}, are drawn independently from an extreme value distribution. Individuals observe their values of ε after they submit applications and before making an enrollment choice.[9] These assumptions yield an indirect utility function for individual i at college j of the form

$$U_{ij} = X_{ij}\beta + \mu_i + \xi_{ij} + \varepsilon_{ij}. \tag{1}$$

Because opportunity cost (*i.e.,* foregone income) is the greatest cost associated with college attendance and it is not captured in the X_{ij} variables discussed above, I incorporate this cost into the model by providing individuals with several "outside options," one of which is entering the work force. Any high school senior choosing *not* to purchase a college education from a four-year degree-granting institution following graduation is assumed to either enter the labor force, which yields utility U_{ilf}, or purchase a postsecondary education from a community college, which generates U_{icc} for individual i. Individual-specific taste for college, μ_i, does not appear in either U_{ilf} or U_{icc}, although both of these outside options include pre- and post-application errors, ξ and ε. I assume that ε_{ilf} and ε_{icc} are also drawn from the extreme value distribution, independently of the other ε_{ij}, and are unknown to i until after the application stage.

3.1 Application Decision

Applying to college entails costs that must be weighed against the perceived benefits of a college education. Nearly all postsecondary institutions charge some application fee that can

[9] One of the benefits of this assumption is that it allows individuals to apply to college and even be offered admission, but still choose to enter the labor market in the enrollment stage of the decision-making process. The assumption has other nice statistical advantages that will be discussed in the next section.

range anywhere from \$20 at the least selective colleges to \$70 at the most prestigious universities. In addition to these pecuniary costs, the time costs associated with college application can be substantial.[10] I assume that individual i incurs a fixed cost, κ_i, of applying to any positive number of colleges and a marginal cost for each specific institution j to which he applies, given by c_{ij}.[11]

Much like a person hunting for a new apartment or a worker searching for a new job, college-bound individuals often submit applications to several colleges because of the length of time between applying and learning whether or not an application was successful. Therefore, it is reasonable to assume that individuals who elect to apply to college submit multiple applications simultaneously or search non-sequentially.[12] This means that individuals simultaneously choose how many applications to submit as well as to which postsecondary institutions to apply.

I begin the analysis by defining a $(J \times 1)$ binary vector a_i such that $a_{ij} = 1$ if and only if individual i applies to the j^{th} college alternative. Individual i's application strategy is then defined by the set $S_{ia} = \{j \,|\, a_{ij} = 1\}$, which contains n_a elements. To be clear, S_{ia} includes only applications to four-year degree-granting institutions because I assume that all individuals have access to the outside options, which do not require an "application" in the same sense that most four-year colleges do. The value of an application strategy depends upon the expected utility generated by each alternative in S_{ia}, the probability of admission at each of these alternatives, and the cost of application. Consider a simple example where individual i applies to a single four-year institution, State College #2 (*i.e.,* $a_i = (0\ 1\ 0 \ldots 0)$, $S_{ia} = \{2\}$, and $n_a = 1$). This individual has up to three options: he may enter the labor force, enroll in community college, or attend State College #2 if offered admission. In calculating the value of this application strategy, the utility that would be generated by each of these options must be weighted by the probability

[10] In recent years, the application process has become quite streamlined through on-line, CD-based, or common application forms. The individuals in the sample I use, however, were applying to college in 1991 and likely had it about as rough as I did in 1989.

[11] Because there are most likely significant economies of scale involved with applying to multiple colleges, costs are specified such that the average cost of applying is diminishing in the number of applications submitted.

[12] Early action and early decision, which may be thought of as more sequential search methods, dramatically increased in popularity during the latter half of the 1990s. Prior to that, these programs were little-used options for exceptional students who were certain about where they wanted to go. During the sample period I examine (applications in the 1991/1992 academic year), colleges were just beginning to respond to declining high school graduation rates with increased reliance on early action/decision programs (Williams (2001), Mahoney (2002)). See Avery, Fairbanks, and Zeckhauser (2001) for a more explicit treatment of early decision/action programs.

that they are truly options. Denote P_{ij} as the probability that individual i is offered admission to postsecondary alternative j and $E\left[\max_j \{U_{ij}\}\right]$ as the expected value of U_{ij} conditional on U_{ij} being the maximum utility generated by any of the $j \in J$ alternatives to which i is admitted. I assume that the probability of admission is zero at institutions to which individuals do not apply, but that individuals can always enter the labor force or community college ($P_{ilf} = P_{icc} = 1$). I also normalize the costs of applying to community college or the labor force by setting them equal to zero ($c_{ilf} = c_{icc} = 0$). The value to individual i of following the application strategy in the current example, $S_{ia} = \{2\}$, is then given by

$$V\left(S_{ia}\right) = P_{i2}\, E\left[\max\left\{U_{ilf}, U_{icc}, U_{i2}\right\}\right] \;+\; \left(1 - P_{i2}\right)\, E\left[\max\left\{U_{ilf}, U_{icc}\right\}\right] \;-\; \left(\kappa_i + c_{i2}\right). \qquad (2)$$

If i is admitted to College #2, he gets the expected utility associated with the greater of the labor force, community college, or College #2; if i is *not* admitted to College #2, he gets the expected utility associated with the greater of the labor force and community college alternatives.[13]

When ε_{ij} is independently drawn from an extreme value distribution with standard deviation parameter τ_ε, I can write $E\left[\max_j \{U_{ij}\}\right] = \tau_\varepsilon \ln\left[\sum_{j=0}^{n} \exp\left\{\frac{X_{ij}\beta + \mu_i + \xi_{ij}}{\tau_\varepsilon}\right\}\right]$.[14] Utilizing this result and defining $\psi_{ij} = \frac{X_{ij}\beta + \mu_i + \xi_{ij}}{\tau_\varepsilon}$, equation (2) becomes

$$\begin{aligned} V\left(S_{ia}\right) \;=\; & P_{i2}\, \tau_\varepsilon \left[\ln\left(\sum_{j=lf,cc,2} \exp\left\{\psi_{ij}\right\}\right)\right] + \\ & \left(1 - P_{i2}\right)\, \tau_\varepsilon \left[\ln\left(\sum_{j=lf,cc} \exp\left\{\psi_{ij}\right\}\right)\right] - \left(\kappa_i + c_{i2}\right). \end{aligned} \qquad (3)$$

The value of an application portfolio containing $2, 3, ..., n$ colleges is defined in a similar fashion, although the expressions become increasingly complex as the number of alternatives increases. Since each of the n_a colleges in S_{ia} may deny or admit individual i, there are 2^{n_a} different admission outcomes that an individual might encounter. These outcomes, or scenarios, are summarized for notational purposes in the $(2^{n_a} \times n_a)$ binary matrix, d_{n_a}, where

[13] Similarly, if i added an application to State College #3 (*i.e.*, $a_i' = (0\ 1\ 1\ 0 \ldots 0)$, $S_{ia}' = \{2{,}3\}$, and $n_a' = 2$), then the value of following this new strategy S_{ia}' is

$$\begin{aligned} V\left(S_{ia}'\right) = {} & P_{i2}\, P_{i3}\, E\left[\max\left\{U_{ilf}, U_{icc}, U_{i2}, U_{i3}\right\}\right] + P_{i2}\, \left(1 - P_{i3}\right) E\left[\max\left\{U_{ilf}, U_{icc}, U_{i2}\right\}\right] \\ & + \left(1 - P_{i2}\right) P_{i3} E\left[\max\left\{U_{ilf}, U_{icc}, U_{i3}\right\}\right] + \left(1 - P_{i2}\right)\left(1 - P_{i3}\right) E\left[\max\left\{U_{ilf}, U_{icc}\right\}\right] - \left(\kappa_i + c_{i2} + c_{i3}\right). \end{aligned}$$

[14] The standard deviation parameter τ_ε captures uncertainty about information revealed between the application and enrollment decisions. This helps to explain why an individual with a strong taste for college j (large ξ_{ij}) and a high probability of admission at j (large P_{ij}) would ever apply to multiple colleges.

$d_{n_a}^{(l,j)} = 1$ (admitted to the j^{th} college in S_{ia} under admission scenario l).[15] Each admission scenario, indexed by l below, occurs with different probability and potentially involves a different expected maximum utility. Define $\rho_l(S_{ia})$ to be the probability that admissions scenario l occurs and $E_l[\max_{j\in S_{ia}}\{U_{ij}\}]$ as the expected maximum utility under scenario l. Thus, a general expression for the value to individual i of having an application portfolio with n_a applications to the four-year colleges in S_{ia} is

$$V(S_{ia}) = \sum_{l=1}^{2^{n_a}} \left(\rho_l(S_{ia}) \;\; E_l\left[\max_{j\in S_{ia}}\{U_{ij}\}\right]\right) - \left(\kappa_i + \sum_{j\in S_{ia}} c_{ij}\right), \tag{4}$$

$$\begin{aligned} E_l\left[\max_{j\in S_{ia}}\{U_{ij}\}\right] &= \tau_\varepsilon \ln\left[\exp\left\{\psi_{ilf}\right\} + \exp\left\{\psi_{icc}\right\} + \sum_{j=1}^{n_a} d_{n_a}^{(l,j)} \exp\left\{\psi_{_{S_a(j)}}\right\}\right] \\ \rho_l(S_{ia}) &= \prod_{j=1}^{n_a}\left[P_{iS_a(j)}\right]^{d_{n_a}^{(l,j)}} \;\; \left[1 - P_{iS_a(j)}\right]^{1-d_{n_a}^{(l,j)}}, \end{aligned}$$

where $S_a(j)$ denotes the j^{th} element of the application set S_{ia}.[16] For example, under the scenario where individual i is admitted to all n_a colleges to which he applies, the first term in the sum in equation (4) is the expected value of U_{ij} conditional on it being the maximum utility generated by having all n_a colleges and the outside options as postsecondary alternatives. The final term in equation (4) is the cost of applying to the n_a institutions in the set S_{ia}. I assume that individuals are rational and choose the application strategy that maximizes their value function. Thus, the probability of observing a particular application strategy S_{ia}, conditional on the characteristics of individual i and the attributes of all postsecondary alternatives, is the probability that $V(S_{ia})$ exceeds the value from following any other application strategy available to individual i,

$$\Pr(i \text{ applies to } S_{ia} \,|\, X_{ij}) = \Pr\left[\, V(S_{ia}) > V(S_{ib}) \;\; \forall b_i \neq a_i \;|\; X_{ij}\right]. \tag{5}$$

[15] For example, $d_{n_a}^{'} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \end{bmatrix}$ when $n_a = 2$ because the individual may be admitted at both colleges, only one of the two colleges, or neither college.

[16] The value of an application set specified in Arcidiacono (2001) includes an additive "application stage" error that is specific to the application portfolio, rather than each college in the portfolio (*e.g.*, ξ_{ij} in the current model). This choice is presumably made so that an *iid EV* assumption on the portfolio-specific error term yields a multinomial logit expression for the probability of choosing one application strategy from among all possible strategies. Allowing for an institution-specific error in the application stage makes the probability much more complicated, as is seen below, but also involves less restrictive assumptions on individual behavior.

The expressions in equations (4) and (5) are useful for deriving first order conditions that describe an individual's optimal behavior. In order to derive these optimality conditions, however, I first develop a more technical notion of the "marginal" value of an application, which is instrumental in expressing the probability in equation (5) more explicitly.

There are many potential b_i vectors that could serve as an alternative strategy to a_i in equation (5). I start with the simplest case where the vectors a_i and b_i are exactly alike with the exception of a single element. Consider a change in individual i's application behavior with regard to college k. Let a_i/k equal a_i except that $(a_i/k)_k = 1 - a_{ik}$. Thus, when $a_{ik} = 1$, $(a_i/k)_k$ refers to altering the application strategy such that an application to college k is dropped from S_{ia}, and when $a_{ik} = 0$, $(a_i/k)_k$ indicates that the strategy is altered such that an application to college k is added to S_{ia}. The application set and the number of elements it contains when the application strategy is modified in this way are then defined as

$$S_{ia/k} = \begin{cases} \{j \mid j \in S_{ia},\ j \neq k\} & \text{if } k \in S_{ia} \\ \{j \mid j \in S_{ia}\} \cup \{k\} & \text{if } k \notin S_{ia} \end{cases} \quad \text{and} \quad n_{a/k} = \begin{cases} n_a - 1 \text{ if } k \in S_{ia} \\ n_a + 1 \text{ if } k \notin S_{ia} \end{cases}. \tag{6}$$

An individual's net marginal value from changing the application strategy S_{ia} with regard to a single college k is expressed as follows for $t = \begin{cases} a_i, & k \in S_{ia} \\ a_i/k, & k \notin S_{ia} \end{cases}$:

$$MV_{a/k} = V(S_{ia}) - V\left(S_{ia/k}\right) = P_{ik} \sum_{l=1}^{2^{n_t}} \rho_l(S_t)\ D\left(E_l\left[\max_{j,k}\right]\right) - c_{ik} \tag{7}$$

$$D\left(E_l\left[\max_{j,k}\right]\right) = \begin{cases} E_l\left[\max\limits_{j \in S_{a/k}} \{U_{ij}, U_{ik}\}\right] - E_l\left[\max\limits_{j \in S_{a/k}} \{U_{ij}\}\right], & k \in S_{ia} \\ E_l\left[\max\limits_{j \in S_a} \{U_{ij}\}\right] - E_l\left[\max\limits_{j \in S_a} \{U_{ij}, U_{ik}\}\right], & k \notin S_{ia} \end{cases}$$

$$E_l\left[\max_{j \in S_t} \{U_{ij}, U_{ik}\}\right] = \tau_\varepsilon \ln\left[\exp\{\psi_{ilf}\} + \exp\{\psi_{icc}\} + \sum_{j=1}^{n_t} d_{n_t}^{(l,j)} \exp\left\{\psi_{S_{a(j)}}\right\} + \exp\{\psi_{ik}\}\right].$$

$\rho_l(S_t)$ and $E_l[\max\{U_{ij}\}]$ are defined as in equation (4).

Several nice properties of the model emerge from the marginal value expression above. It is straightforward to show that the net marginal value of applying to college k is increasing in the utility and probability of admission at k, decreasing in the cost of applying to k, and decreasing in the utility and probability of admission at other colleges in $S_{ia/k}$. These properties demonstrate the quasi-concavity of the value function, which is necessary for the existence of an equilibrium.

Equipped with this more concrete definition of the marginal value of a college application, the first order conditions describing optimal individual behavior are written succinctly as

$$\begin{array}{l} MV_{a/j} > 0, \quad \forall j \in S_{ia} \\ MV_{a/k} < 0, \quad \forall k \notin S_{ia} \end{array}. \tag{8}$$

The conditions in equation (8) state that, for each college to which individual i applies ($\forall j \in S_{ia}$), it must be the case that the expected marginal benefit from adding that application to his set exceeds the marginal cost of doing so. Similarly, for each college to which individual i does *not* apply ($\forall k \notin S_{ia}$), it must be the case the expected marginal benefit from adding an application to that college is exceeded by the marginal cost of doing so.

Given that the number of four-year postsecondary alternatives in the U.S. exceeds 1000 institutions, the number of marginal value calculations and comparisons associated with the first order conditions in equation (8) is enormous for each individual in the sample. The fact that these comparisons would have to be made for each iteration of the model parameters makes the problem computationally intractable. In order to address this issue, I look to the theoretical properties of the model for a solution. Several theoretical results indicate that many of these value function comparisons can be avoided by eliminating strategies that are dominated. Explaining the process of identifying dominated strategies requires a few additional definitions.

In order to compare S_{ia} to alternative strategies, I categorize all of the other strategies into four distinct groups: adjacent strategies, single-swap strategies, multiple-swap strategies, and non-adjacent strategies. If $S_{ia} = \{\text{MIT, Princeton, UVa}\}$, for example, then removing the MIT application from S_{ia} is an adjacent strategy to S_{ia}; it is *adjacent* to S_{ia} because only one element of the vector a_i changes. Removing applications at MIT and Princeton is considered a non-adjacent strategy to S_{ia}; it is *non-adjacent* because more than one element of the vector a_i changes. *Swap* strategies are a special case involving multiple changes to a_i where the total number college applications is maintained. In the context of the example above, dropping the application to MIT and replacing it with an application to Yale is a *single-swap* strategy; dropping applications to MIT and Princeton and replacing them with applications to Yale and

Duke is a *multiple-swap* strategy. Given these definitions, the number of necessary marginal value calculations is reduced by showing that when $V(S_{ia})$ exceeds the value of all adjacent and single-swap strategies, all non-adjacent and multiple-swap strategies to S_{ia} are dominated.[17] Consider three theorems.[18]

The first theorem says that, if an application strategy S_a is preferred to all adjacent strategies $S_{a/j}$, then that application strategy is also preferred to all non-adjacent (non-swap) strategies $S_{a/j,k}$ (where $n_{a/j,k} \neq n_a$).

Theorem 1 *If* $V(S_a) > V\left(S_{a/j}\right)\ \forall j \in J$, *then* $V(S_a) \geq V\left(S_{a/j,k}\right)\ \forall j,k \in J : j \neq k$ *and* $n_{a/j,k} \neq n_a$.

The second theorem states that, if an application strategy S_a is preferred to all single-swap strategies $S_{a/j,k}$ (where $n_{a/j,k} = n_a$), then that application strategy is also preferred to all multiple-swap strategies $S_{a/\{b\}}$ (where $n_{a/\{b\}} = n_a$ and $\{b\}$ contains more than two elements).

Theorem 2 *If* $V(S_a) > V\left(S_{a/j,k}\right)\ \forall j,k \in J : j \neq k$ *and* $n_{a/j,k} = n_a$, *then* $V(S_a) \geq V\left(S_{a/\{b\}}\right)\ \forall \{b\} \subseteq J : n_{a/\{b\}} = n_a$ *and* $n_b > 2$.

Theorems 1 and 2 are combined in a third theorem which states that, if an individual's application strategy is preferred to all adjacent and all single-swap strategies, then it is preferred to all non-adjacent and multiple-swap strategies.

Theorem 3 *If* $V(S_a) > V\left(S_{a/j}\right)$ *and* $V(S_a) > V\left(S_{a/j,k}\right)\forall j,k \in J : j \neq k$ *and* $n_{a/j,k} = n_a$, *then* $V(S_a) > V\left(S_{a/\{b\}}\right)\ \forall \{b\} \subseteq J : n_{a/\{b\}} \neq n_a$ *and* $n_b > 2$.

The extent of this result's usefulness may not be readily apparent, so I preview it briefly here. Details are presented in the data and estimation sections. Calculating the probability that i applies to a particular application set S_{ia} in equation (5) requires (among other things) comparing $V(S_{ia})$ to $V(S_{ia}, S')\ \ \forall S' \subseteq \Psi_{/S_{ia}}$, where $\Psi_{/S_{ia}}$ is the set of all possible application sets S' that exclude the colleges in S_{ia} and involve the correct total number of applications reported by i. The theorems simplify this search over *sets* in $\Psi_{/S_{ia}}$ to a search over *colleges* $k \in \Psi_{/S_{ia}}$ by identifying and eliminating dominated strategies. For example, if I determine that college

[17] The theory here is based on job search strategy research by Blau and Stern (1988).

[18] The proofs rely on the necessary conditions for an optimal application strategy in equation (8) and are found in the technical appendix. The i-subscript is suppressed below for notational ease.

$m : V(S_{ia}, m) > V(S_{ia}, k)$, $k, m \notin S_{ia}$, then the value associated with any S' that excludes college m is also less than or equal to $V(S_{ia}, m)$ and those dominated strategies can be eliminated without having to compute their value. Thus, the theorems enable the conditional probability of following application strategy S_{ia} to be written in terms of a significantly smaller number of marginal value expressions,

$$\Pr(i \text{ applies to } S_{ia} \mid X_{ij}) = \Pr\left[MV_{a/j} > 0,\, MV_{a/k} < 0 \forall j \in S_{ia},\, k \notin S_{ia} \mid X_{ij}\right]. \tag{9}$$

This specification is less restrictive of individual application behavior than the assumptions made by Arcidiacono (2001).[19]

3.2 Enrollment Decision

An individual's final choice set is determined by both his application strategies and university admissions and financial aid decisions. Define S_{ia}^A as the subset of colleges in S_{ia} which offer i admission as well as the labor force and community college alternatives, which are guaranteed. As in the standard random utility framework, individual i chooses the alternative in his choice set, S_{ia}^A, that yields the greatest utility. Conditional on unobservables μ_i and ξ_{ij} $\forall j \in S_{ia}^A$, the enrollment probability takes the multinomial logit form based on the assumption that ε_{ij} values are independently drawn from an extreme value distribution. Thus, the conditional probability that individual i chooses postsecondary alternative $m \in S_{ia}^A$, conditional on his application set, observables, and unobservables is

$$\Pr\left(i \text{ enrolls at college } m \mid S_{ia}^A, X_{ij}, \mu_i, \xi_{ij}\right) = \frac{\exp\{\psi_{im}(\mu_i, \xi_{im})\}}{\sum\limits_{j \in S_{ia}^A} \exp\left\{\psi_{ij}\left(\mu_i, \xi_{ij}\right)\right\}}. \tag{10}$$

Recall that an individual's realizations of the extreme value error, ε_{ij}, occur *after* all application decisions but before the final enrollment choice is made. This timing is important for

[19] Because Arcidiacono has to search over *sets* of colleges, he constrains individuals so that they can consider at most eight colleges in the application stage, and then they must choose any combination of up to three colleges from within those eight. These assumptions limit the number of sets over which he has to search to $\binom{8}{1} + \binom{8}{2} + \binom{8}{3} = 92$, which is necessary to make his model computationally tractible.

several reasons. First, the inclusion of a post-application stage error is consistent with observed choices in the data, such as choosing to enter the labor force or a community college despite being admitted to any number of four-year college alternatives.[20] A second benefit of the timing distinction is the tractability gained by having a closed form probability in equation (10) conditional on unobservables. Although the extreme value assumption on the distribution of ε is essential for generating the multinomial logit form, the fact that the ε_{ij}'s are not permitted to drive individuals' application behavior is also a necessary assumption. If realizations of ε occurred before application, then the ε_{ij}'s associated with the colleges in i's application set would no longer be *iid* in the enrollment stage, which is also a necessary condition for the multinomial logit form. The fact that there exists a timing difference in the realizations of ξ and ε does not imply that the *enrollment decision* is independent of the application-stage error vector, ξ. It simply means that the stochastic errors associated with the enrollment decision are independent of ξ.[21] It might be helpful to think of ξ_{ij} as representing information from individual i's guidance counselor about college j before he applies and ε_{ij} as additional information gathered through a campus visit to j after applying.

The *iid EV* assumption on the distribution of ε also involves a drawback known as the independence of irrelevant alternatives (IIA) property. The IIA property, in the context of the current model, means that the ratio of any two enrollment probabilities is not sensitive to the attributes of other alternatives in the choice set. If, for example, i is offered admission at both College A and College B, then the distributional assumption on ε implies that $\frac{\Pr(i \text{ enrolls at A})}{\Pr(i \text{ enrolls at B})}$ is independent of whether or not College C is also an option in S_{ia}^{A} and C's characteristics. If, in fact, B and C are such close substitutes that i is practically indifferent between them (*i.e.*, $\Pr(i \text{ enrolls at B}) \simeq \Pr(i \text{ enrolls at C})$), it may be reasonable to expect the $\Pr(i \text{ enrolls at A})$ to be unaffected by adding College C to i's choice set and $[1 - Pr\,(i \text{ enrolls at A})]$ to be split more or less evenly between alternatives B and C. The *iid* assumption does not permit the type of correlation between ε_{iB} and ε_{iC} alluded to here and, when combined with the extreme

[20] Of those who applied to at least one four-year college and had at least one admissions offer, 14 percent opted to enter a community college or the work force.

[21] Any correlation between the stochastic portions of the application and enrollment choices would be anticipated and, therefore, captured by ξ rather than ε according to the Law of Iterated Expectations.

value assumption, the counterintuitive result is that all three probabilities change to preserve the odds ratio of choosing A to B above. Allowing for such correlation between ε_{ij} values requires restrictive assumptions about the covariance matrix of ε and is not undertaken in the present study. I do test for the IIA property using the specification error test suggested by Hausman and McFadden (1984).

Conditional on observables and unobservables, the joint probability of observing a specific application strategy and matriculation decision given that application strategy, yields a complete description of individual behavior,

$$\begin{gathered}\Pr\left(i \text{ applies to } S_{ia} \text{ \& enrolls at } m \mid X_{ij}, \mu_i, \xi_{ij}\right) = \\ \Pr\left(i \text{ applies to } S_{ia} \mid X_{ij}\right) \cdot \Pr\left(i \text{ enrolls at } m \mid S_{ia}^{A}, X_{ij}, \mu_i, \xi_{ij}\right).\end{gathered} \tag{11}$$

Colleges and universities take this behavior into consideration when they determine their admissions rules and financial aid allocation.

4 Theoretical Model of University Behavior

Distinctive features of the market for higher education include the presence of both public and private suppliers, large federal and state subsidies, and differentiation along both vertical and horizontal dimensions. The demanders of the output produced are also employed as inputs in the production process, and some products (*e.g.,* research and graduate education) may be heavily subsidized by the production of others (*e.g.,* undergraduate education).[22] Individual institutions in the market for higher education are complex organizations comprised of various economic agents who, undoubtedly, have disparate utility functions. All of these factors make the task of modeling university decision-making quite daunting. The model presented below strives to incorporate as many of these factors as possible, but emphasis is placed on the decisions of public and private not-for-profit institutions that are related to potential undergraduate applicants and enrollees. Thus, the model of college behavior presented below abstracts from decisions regarding

[22] See James (1990) and Rothschild and White (1993,1995) for models incorporating students as production inputs and the practice of cross-subsidization.

curriculum and faculty hiring, for example, and instead concentrates on the determinants of admissions and financial aid decisions made by postsecondary institutions.

One potentially uniting factor for students, professors, administrators, alumni, donors, and legislators is the reputation or prestige of the university with which these agents are affiliated. *U.S. News & World Report's* (USNWR) annual college rankings are compelling enough that many students and their parents cite the influence of the USNWR statistics in choosing a college and that many college officials openly admit to engaging in a variety of reputation- and statistics-enhancing activities.[23] Generally speaking, the stronger an institution's reputation, the larger and smarter the applicant pool it faces, the more generous the donations (and, potentially, the state funding) it receives, the higher the quality of students and faculty it is able to attract, the better its reputation, and so the cycle continues. Colleges are aware that institutional reputation may be particularly important to potential students because a college education is an experience good; it is difficult for individuals to determine the quality of the product prior to purchasing. The industrial organization literature on experience goods indicates that reputation plays a significant role in firm behavior when the possibility of repeat purchases exists.[24] Given that a college almost certainly values repeat purchases from current students who re-enroll and from "feeder" high schools who routinely encourage their students to apply/enroll, I assume that college decisions regarding undergraduate enrollment are motivated by factors affecting institutional reputation or prestige. Each college in the model chooses a threshold admission rule that is a function of observable applicant characteristics and an unobservable (to the econometrician and applicant) match value. By calculating the expected net marginal benefit from admitting an applicant with a particular set of characteristics, the admission rule determines the subset of applicants that are offered admission.

[23]For example, college officials increasingly advertise themselves to peer institutions in an attempt to influence responses on USNWR's Academic Reputation Survey, the most heavily weighted factor in the overall ranking. See any number of recent popular press articles on these topics, such as Argetsinger (2002) and Mathews (2000).

[24]See Kreps and Wilson (1982) and Milgrom and Roberts (1986) for more on signaling product quality through advertising, reputation, and price.

4.1 Model Properties

Consider a college j with the capacity to enroll N_j total undergraduate students and room for N_{jf} students in its entering freshman class. The substantial fixed cost of providing a college education implies that this institution will attempt to fill all empty spaces each academic year. I assume that all colleges use need-blind admission processes where admissions decisions precede the distribution of financial aid funds, so the theoretical model addresses admissions decisions first.

Let the utility of college j, R_j, be an unspecified function of observable and unobservable (to the econometrician) student body characteristics, denoted by Z_j and M_j, respectively, and parameters α_t describing the relative importance of these characteristics to the institution's utility,

$$R_j = R\left(Z_j, M_j;\ \alpha_t\right). \tag{12}$$

The parameter vector α does not vary by institution; instead, the parameters are permitted to vary by institution type, t. *Types* are categories of institutions with shared characteristics like sector (public or private), academic mission, and admissions selectivity.

Colleges face a budget constraint where all sources of revenue are assumed to be exogenously governed by the processes underlying state appropriation and private donation decisions.[25] List tuition charged at college j, T_j, is exogenous by assumption and the number of enrolled students at j, N_j^e, may or may not equal institutional capacity N_j because it is a function of the matriculation choices of individuals. Uses of funds include discretionary institution-specific financial aid G_{ij}, which is distributed to enrolled students N_j^e, expenditures per student EPS_j, and an

[25] It may be the case that a public college's state appropriation is a function of student body quality, how well the racial composition of the student body reflects state demographics, or the reputation of the institution in general. It is also true that private institutions generally set their own list tuition, but modeling this choice is beyond the scope of this research.

aggregated "other uses" of funds category.[26] A simple linear budget constraint is given by

$$N_j^e T_j + Other\, Sources = \sum_{i=1}^{N_j^e} G_{ij} + N_j^e EPS_j + Other\, Uses. \tag{13}$$

The admissions and institutional aid allocation rules that are optimally chosen by the university maximize expected R_j subject to the capacity and budget constraints.

Most colleges request several items, such as essays and letters of recommendation, that relay additional information about the applicant to admissions officers. Neither the econometrician nor the applicant observe how postsecondary institutions interpret and value these supporting materials, however. Define m_{ij} as college j's assessment of the supporting materials included in i's application. Because the attributes captured by m_{ij} may include anything from leadership skills, to the ability to overcome personal hardship, to volunteer experiences, and/or artistic talent, m_{ij} is best thought of college j's beliefs of how well individual i fits in at institution j, or the *match value* between i and j.[27] While an applicant's own match value is unknown to him, I assume that he knows the distribution of match values and uses this information to gauge his probability of being offered admission. Aggregating values of m_{ij} over all students enrolled at college j yields M_j in equation (12).

If I separate out the attributes specific to the i^{th} individual in equation (12) and denote the observed and unobserved qualities of all other individuals by $Q_{j/i}$, equation (12) is transformed into an expression that is more useful for analyzing the theoretical implications of the model,

$$R_j = R\left(Z_{ij},\, m_{ij},\, Q_{j/i};\ \alpha_t\right). \tag{14}$$

Define $\tilde{R}_j$ as the highest level of utility attainable by college j given its expected budget and capacity constraints. Conditional on $\tilde{R}_j$ and the characteristics of all other enrollees at j, I can determine the minimum m_{ij} that college j would accept in exchange for an admission offer to

[26] Financial aid that is independent of a student's enrollment choice, as is most need-based aid, is assumed to be a deterministic function of observable individual characteristics. The Federal Methodology for calculating Expected Family Contribution (EFC), which determines financial need, is used to develop an approximation for EFC (see http://www.ifap.ed.gov/eannouncements/attachments/wkshtsTablesEFC.pdf for a form describing this calcuation).

[27] The inclusion of this match value is important when analyzing changes in university policies that force admissions officers to put a larger weight on less- or non-quantifiable attributes of applicants. University officials in Texas and California, where affirmative action has already been banned for several years, have cited such a change in their policies following the bans in those states in an attempt to maintain the yield rates of minorities.

applicant i. This minimum, or reservation, match value is denoted by $m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\ \alpha_t\right)$. It is a function that defines a threshold admissions rule because college j admits i iff $m_{ij} > m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\ \alpha_t\right)$ and denies i otherwise.[28] If the preferences of colleges are continuous, monotonic, and convex, then the admissions rule is monotonically decreasing in any attribute of individual i that increases the reputation or prestige of the college. The following theorem formally states this monotonicity property. It says that the more valuable applicant i is to college j in terms of his observable characteristics Z_{ij} and their effect on R_j, the lower the match value threshold he must clear to gain admission given the characteristics of other individuals. See appendix A.1 for the proof.

Theorem 4 *If* $\frac{\partial R}{\partial Z_{ij}} > 0$ *and* $\frac{\partial R}{\partial m_{ij}} > 0$*, then* $\frac{d\, m^r\left(Z_{ij}, Q_{j/i}, \tilde{R}_j;\, \alpha_t\right)}{d\, Z_{ij}} < 0.$

The monotonicity of the admissions rule is an appealing property. It implies, for example, that if college j values academic ability and racial diversity in its students, then the probability of admitting a low–quality applicant can not exceed the admission probability of a high-quality applicant in the same racial group.

Denote the joint density of observable and unobservable individual characteristics by $f\,(Z, m)$ and assume that m is independent of all attributes contained in Z.[29] The existence of a reservation match value and the independence of m from Z allows the conditional probability of admission to be written as

$$\Pr(i \text{ admitted to } j \mid Z_{ij}) = \Pr\left(m_{ij} \geq m^r\left(Z_{ij},\ Q_{j/i},\ \tilde{R}_j;\ \alpha_t\right) \mid Z_{ij}\right) \tag{15}$$
$$= \int_{m^r\left(Z_{ij}, Q_{j/i}, \tilde{R}_j;\, \alpha_t\right)}^{\infty} f\,(m \mid Z_{ij})\ dm \quad = \int_{m^r\left(Z_{ij}, Q_{j/i}, \tilde{R}_j;\, \alpha_t\right)}^{\infty} f_m\,(m)\ dm.$$

Finally, consider the following partial derivative of i's admission probability with respect to his

[28] If I were to assume a specific functional form for $R\,(\cdot)$, the reservation match value $m^r\,(\cdot)$ would be found by setting utility equal to its highest level given the budget constraint, $\tilde{R}_j$, and solving for m_{ij}. Demonstrating the basic properties of the admission rule does not require a functional form assumption.

[29] It is true that individuals with more academic ability (a characteristic in Z) may also have better recommendation letters and essays, and therefore, higher match values. Conditioning on, or controlling for observable characteristics, however, leaves only the portion of m that is independent of those characteristics.

k^{th} observable characteristic,

$$\frac{\partial\, \Pr\left(i \text{ admitted to } j \,|\, Z_{ij}\right)}{\partial\, Z_{ijk}} = -f_m\left(m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\; \alpha_t\right)\right)\frac{\partial\, m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\; \alpha_t\right)}{\partial\, Z_{ijk}} > 0. \tag{16}$$

If the university views individual characteristic k as an economic good, Theorem 4 implies that equation (16) is positive, and the model of university admissions behavior is consistent with a basic stylized fact; better applicants (as defined by university preferences) are more likely to be offered admission.

4.2 The Empirical Model

To see that the model presented in the previous section actually corresponds to a well known limited dependent variables model, define j's unobserved propensity to admit applicant i, A^*_{ij}, as the amount by which i's match value exceeds the relevant threshold,

$$A^*_{ij} = m_{ij} - \; m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\; \alpha_t\right).$$

A^*_{ij} is not observed to the econometrician (or the applicant); instead, $A_{ij} = 1\left(A^*_{ij} > 0\right) = 1\left(m_{ij} > m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\; \alpha_t\right)\right)$ is observed and the probability that college j admits applicant i is exactly the same as in equation (15).

While it is true that need-blind admissions decisions generally precede financial aid decisions in a real university setting, the potential for correlation between the two decisions due to the presence of unobserved heterogeneity and the prevalence of merit-based aid awards makes it more reasonable to model them together. An individual with a high value of m_{ij}, and therefore a high probability of admission, is also likely to have unobservable attributes that increase the probability of receiving merit-based financial aid and even increase the amount and composition of the aid offered. Even colleges opposed to the use of merit-based financial aid often have some element of a merit system *within* the need-based system employed.[30] It is also quite likely that admissions officers anticipate the amount of financial aid an applicant would require to attend,

[30] See McPherson and Schapiro (1998), as well as some of their work in progress, for evidence on this point.

and take this into consideration when making admissions decisions. Like admissions, discretionary institutional aid is a limited dependent variable; colleges may want to award *negative* aid packages by charging some students tuition *above* the list price, but all observed aid awards are strictly non-negative. Define college j's desired financial aid offer to applicant i as the latent variable, G^*_{ij}. G^*_{ij} is an unspecified function of individual and college attributes that were important to the admissions decision, as well as family income, Y_i, and an additive error,

$$G^*_{ij} = G\left(Z_{ij},\, m_{ij},\, Y_i,\, Q_{j/i};\; \gamma_t\right) + \zeta_{ij},$$

where $G_{ij} = \max\left\{G^*_{ij},\, 0\right\}$ is actually observed. If unobserved qualities of applicant i make him both more likely to be admitted and to be offered financial aid, then there exists correlation between m_{ij} and ζ_{ij}. I allow for correlation in the college's two decisions by assuming that the joint distribution of m and ζ is given by F^* and characterized by correlation parameter ρ^*.

There are three different potential admission/aid outcomes that may be observed for applicant i,

(1) i is not admitted at j and no financial aid offer is observed

$$\Pr\left[m_{ij} < m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\; \alpha_t\right)\right] = F^*_m\left[m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\; \alpha_t\right)\right]$$

(2) i is admitted at j and a financial aid offer of zero is observed

$$\Pr\left[m_{ij} > m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\; \alpha_t\right),\; \zeta_{ij} < -G\left(Z_{ij},\, m_{ij},\, Y_i,\, Q_{j/i};\; \gamma_t\right)\right] = \tag{17}$$

$$\int_{m^r(\cdot;\,\alpha_t)}^{\infty} \int_{-\infty}^{-G(\cdot;\,\gamma_t)} f^*\left(m, \zeta\right)\; d\zeta\; dm$$

(3) i is admitted at j and a positive financial aid offer is observed

$$\Pr\left[m_{ij} > m^r\left(Z_{ij},\, Q_{j/i},\, \tilde{R}_j;\ \alpha_t\right),\ \zeta_{ij} = G_{ij} - G\left(Z_{ij},\, m_{ij},\, Y_i,\, Q_{j/i};\ \gamma_t\right)\right] = \int_{m^r(\cdot;\ \alpha_t)}^{\infty} f^*\left(m, \zeta_{ij}\right)\ dm.$$

These three probabilities are used to construct college j's likelihood contribution. The parameters, α, γ, and ρ can be estimated parametrically by specifying the joint distribution $F^*(\cdot)$, semiparametrically (along with f^*) using methods from Cosslett (1983), or nonparametrically (along with f^*) using the method presented in Matzkin (1992). The costs and benefits of each of these approaches are discussed in more detail in the estimation section.

5 Equilibrium

Equilibrium in the higher education market occurs when each individual has no incentive to change his application and enrollment choices, taking the behavior of other high school seniors and all colleges as given, and each college has no incentive to alter its admissions rules, taking the behavior of other institutions and all individuals as given. The intuition about how the existence of an equilibrium is determined is as follows. Holding individual behavior fixed, I show that there exists an equilibrium among colleges. Holding college admissions behavior fixed, I show that there exists an equilibrium among individuals. See the Appendix A.2 for a sketch of this existence proof.

6 Data

The National Education Longitudinal Study of 1988 (NELS) and the Integrated Postsecondary Education Data System (IPEDS) are the data sources used to estimate the parameters of the model. NELS consists of a cohort of eighth graders in 1988 who were surveyed through 2000 by the National Center for Education Statistics. I use all students who were seniors during the

1991-1992 academic year, which yields a nationally representative sample of 9,482 observations.[31] Available information includes the number of postsecondary institutions to which each individual applied, the identity of their first and second college choices, the admissions decisions at these colleges, financial aid application and receipt, and the college in which the student enrolled, if any. Occupation and wage data are available for those students who chose to enter the labor force immediately after high school graduation. The NELS data also contains detailed information on parental education and income – as reported by the parents – as well as school-reported student outcomes. Test scores from NELS-administered reading and mathematics standardized tests are used as the measure of academic ability because SAT and/or ACT score information is available only for a select sample of individuals. Students' expectations about their future educational choices, wages, and occupations are also available. Locational coordinates for each high school represented in the NELS sample were compiled with the aid of the Geospatial & Statistical Data Center (Geostat) at the University of Virginia. Gathering the geocode data required accessing high school and school district addresses from the Common Core of Data (CCD) database maintained by the National Center for Education Statistics (NCES). Each sample member's coordinates are used to calculate distance from each of the college alternatives.

The individual-level data in NELS are supplemented by data on the supply side of the U.S. higher education market from IPEDS. This dataset contains information on all postsecondary institutions' affiliation, enrollment, tuition, faculty size and quality, accreditation, and admission requirements. IPEDS also collects very detailed financial information, including endowment income and appropriations from federal, state, and local governments. Although IPEDS is actually a panel dataset, only 1992 information is used for the present study. There are several pieces of information that are not collected by IPEDS but that are available through *Barron's Profiles of American Colleges* (1992, 1993). Electronic data from Barron's as well as the paper copy of the annual college guide provide information on student-to-faculty ratios, median SAT/ACT scores

[31]There are 12,396 seniors in NELS. Less than 500 observations, or roughly 5% of respondents, are dropped due to missing income data. The largest exclusion is respondents with missing test score data for the NELS-administered standardized test; nearly 20% of seniors (2371 seniors) are missing test scores. These omitted individuals actually have a slightly higher average family income and are a bit more likely to be white and have college-educated fathers. Thus, the typical concerns about non-random missing data doesn't seem to be an issue here. The final sample size is 9,482 individuals.

of colleges, and the number of applicants, admittees, and enrollees; all of which are potential measures of selectivity. Locational coordinates for all IPEDS colleges were also obtained with the aid of Geostat.

Combining all of these data sources links the individual micro-level data and the attributes of the postsecondary institutions to which they apply and enroll. Table 1 summarizes the sample of NELS seniors as well as the subsamples of those who apply to and enroll in a four-year college. The NELS seniors represent roughly 1,000 unique high schools and have a racial composition that corresponds closely to the 1990 Census Bureau population statistics. 56 percent of seniors apply to at least one four-year college and 33 percent submit applications at multiple four-year colleges. In the second and third columns of Table 1, the sample is restricted to college applicants and enrollees, respectively. Applicants and enrollees are more likely than the sample of seniors to be white and female, have fathers with college experience, attend private high schools, submit more college applications, and have larger family incomes.

There are more than 10,000 postsecondary institutions in the United States, 1,370 of which are public or private not-for-profit four-year institutions; the remainder are predominantly community colleges and trade schools. NELS seniors apply to over 2,500 unique postsecondary institutions, although only 1,029 of them are four-year public or private not-for-profit colleges. Thus, 75 percent of all four-year colleges in IPEDS appear in at least one NELS respondent's application portfolio. Figures 1 and 2 compare the universe of four-year degree-granting colleges available in IPEDS to the institutions represented in NELS. The top panel of Figure 1 indicates that approximately one third of the IPEDS colleges are public institutions and that a slightly larger proportion (43%) of NELS colleges are public. Examining the distribution of total fall enrollment at publics and privates in the bottom panel of Figure 1 reveals that two thirds of NELS respondents choose a public college, which closely matches the choices made by all students nationwide. In Figure 2, the top panel presents the number of IPEDS and NELS institutions falling into various Barron's selectivity categories.[32] Nearly half of all institutions

[32] Selectivity categories are combinations of Barron's ten categories. Most competitive category includes the Barron's descriptors Most, Highly+, and Highly Comp.; Very competitive includes Very+ and Very Comp.; Somewhat competitive includes Comp.+ and Comp.; Less/Non-competitive includes Less and Non-comp. and Special.

(47 percent) are classified by Barron's as being somewhat competitive with regard to admissions selectivity and just under 10 percent of all colleges are in the most competitive category. The NELS colleges are more heavily represented in the most and very competitive categories compared to all colleges in IPEDS. The bottom panel of Figure 2, which looks at the proportion of total enrollment in these types of institutions, also reflects this pattern, although the differences between IPEDS and NELS are not particularly large.

Table 2 presents the number and proportion of college applicants and enrollees listing various types of colleges as their first and second choice.[33] For example, 903 seniors, or 17.3 percent of the pool of 5,217 college applicants providing a first choice, list a college that is classified as *most competitive* by Barron's. Information on a second application is reported by 3,083 seniors and 19.9 percent of their second choices are *most competitive* schools. According to the bottom panel of Table 2, the vast majority of applicants apply to colleges close to home; 85-90 percent apply within 300 miles of their high school. Columns 3 and 4 contain the same information for the application choices of those individuals that eventually matriculate. A comparison with the first two columns indicates that a larger proportion of enrollees than applicants list first and second choices to competitive colleges. Additionally, the second application choices provided by both groups tend to be to more selective colleges than the first choices on average. There does not appear to be any significant difference in the distances of colleges to which applicants and matriculants apply. The final column in Table 2 indicates the number and proportion of enrollment, as opposed to application, choices that fall into the various categories. The colleges in which individuals actually enroll are proportionately less selective than the colleges to which they apply, which is a logical result if individuals include a "reach" school(s) in their portfolio. The tendency to stay close to home is even stronger for enrollment choices; 92 percent of individuals who matriculate do so within 300 miles of their high school.

One shortcoming of the NELS data directly affects the estimation strategy employed and should be addressed. Although NELS respondents were asked to how many postsecondary institutions they submitted applications, the variable is reported categorically as 0, 1, 2-4, and

[33]The wording of the specific questions asked of NELS respondents was, "What is the name and location of the institution you applied to that was your first (second) choice?"

5 or more.[34] This variable is problematic for several reasons. Because each respondent is asked only for his top two college choices, the two applications observed in the data may be only a subset of the full portfolio of college applications. This truncation problem is further complicated by the fact that the extent of the truncation is sometimes unclear. For example, an individual providing his top two college choices and claiming to have submitted 5 or more total applications clearly has a truncated application set. If this same individual instead reported 2-4 total applications, his application set may or may not be truncated since the number of observed college applications falls within the reported range. Truncation is a concern for 53.1 percent of all applicants to four-year institutions; 13.6 percent of applicants' sets are obviously truncated because the individuals report applying to 5 or more colleges, and another 39.5 percent are potentially truncated because the number of observed applications falls within the reported range.[35] The truncation issue is dealt with by simulating applications where an application set is either obviously or potentially truncated. The simulation algorithm and its effect on the probability of observing an individual's application set is discussed in the estimation section.

Note that the only true alternative to addressing the complications created by the categorical variable on the total number of applications is to ignore the additional information provided by this variable and assume that none of the application sets are truncated.[36] I choose not to make this assumption, given that truncation potentially occurs over half of the sample of NELS college applicants, and justify the added complexity and computational burden in two ways. First, the total number of applications submitted varies with important observable characteristics of sample members. Table 3 contains a break down of number of applications by individual characteristics for the sample of NELS seniors. Hispanics, Native Americans, and those from low-income families are the most likely not to apply to college at all. In contrast, only 8.5 percent of individuals from families with income in excess of $100,000 submit zero applications. Asian students are the most likely racial/ethnic group to submit five or more applications (16.9

[34] For the purposes of estimation, I top code the 5 or more category at 8 applications.

[35] Once I observe individuals reporting an application to a community college or trade school, I assume that they apply to no more four-year institutions than those that I already observe and, therefore, do not treat these application sets as truncated.

[36] Arcidiacono (2001) assumes that the application sets observed in the NLS-72 are not truncated. NLS-72 respondents were asked for their top three college choices, however, so this assumption may be less problematic given that a smaller proportion of his sample is likely to have a truncated set.

percent) and 70 percent of those with high family incomes submit multiple applications.

The second justification for dealing with the complexities associated with the categorical number of applications variable relates to how this information affects the decisions of college admissions officers. Many college applicants apply to more than two institutions, and admissions officers have strong incentives to take this feature of student behavior into account when setting their admission policies. This is particularly true if one believes that there is a positive correlation between the number of applications submitted by an individual and the academic quality and potential of the individual. The correlation coefficient between the standardized test score and the total number of college applications submitted is 0.50 for NELS respondents. A college's yield rate, the fraction of applicants offered admission who then choose to enroll in that college, may be perceived as a signal of selectivity and, therefore, quality (Mathews, 2000). *U.S. News & World Reports* publishes colleges' yield rates annually and its website even enables colleges to be ranked by this measure. Clearly, there exists some pressure on admissions officers to avoid admitting too many applicants who are also applying to competing colleges in an attempt to increase or maintain yield rates. Simultaneously, however, admissions officers are expected to successfully recruit as many of these high quality applicants as possible and maintain total enrollment. Juggling these competing pressures is made more manageable by accurately forecasting which applicants are likely to enroll and which are not.[37] Appendix A.3 demonstrates the substantial difference in expected yield rates, from an admissions officer's perspective, when an applicant's total number of applications is taken into account and when it is not. The exercise demonstrates the importance of using the number of applications variable, despite the complications that arise in estimation. Without this piece of data, estimated yield rates are often much higher than when calculated with the data, and therefore, potentially inconsistent with the amount of over-admitting in which colleges typically engage to fill their freshman class. Although the model of university behavior is not particularly complicated with regard to modeling competition between colleges, including the available data on this aspect of individuals' application behavior does begin to capture colleges' competition over students.

[37]Although admissions officers generally do not know to which other colleges an applicant has applied, they certainly have a sense of which colleges are their primary competitors and how likely an applicant is to be admitted by a competing institution given his credentials.

7 Estimation Strategy

7.1 The Individual Likelihood Function

The first step in specifying an estimable empirical model is constructing likelihood contributions for each sample individual and each sample college. Intuitively, an individual's likelihood contribution is simply the joint probability of observing his choice of application portfolio and his particular enrollment choice conditional on the admissions and aid offers received. I begin with the demand side of the empirical model by writing the joint probability in an individual's likelihood contribution, L_i, as separate pieces using conditional probability,

$$\begin{aligned} L_i &= \Pr\left(\text{enrolls at } m \,|\, \text{admissions outcomes } \forall j \in S_{ia}, \text{ application set } S_{ia}\right) \cdot \\ &\quad \Pr\left(\text{application set } S_{ia}\right). \end{aligned} \tag{18}$$

The first piece of L_i, the conditional probability of enrollment, is already specified in equation (10) as a multinomial logit probability, conditional on unobservables.

The second piece of the likelihood function, which is the probability that individual i follows application strategy S_{ia}, was specified in equation (9) in terms of the marginal value associated with applying to each college alternative. Unfortunately, this probability does not possess nice properties and is intractable to compute.[38] Rather than discard the theoretical model of individual behavior developed in Section 3, the kernel smoothed frequency simulator proposed by McFadden (1989) is used to approximate the probability in equation (9). Essentially, $\Pr\left[MV_{a/m} \gtrless 0\right]$ is approximated by $\Pr\left[MV_{a/m} \gtrless \eta_{im}\right]$ for $m = j, k$, where η is distributed *iid* extreme value with standard deviation parameter, τ_η. τ_η is chosen so that η has a small variance because, as $Var(\eta) \longrightarrow 0$, the approximation converges to the true probability in which I am interested.[39] These assumptions allow the probability of applying to the set of colleges in S_{ia} to

[38] Specifically, the marginal value associated with a single-swap strategy is not monotonic in μ_i. The sign of the first derivative depends on the relative admissions probabilities and expected value of the maximum terms of the colleges being swapped. The intuition here is that, as i's unobserved taste for college increases, it is unclear whether i will want to apply to fewer colleges with higher admissions probabilities or more colleges with lower admissions probabilities. This is really about the fact that two colleges in an application set may be complements for one person and substitutes for another.

[39] Even if the variance of η does not go to zero, this is still a very good approximation of the true probability. See Keane and Wolpin (1997), Eckstein and Wolpin (1999), and Todd and Wolpin (2002) for applications of this method.

be expressed as the product of Logit probabilities,

$$\begin{aligned}\Pr\left(i \,\text{applies to}\, S_{ia} \mid X_{ij}\right) &= \prod_{j\in S_{ia}} \left(MV_{a/j} > \eta_{ij}\right) \prod_{k\notin S_{ia}} \left(MV_{a/k} < \eta_{ik}\right) \\ &= \prod_{j\in S_{ia}} \left[\frac{\exp\left\{\frac{MV_{a/j}}{\tau_\eta}\right\}}{1+\exp\left\{\frac{MV_{a/j}}{\tau_\eta}\right\}}\right] \prod_{k\notin S_{ia}} \left[\frac{1}{1+\exp\left\{\frac{MV_{a/k}}{\tau_\eta}\right\}}\right].\end{aligned} \tag{19}$$

The likelihood contribution of individual i, conditional on the parameter vector θ and unobservables μ_i and ξ_{ij}, is the product of the two pieces laid out in equation (18),

$$L_i\left(\theta,\mu_i,\xi_{ij}\right) = \left[\frac{\exp\left\{\psi_{im}\left(\theta,\mu_i,\xi_{im}\right)\right\}}{\sum\limits_{j\in S_{ia}^A} \exp\left\{\psi_{ij}\left(\theta,\mu_i,\xi_{ij}\right)\right\}}\right] \cdot \tag{20}$$

$$\prod_{j\in S_{ia}} \left[\frac{\exp\left\{\frac{MV_{a/j}\left(\theta,\mu_i,\xi_{ij}\right)}{\tau_\eta}\right\}}{1+\exp\left\{\frac{MV_{a/j}\left(\theta,\mu_i,\xi_{ij}\right)}{\tau_\eta}\right\}}\right] \prod_{k\notin S_{ia}} \left[\frac{1}{1+\exp\left\{\frac{MV_{a/k}\left(\theta,\mu_i,\xi_{ik}\right)}{\tau_\eta}\right\}}\right].$$

The unconditional likelihood contribution is found by integrating equation (20) over the values of μ_i and ξ_{ij} that satisfy Theorems 1, 2 and 3,

$$L_i\left(\theta\right) = \int\limits_{\Lambda}\int L_i\left(\theta,\mu,\xi\right)\ f\left(\mu,\xi\right)\ d\xi\ d\mu, \tag{21}$$

where $f\left(\mu,\xi\right)$ is the joint distribution of the unobservables and

$\Lambda = \left\{\mu_i,\xi_{ij} : V\left(S_{ia}\right) \geq V\left(S_{ia/j}\right) \text{ and } V\left(S_{ia}\right) \geq V\left(S_{ia/j,k}\right)\ \forall j,k \in J : j \neq k \ \&\ n_{a/j,k} = n_a\right\}.$

The likelihood contribution in equation (21) raises several issues. First, the multidimensional integral can not be computed analytically. Simulation methods are used to approximate the multidimensional integral instead. Second, the function $L_i\left(\theta,\mu_i,\xi_{ij}\right)$ is not continuous in the parameter vector θ because the number of applications in the set is discrete. This means that small changes in θ may cause discontinuous jumps in the application set, which make it impossible to employ derivative-based optimization methods in maximizing the likelihood function. Thus, in order to have derivatives that actually converge on a set of parameter estimates, the simulator chosen must also possess nice smoothness properties. An importance sampling technique solves both of these problems and does so with smaller levels of simulation error than other simulators available (Stern, 1997).

7.2 Simulation and the Estimated Individual Likelihood Function

Define $g(\mu, \xi)$ to be a density with the support Λ, where Λ is defined as above. Multiplying and dividing equation (21) by $g(\mu, \xi)$ yields

$$L_i(\theta) = \int_\Lambda \int \frac{L_i(\theta, \mu, \xi)\ f(\mu, \xi)}{g(\mu, \xi)}\ g(\mu, \xi)\ d\xi\ d\mu. \tag{22}$$

The density $g(\cdot)$ is chosen to have the same support as ξ, μ and such that $\frac{L_i(\theta,\mu,\xi)\ f(\mu,\xi)}{g(\mu,\xi)}$ is bounded, smooth in θ, and easy to evaluate given μ and ξ. The importance sampling simulator for $L_i(\theta)$ is

$$L_i^R(\theta) = \frac{1}{R}\sum_{r=1}^{R} \frac{L_i\left(\theta, \mu_i^r, \xi_{ij}^r\right)\ f\left(\mu_i^r, \xi_{ij}^r\right)}{g\left(\mu_i^r, \xi_{ij}^r\right)}, \tag{23}$$

where r indexes R draws of μ_i and ξ_{ij}. The specific form of the importance sampler $g\left(\mu_i^r, \xi_{ij}^r\right)$ is motivated by a data limitation in NELS. Please see Appendix A.4 for details.

The simulated log-likelihood function that is maximized is the sum of all individuals' simulated log-likelihood contributions,

$$\ln L^R(\theta) = \sum_{i=1}^{N} \ln L_i^R(\theta), \tag{24}$$

where the parameters to be estimated are $\theta = \left\{\boldsymbol{\beta}, \mu_\mu,\ \sigma_\mu^2,\ \mu_\xi,\ \sigma_\xi^2, \tau_\varepsilon\right\}$. The maximum simulated likelihood estimates of θ, denoted by $\widehat{\theta}$, are the values of those parameters that make the choice probabilities and the observed choices of NELS sample members most closely correspond.[40]

7.3 The University Likelihood Function

The likelihood contribution of a college is the joint probability of observing that college's admissions and financial aid decisions. Recall that there are three possible admission/aid outcomes that may be observed in the data. The product of the probabilities associated with these outcomes defines college j's likelihood contribution,

[40] MSL is consistent if $R \to \infty$ as $N \to \infty$. This result should not interfere with inference based on MSL estimate of θ because Börsch-Supan and Hajivassiliou (1993) show that MSL yields precise parameter estimates in polychotomous choice models with a small, fixed number of simulations R.

$$
\begin{aligned}
L_j \quad = \quad \prod_{i \in \Upsilon_j} & \left[\Pr \left(\text{ college } j \text{ denies } i, \, G_{ij} \text{ unobs} \right) \cdot \right. \\
& \Pr \left(\text{ college } j \text{ admits } i, \, G_{ij} = 0 \right) \cdot \qquad (25) \\
& \left. \Pr \left(\text{ college } j \text{ admits } i, \, G_{ij} = G^*_{ij} \right) \right] ,
\end{aligned}
$$

where Υ_j is the set of NELS respondents who apply to college j. Using the specification for these three pieces given in equation (17), the likelihood contribution of college j is

$$
\begin{aligned}
L_j(\alpha, \gamma, \rho) \quad = \quad & \prod_{i \in \Upsilon_j} F^*_m \left[m^r \left(Z_{ij}, Q_{j/i}, \tilde{R}_j; \ \alpha_t \right) \right]^{1 - A_{ij}} \qquad (26) \\
& \left(\int_{m^r(\cdot;\, \alpha_t)}^{\infty} \int_{-\infty}^{-G(\cdot;\, \gamma_t)} f^*(m, \zeta) \ d\zeta \ dm \int_{m^r(\cdot;\, \alpha_t)}^{\infty} f^* \left[m, \zeta_{ij} \right] \ dm \right)^{A_{ij}} ,
\end{aligned}
$$

and the function maximized is the sum of all colleges' log-likelihood contributions,

$$
L(\alpha, \gamma, \rho) = \sum_{j=1}^{J} \ln \left[L_j(\alpha, \gamma, \rho) \right] \qquad (27)
$$

There are several options for estimating the college likelihood function parameters in equation (27). First, I can estimate the parameters parametrically by assuming a joint distribution for m and ζ. A fairly common assumption is that these two errors have a joint normal distribution, which assigns F^* a functional form given by the standard normal cdf, Φ.[41] As Cosslett (1983) points out, there is generally no *a priori* knowledge about F^* and even the assumption of normality can lead to inconsistent parameter estimates in a limited dependent variables model. Applying the semiparametric distribution-free estimator of Cosslett (1983) to the current problem involves assuming that the nonstochastic portions of A^*_{ij} and G^*_{ij} (m^r and G, respectively) are known functions of the parameters and then estimating the likelihood function over a space of functions and parameters.[42] This approach permits f^* to be simultaneously estimated with the

[41] Manski and Wise (1983) take this approach in jointly modeling the a binary application choice and admission outcome (see Chapter 4).

[42] As he points out, making incorrect assumptions about the nonstochastic portions of A^*_{ij} and G^*_{ij} is a specification error that arises in all economic modeling, rather than a problem associated with binary or censored outcome models.

parameters of the model. The final option for estimating equation (27) is the fully nonparametric method of Matzkin (1992). She assumes that known properties of $m^r(\cdot)$ and $G(\cdot)$ are useful for estimating these functions from the subset of functions known to have these specific properties. In practice, this nonparametric method would involve estimating equation (27) over the triple (m^r, G, F^*).

While both the semiparametric and nonparametric estimators are less restrictive, and therefore preferable, neither is identified by the data available in NELS. I observe approximately 5,000 admissions decisions for the NELS respondents at more than 1,000 different colleges, yielding less than five admissions decisions per college on average. In reality, the applications are lumpier (*e.g.,* 20 applications to the University A and 1 application each to Colleges B, C, and D). Thus, I opt for the parametric approach and assume that the joint distribution of m and ζ is normal.[43]

7.4 Identification

The parameters in the individual indirect utility function, which describe the importance of interactions of student and college attributes, are identified by observed application and enrollment choices. Data on the income earned by an earlier cohort of individuals with varying levels/qualities of postsecondary education and wage data from the latest wave of the NELS survey (conducted in 2000) identify the effect of expected future income on indirect utility. Variation in local labor market conditions and wages identifies the marginal utility from working, while differing access to community colleges (which vary by number and quality in each state) provides information about the marginal utility from choosing a community college. The total number of college applications submitted identifies variation in the distribution of the college taste parameter μ and variation in the distribution of post-application, pre-matriculation information ε. Additionally, some identification arises from the nonlinear functional forms that are generated by the *iid EV* assumption on ε. Finally, the parameters describing the weights on various student attributes in the college reputation function are identified by reported admission offers/denials

[43] Due to limited financial aid information in NELS, I currently estimate only the parameters associated with the admission decision and assume that financial aid is exogenously determined. An alternative to this approach is to utilize better financial aid information from the National Postsecondary Student Aid Survey (NPSAS) to estimate the joint admissions and aid likelihood function. The latter approach is preferable, but the former is employed temporarily in order to estimate a preliminary set of structural demand parameters.

and variation across colleges in median SAT score, racial composition of the student body, and proportion of enrollees who are state residents.

8 Results

In this section I present some preliminary data analysis, estimates of the structural parameters, and then discuss several specification tests of the model.

8.1 Preliminary Data Analysis

The distribution of applications in Table 3 was discussed previously, but it is also informative to examine the distribution of admissions offers. Table 4 contains the breakdown of admissions outcomes for first and second application choices and by total number of applications submitted. Out of the pool of 5,217 college applicants, 4,267 (or 82 percent) were offered admission at the college listed as their first choice. Of the 2,980 individuals providing a second choice, 2,020 (or 68 percent) were admitted to their second choice. The high rates of admission, especially at first choice colleges, indicate substantial self-selection (*e.g.,* individuals apply where they are likely to be admitted) and may make a case for the notion that all of the action is going on in the application stage when individuals are self-selecting. The admission rates in Table 4 may be overstated,[44] but they are actually a bit lower than comparable measures in the literature. Kane (1998) found that 89 percent of his sample of four-year college applicants reported being offered admission (High School & Beyond database, high school class of 1982). Similarly, the admission rate reported by Manski & Wise (1983) was 90 percent for the college applicants in the class of 1972 (NLS-72 database). Additional patterns consistent with the literature emerge when I estimate a probit of admissions outcomes by college selectivity (see Kane (1998), Table 12-2). Table 5 examines the difference in the probability of admission associated with various individual characteristics. Holding constant individual test scores and the median SAT score at the college to which each applies, Table 5 shows that black and Hispanic applicants to the most selective

[44] The reporting incentives are problematic for both applicants and colleges; students may prefer not to admit they've been denied and colleges may wish to overstate selectivity.

colleges are 13 and 6 percent, respectively, more likely that observationally equivalent white applicants to be offered admission. These marginal effects are consistent with Kane (1998), who reports a 10 percent estimated effect for Blacks and 8.6 percent for Hispanics ten years earlier. The effect of being an underrepresented minority on probability of admission is actually negative and statistically insignificant at colleges with lower selectivity and in the full sample of colleges.

8.2 Structural Parameter Estimates

To be written.

8.3 Specification Tests

The first specification test examines whether it is important to correct for truncation of the college application sets observed in the data. I impose a maximum of two on the total number of applications an individual may submit, which is the maximum number of college applications I observe in the NELS data. If, when I re-estimate the model parameters, I discover that this restriction has no effect on individual postsecondary choices, then I have some evidence that I should not bother with the complications added by using the categorical variable on total number of applications submitted. If this restriction does affect individual behavior, then I have some justification for including this piece of data.

The second specification test addresses the independence of irrelevant alternatives (IIA) property resulting from the *iid EV* assumption on the distribution of ε. If S_{ia}^A is i's choice set going into the enrollment stage and $\widehat{S}_{ia}^A$ is a subset of the colleges in S_{ia}^A, then the multinomial logit model is supported if the probability of choosing alternative j from S_{ia}^A equals the probability of choosing j from $\widehat{S}_{ia}^A$, given $j \in \widehat{S}_{ia}^A$. I estimate the model's parameters under both choices sets, S_{ia}^A and $\widehat{S}_{ia}^A$, and then compare them. If the parameter estimates are similar enough, the multinomial logit model is supported given the specification of the explanatory variables; if the estimates are statistically different, the IIA property does not hold and either multinomial logit is too restrictive or the explanatory variables are misspecified (Hausman and McFadden, 1984).

9 Discussion of Policy Experiments

9.1 Affirmative Action

As mentioned in the introduction, legal decisions and political initiatives in Texas, California, Washington, and Florida during the latter half of the 1990s may reveal a trend toward mandated race-neutral admission and financial aid policies at public colleges and universities. Enrollments by various minority groups at the affected institutions in these states have declined and shifted from more selective to less selective institutions within tiered systems like the University of California. Bob Laird (2002), Director of Undergraduate Admissions at Berkeley during the mid-late 1990s, points out that many of the minority enrollment statistics reported by the press apply to the University of California system as a whole, when in fact there is evidence of "... a continuing shift of underrepresented minority students, especially African-American students, from Berkeley and UCLA to less competitive UC campuses." These trends are not due to declining yield rates, the proportion of admitted minorities who matriculate, but are driven by changes in application behavior and admission rates of minorities. Figures 3 and 4 depict the underlying causes of the shift described by Laird in terms of application and admission rates of black relative to white California residents from 1995-2000. These graphs make it reasonably clear that the application responses of individuals *and* admission responses of universities have changed over time and vary with race/ethnicity.

Despite information on application, admission, and enrollment trends at a handful of institutions and abundant anecdotal evidence on both sides of the affirmative action debate, it remains unclear how a widespread mandate for race-neutral policies in higher education would affect the choices of all economic agents in the market for higher education. While the proliferation of lawsuits similar to Texas' *Hopwood* case does not necessarily indicate that affirmative action will suffer the same fate on all college and university campuses, these lawsuits do indicate that careful empirical research on this topic is warranted.[45]

[45] Lawsuits regarding affirmative action policies are currently pending or on appeal in Georgia, Maryland, and Oklahoma. The use of race in undergraduate admissions and financial aid at the University of Michigan was very recently upheld on appeal in May 2002. The Supreme Court is currently deciding whether to take up this case and another case involving race-conscious admissions policies by the University of Michigan Law School.

I simulate the effect of four policy changes related to affirmative action in higher education.[46] In the first simulation, I restrict the admission rules set by all public universities such that they do not depend explicitly upon race and then re-estimate all of the parameters in the model. This experiment predicts the affect of a widespread ban on race-sensitive policies while allowing both individuals and all colleges (including private institutions) to re-evaluate their optimal behavior.

The other three policy experiments conducted combine the affirmative action ban from the first simulation with an additional policy change designed to potentially offset the effects of the ban. In the second experiment, I replace race-sensitive policies with a program that guarantees, for a certain percentage of the top graduates from each high school in the state, admission to at least one public state university. These percentage rules, called *x% programs* or *class-rank rules*, were instituted in California, Texas, and Florida following the elimination of affirmative action in their public colleges, where the percentage of top seniors granted admission ranged from 4% to 20%. Again, all of the model parameters are re-estimated to permit institutions and individuals to re-optimize.

The third policy experiment simulates the effect of an affirmative action ban along with increased recruitment efforts by public colleges within a state at state high schools with large minority populations. Multiple admissions offices in states that have banned affirmative action have indicated this type of response to the ban in an attempt to maintain campus diversity. For example, visiting high schools within the state that have historically enrolled few or no students at the state's selective public colleges falls into this category. Such visits may inform students about the application procedure or even explain an *x% program*. A change in recruitment effort is harder to quantify than an *x% program*, so the policy change is simulated in two different ways: (1) assume that increased minority recruitment provides minority students with information about their match value(s) at the public college(s) recruiting them (*i.e.,* reduces the variance of the distribution of m_{ij}), and (2) assume that outreach efforts overcome psychological barriers of minority students, which essentially reduces the cost of applying to those colleges.

A final policy experiment couples the simulated ban at public institutions with programs

[46] The counterfactual questions examined in this paper are very different from the policy experiments conducted by Arcidiacono (2001), in which guaranteed college admission for all, waived tuition for all, and the combination of these two policy changes are examined.

designed to improve the college experience, retention, and success of minorities. Programs that would be classified under this category vary from the provision of pre-college math and science training in minority communities to increased funding for an Office of African-American Affairs and/or other minority student organizations. The pre-college programs are simulated as increases in ξ_{ij} values for minorities at all j public colleges in their state of residence, which directly affects U_{ij}. Recall that ξ_{ij} values are known to individual i prior to applying, so I am implicitly assuming that participation in a pre-college program or awareness of good minority student services affects an individual's affinity for the specific colleges providing the service prior to applying.[47]

The policy simulation results will be compared to the patterns observed in Texas and California following race-neutral admissions, as well as following the implementation of *x% programs* in both states. Tables 6 and 7 show the patterns of enrollment at selective public universities in these states beginning in 1995. The *Hopwood* decision first affected individuals applying for the fall of 1997. As indicated in Table 6, the number and proportion of first-time black and Hispanic freshman in selective Texas public institutions fell in both 1997 and 1998. The small rebounds in these populations evident in 1999 and 2000 likely reflects the *Top 10 Percent Law*, which was passed in 1997 and implemented beginning with the fall class of 1998.[48] Table 7 tells a similar story for the University of California at Berkeley, the most selective of the UC schools. Although *Proposition 209* was passed in 1996, the first class affected was the entering class of 1998. As in Texas, the number and proportion of black and Hispanic Berkeley enrollees falls dramatically in 1998. Asian students represent an increasing proportion of first-time freshman in both states.

Research utilizing these observable pre- and post-ban outcomes is informative and viewed as complementary to the present study.[49] It is difficult, however, to extrapolate to a wider set of

[47]It should be noted that all of the policy experiments that are coupled with a simulated affirmative action ban can be conducted on their own. Several states that were not affected by the recent court rulings or voter initiatives have implemented or considered *x% programs*, for example.

[48]It is interesting to note that UT-Austin had an existing top ten percent rule in effect prior to the *Hopwood* case and the late 1990s, which did not receive as much publicity. Thus, observable changes in minority enrollment patterns following the 1998 ten percent rule may be capturing some sort of announcement effect rather than the effect of a change in policy.

[49]See, for example, Chan and Eyster (1999), Kain and O'Brien (2001), and Long (2001).

states/institutions based on the outcomes observed in these few states/institutions. Additionally, the observed changes in the behavior of individuals and public colleges within these states tell us little or nothing about secondary effects on the choices of private institutions and colleges in other states. The affirmative action replacement policies that have been implemented in several states serve to confound the otherwise ideal natural experiments resulting from these policy changes. For example, financial aid to minorities was increased dramatically at public colleges in Florida simultaneously with the elimination of race-sensitive admissions. Minority enrollment in the Florida system actually *increased* as a result (although not at selective campuses), but the individual effects of the two policy changes are impossible to separate, making it even more difficult to extrapolate observed outcomes to a wider set of states and institutions. The structural approach taken here is able to distinguish between the effect of an affirmative action ban and the effect of additional changes in education policy following a ban.

10 Conclusion

This paper specifies a model of the process by which individuals are matched with postsecondary alternatives, which incorporates the two-sided, interdependent nature of the matching process. Additional attention is given to modeling individual decision-making in the application stage in order to omit bias from parameter estimates and based on observed changes in application behavior in states that have banned Affirmative Action. Estimation of the structural parameters will allow an analysis of the policy simulations described in the previous section. The predicted effects of these changes to higher education policy will ideally shed new light on the debate over the potential effects of a widespread affirmative action ban and the usefulness of several new policies in maintaining minority access to higher education.

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A Appendix

A.1 Proofs of Theorems

Theorem 1: If $V(S_a) > V(S_{a/j})\ \forall j \in J$, then $V(S_a) \geq V(S_{a/j,k})\ \forall j,k \in J : j \neq k$ and $n_{a/j,k} \neq n_a$.

The assumption that $V(S_a) > V(S_{a/j})\ \forall j \in J$ in Theorem 1 produces conditions that state, for all colleges to which an individual applies, the marginal cost of applying must be less than the expected marginal benefit associated with the college and, for all colleges to which an individual doesn't apply, the marginal cost of applying must be greater than the expected net marginal benefit associated with the college. If ρ and the expected value of the maximum utility are defined as in the text of the paper, then these conditions are given by

$$c_{ij} \begin{cases} < P_{ij} \sum_{r=1}^{2^{n_{a/j}}} \rho_{ir}\left(S_{a/j}\right)\left(E_r\left[\max_{l \in S_{a/j}} \{U_{il}, U_{ij}\}\right] - E_r\left[\max_{l \in S_{a/j}} \{U_{il}\}\right]\right), & \forall j \in S_a \\ > P_{ij} \sum_{r=1}^{2^{n_a}} \rho_{ir}\left(S_a\right)\left(E_r\left[\max_{l \in S_a} \{U_{il}\}\right] - E_r\left[\max_{l \in S_a} \{U_{il}, U_{ij}\}\right]\right), & \forall j \notin S_a \end{cases}.$$

For simplicity, consider the conditions that are applicable to colleges in an individual's application strategy (*i.e.*, $j \in S_a$).[1] Adding two of these conditions together for two of the colleges in the set S_a results in an expression in terms of marginal costs and expected marginal benefits,

$$\begin{aligned} c_{ij} + c_{ik} \quad < \quad & P_{ij} \sum_{r=1}^{2^{n_{a/j}}} \rho_{ir}\left(S_{a/j}\right)\left(E_r\left[\max_{l \in S_{a/j}} \{U_{il}, U_{ij}\}\right] - E_r\left[\max_{l \in S_{a/j}} \{U_{il}\}\right]\right) \\ & + P_{ik} \sum_{r=1}^{2^{n_{a/k}}} \rho_{ir}\left(S_{a/k}\right)\left(E_r\left[\max_{l \in S_{a/k}} \{U_{il}, U_{ik}\}\right] - E_r\left[\max_{l \in S_{a/k}} \{U_{il}\}\right]\right). \end{aligned}$$

[1] The proof works analogously if the conditions for colleges not in the individual's application strategy (*i.e.*, $j \notin S_a$) are used.

The right hand side of the above expression can be split into more pieces and written as

$$
\begin{aligned}
c_{ij}+c_{ik} < P_{ij}\Bigg[& (1-P_{ik})\sum_{r=1}^{2^{n_{a/j,k}}}\rho_{ir}\left(S_{a/j,k}\right)\left(E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij}\}\right]-E_r\left[\max_{l\in S_{a/j,k}}\{U_{il}\}\right]\right) \\
& + P_{ik}\sum_{r=1}^{2^{n_{a/j,k}}}\rho_{ir}\left(S_{a/j,k}\right)\left(E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij},U_{ik}\}\right]-E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ik}\}\right]\right)\Bigg] \\
+P_{ik}\Bigg[& (1-P_{ij})\sum_{r=1}^{2^{n_{a/j,k}}}\rho_{ir}\left(S_{a/j,k}\right)\left(E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ik}\}\right]-E_r\left[\max_{l\in S_{a/j,k}}\{U_{il}\}\right]\right) \\
& + P_{ij}\sum_{r=1}^{2^{n_{a/j,k}}}\rho_{ir}\left(S_{a/j,k}\right)\left(E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij},U_{ik}\}\right]-E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij}\}\right]\right)\Bigg].
\end{aligned}
$$

Combining terms yields the simplified expression

$$
\begin{aligned}
c_{ij}+c_{ik} < \sum_{r=1}^{2^{n_{a/j,k}}}\rho_{ir}\left(S_{a/j,k}\right)\ \Bigg(& P_{ij}\left(1-P_{ik}\right)\ E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij}\}\right] \\
+\ P_{ik}\left(1-P_{ij}\right)\ E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ik}\}\right] & +\left(P_{ij}P_{ik}-P_{ij}-P_{ik}\right)\ E_r\left[\max_{l\in S_{a/j,k}}\{U_{il}\}\right] \\
& +\ P_{ij}P_{ik}\ E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij},U_{ik}\}\right]\ +\chi\Bigg),
\end{aligned}
$$

where

$$
\begin{aligned}
\chi \;=\; & P_{ij}P_{ik}\Bigg(E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij},U_{ik}\}\right]+E_r\left[\max_{l\in S_{a/j,k}}\{U_{il}\}\right] \\
& -\ E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij}\}\right]-E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ik}\}\right]\Bigg).
\end{aligned}
$$

Due to the concavity of the natural logarithm function in the expected value of the maximum utility term, χ is negative. Thus, it must be true that the following three inequalities hold,

$$
\begin{aligned}
(1)\quad c_{ij}+c_{ik} < \sum_{r=1}^{2^{n_{a/j,k}}}\rho_{ir}\left(S_{a/j,k}\right)\ \Bigg(& P_{ij}\left(1-P_{ik}\right)\ E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij}\}\right]+ \\
+P_{ik}\left(1-P_{ij}\right)\ E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ik}\}\right] & +\left(P_{ij}P_{ik}-P_{ij}-P_{ik}\right)\ E_r\left[\max_{l\in S_{a/j,k}}\{U_{il}\}\right] \\
& +\ P_{ij}P_{ik}\ E_r\left[\max_{l\in S_{a/j,k}}\{U_{il},U_{ij},U_{ik}\}\right]\Bigg)\ ,
\end{aligned}
$$

$$(2) \quad c_{ij} + c_{ik} < \sum_{r=1}^{2^{n_{a/j,k}}} \rho_{ir}\left(S_{a/j,k}\right) \Bigg((1-P_{ij})(1-P_{ik}) \; E_r \left[\max_{l \in S_{a/j,k}} \{U_{il}\} \right]$$

$$+ (1-P_{ij}) P_{ik} \; E_r \left[\max_{l \in S_{a/j,k}} \{U_{il}, U_{ik}\} \right] + P_{ij}(1-P_{ik}) \; E_r \left[\max_{l \in S_{a/j,k}} \{U_{il}, U_{ij}\} \right]$$

$$+ P_{ik} \, E_r \left[\max_{l \in S_{a/j,k}} \{U_{il}, U_{ij}, U_{ik}\} \right] \Bigg) - \sum_{r=1}^{2^{n_{a/j,k}}} \rho_{ir}\left(S_{a/j,k}\right) \; E_r \left[\max_{l \in S_{a/j,k}} \{U_{il}\} \right] \text{ , and}$$

$$(3) \quad c_{ij} + c_{ik} < \sum_{r=1}^{2^{n_a}} \rho_{ir}\left(S_a\right) \; E_r \left[\max_{l \in S_a} \{U_{il}\} \right] - \sum_{r=1}^{2^{n_{a/j,k}}} \rho_{ir}\left(S_{a/j,k}\right) \; E_r \left[\max_{l \in S_{a/j,k}} \{U_{il}\} \right]$$

This last result is equivalent to saying that the marginal cost associated with applying to colleges j and k is less than the expected marginal benefit of applying to colleges j and k, which implies that $V(S_a) > V\left(S_{a/j,k}\right)$ when $j, k \in S_a$. Thus, $V(S_a) > V\left(S_{a/j}\right) \; \forall j \in S_a$ implies that $V(S_a) > V\left(S_{a/j,k}\right) \forall \; j,k \in S_a$. Starting with the necessary optimality conditions applicable to colleges *not* in an individual's application strategy (*i.e.*, for $j \notin S_a$) yields a similar result for $j, k \notin S_a$. $\|$

The proofs of Theorems 2 and 3 are analogous and are omitted here in the interest of brevity.

Theorem 4: If $\frac{\partial R}{\partial Z_{ij}} > 0$ and $\frac{\partial R}{\partial m_{ij}} > 0$, then $\frac{d\, m^r\left(Z_{ij}, Q_{j/i};\, \alpha_t\right)}{d\, Z_{ij}} < 0$.

Recall that $R_j = R\left(Z_j,\, M_j;\; \alpha_t\right)$ was rewritten so that the attributes specific to the i^{th} individual are separated from the observed and unobserved attributes of all other individuals by $Q_{j/i}$,

$$R_j = R\left(Z_{ij},\, m_{ij},\, Q_{j/i};\; \alpha_t\right). \tag{1}$$

If $\tilde{R}_j$ is the highest level of utility attainable by college j given its expected budget and capacity constraints and $m^r\left(Z_{ij},\, Q_{j/i};\; \alpha_t\right)$ the reservation match value that defines the admissions rule, then the admissions rule is monotonically decreasing in any attribute of individual i that increases the college's utility.

Consider the case where college j is just indifferent between admitting and denying applicant i, which occurs when $m_{ij} = m^r\left(Z_{ij},\, Q_{j/i};\; \alpha_t\right)$. Finding the total differential of R_j evaluated at this point of indifference yields

$$dR_j = \left(\frac{\partial R}{\partial Z_{ij}}\right) dZ_{ij} + \left(\frac{\partial R}{\partial m_{ij}}\right) d\, m^r + \left(\frac{\partial R}{\partial Q_{j/i}}\right) d\, Q_{j/i} = 0. \tag{2}$$

The total differential in equation (2) is set equal to zero because the change in utility is zero along a given indifference curve. Equation (2) can be used to show that $\frac{\partial m^r\left(Z_{ij}, Q_{j/i};\, \alpha_t\right)}{\partial\, Z_{ij}} < 0$

when characteristic Z_{ij} is an economic "good" for college j,

$$\begin{aligned}\frac{dR_j}{d\,Z_{ij}} &= \left(\frac{\partial R}{\partial Z_{ij}}\right)+\left(\frac{\partial R}{\partial m_{ij}}\right)\frac{d\,m^r}{d\,Z_{ij}}+\left(\frac{\partial R}{\partial Q_{j/i}}\right)\frac{d\,Q_{j/i}}{d\,Z_{ij}}=0\\ &\Rightarrow\ \frac{d\,m^r\left(Z_{ij},\,Q_{j/i};\ \alpha_t\right)}{d\,Z_{ij}}=-\frac{\left(\frac{\partial R}{\partial Z_{ij}}\right)+\left(\frac{\partial R}{\partial Q_{j/i}}\right)\frac{d\,Q_{j/i}}{d\,Z_{ij}}}{\left(\frac{\partial R}{\partial m_{ij}}\right)}=-\frac{\left(\frac{\partial R}{\partial Z_{ij}}\right)}{\left(\frac{\partial R}{\partial m_{ij}}\right)}<0. \qquad (3)\end{aligned}$$

Signing the derivative in which I am interested is simplified by the fact that $\frac{d\,Q_{j/i}}{d\,Z_{ij}}=0$ for all attributes of i included in Z.[2] Clearly, equation (3) demonstrates that the reservation function $m^r\left(Z_{ij},\,Q_{j/i};\ \alpha_t\right)$ is monotonically decreasing in those attributes of applicant i that improve college j's reputation or prestige, R_j. The only assumptions required for this result are that the preferences of colleges are continuous, monotonic, and convex.

A.2 Existence of an Equilibrium

To be written.

A.3 Effect of Total Applications on Estimated Yield Rates

The complications resulting from utilizing the categorical number-of-applications variable available in NELS were discussed in the Data Section. One of the justifications cited there for using this piece of data despite the additional complications was its role in the admissions decisions of colleges. The following exercise demonstrates that the total number of applications submitted by an individual is potentially very important in being able to match observed admissions behavior. Specifically, an admissions officer's expected yield rates for a given type of applicant varies a lot depending upon whether this information is included or not.

The sample of NELS seniors yields a subsample of 9,679 individuals who provide information on at least one college application. College applications could be assigned a Barron's selectivity category for 6,655 of the seniors' first application choices.[3] An additional subsample of 5,118 seniors provides information on a second college application, 3,760 of which could be assigned a Barron's category.

I divided the colleges in these subsamples into four tiers. Tier 1 colleges, such as Stanford, are categorized as most competitive, highly competitive+, and highly competitive, and have median SAT scores ranging from 1066 to 1350. Tier 2 colleges, such as UT-Austin, are

[2] Those familiar with the peer effects literature might question this result if academic ability is one of the variables included in Z. Because the academic quality of individuals will be measured by a pre-college standardized test score, the measured quality of i really does not affect the measured quality of other students enrolled at j. See Hoxby (2000) and Hanushek et al. (2001) for empirical methods of isolating and evaluating peer effects.

[3] The remaining college applicants listed a community or specialty college as their first choice, which Barron's doesn't rank. This number exceeds the number of college applicants discussed in the text (5,217) because some of these 6,655 individuals are missing data that is necessary for estimation of the full model.

categorized as very competitive+ and very competitive, and have median SAT scores ranging from 926 to 1240. Tier 3 colleges, such as Rutgers, are categorized as competitive+ and competitive, and have median SAT scores ranging from 760 to 1120. Tier 4 colleges, such as University of North Dakota, are categorized as less competitive and non-competitive, and have median SAT scores ranging from 590 to 1005.

Let i index these four college tiers, k index individual applicants, and j index the total number of applications submitted by an individual k. Define P_i as the probability that an applicant at a tier i college chooses to enroll in a tier $i+1$ (lower tier) college, and P_{ij} as the probability that a tier i applicant submitting j total applications chooses to enroll in a tier $i+1$ college. Nonparametric estimates of these probabilities are

$$\hat{P}_i = \frac{\sum_k 1\left(k \text{ admitted to a tier } i \text{ college}\right)}{\sum_k 1\left(k \text{ applied to a tier } i \text{ college}\right)}$$

$$\hat{P}_{ij} = \frac{\sum_k 1\left(k \text{ applies to } j \text{ total colleges}\right) \cdot 1\left(k \text{ admitted to a tier } i \text{ college}\right)}{\sum_k 1\left(k \text{ applies to } j \text{ total colleges}\right) \cdot 1\left(k \text{ applied to a tier } i \text{ college}\right)},$$

where $\hat{P}_{ij}$ obviously incorporates the data available on the total number of applications each individual submits and $\hat{P}_i$ does not.

I make several assumptions to simplify the analysis. First, I assume that admissions officers at tier i colleges are only concerned about competition for students from tier $i-1$ (higher tier) colleges and other tier i colleges, which implicitly assumes that applicants always enroll in the highest tier college to which they are admitted. Second, applicants are assumed to be indifferent between multiple admissions offers from colleges within the same tier. Finally, I assume that admissions outcomes are perfectly correlated within a tier. This last assumption is not particularly unreasonable; 65% of the admissions outcomes of individuals providing information on two colleges are perfectly correlated.[4] Given these simplifying assumptions, I can define Q_i as the probability that a tier i college is able to successfully enroll an applicant who has also applied to a tier $i-1$ (higher tier) college, and Q_{ij} as the probability that a tier i college is able to enroll an applicant who has applied to a tier $i-1$ college and j colleges in total. Let n_i equal the number of tier i college applications observed in the data and then define estimates of Q_i and Q_{ij} as

$$\hat{Q}_i = \left(1 - \hat{P}_{i-1}\right)$$

$$\hat{Q}_{ij} = \frac{\left(1 - \hat{P}_{i-1,j}\right)}{j - n_{i-1}},$$

where $\frac{1}{j-n_{i-1}}$ is the probability the applicant chooses the tier i admissions officer's college over the other $(j - n_{i-1})$ tier i colleges. $\hat{Q}_i$ is a tier i admissions officer's estimate of the

[4]This percentage is lower in the upper-tier colleges and higher in the lower-tier colleges.

yield rate for applicants applying to higher tier colleges; $\hat{Q}_{ij}$ is the same estimate taking into account additional competition from other tier i colleges.[5] The results presented below highlight the potentially substantial difference in expected yield rates based on $\hat{Q}_i$ versus $\hat{Q}_{ij}$.

Probability of Enrolling an Applicant Who Also Applies to a Tier $i-1$ College

Tier	$\hat{Q}_i$	$\hat{Q}_{ij=2}$	$\hat{Q}_{ij=3}$	$\hat{Q}_{ij=4}$	$\hat{Q}_{ij=5}$	$\hat{Q}_{ij=6}$
$i=2$	0.3521	0.3751	0.1876	0.1250	0.0959	0.0767
$i=3$	0.2599	0.2991	0.1496	0.0997	0.0722	0.0577
$i=4$	0.2316	0.2773	0.1387	0.0924	0.0635	0.0508

Note: $\hat{Q}_{ij}$ columns assume that additional (>2) applications are in tier i.

The column labeled $\hat{Q}_i$ says that a tier 2 college has a 35.21% probability of enrolling an applicant who also applies to a tier 1 college, that a tier 3 college has a 25.99% probability of enrolling a tier 2 applicant, and a tier 4 college has a 23.16% probability of enrolling a tier 3 applicant. The estimated yield rate falls within each column because the nonparametric estimates of admission probabilities increase as we move to lower tiers. There are several other notable patterns in the table. First, when $j=2$ there is little difference between $\hat{Q}_i$ and $\hat{Q}_{ij}$. In this case, there is virtually no effect of using the information on total number of applications because $\hat{Q}_{ij=2}$ essentially assumes that application sets are not truncated.[6] As j increases beyond two, however, the probability that a tier i college is able to enroll a tier $i-1$ applicant falls dramatically. This result stems entirely from the assumption that additional applications are to other tier i colleges, which increases the competition for students within the tier. If I assume that additional applications are to either tier $i-1$ or $i+1$ colleges, the estimated yield rates would continue to closely mimic $\hat{Q}_i$ because admissions outcomes are perfectly correlated and individuals enroll in the highest tier possible.

I conclude from this exercise that the inclusion of the categorical number of applications variable may be quite important in explaining application and admissions behavior. Of the subsample of NELS respondents listing two college applications, 45% list colleges in the same tier and 85% list colleges in adjacent tiers. Thus, it is quite likely that the pattern apparent in the above table applies to quite a large proportion of the sample.

A.4 Importance Sampler Details

Recall that $g(\mu,\xi)$ was defined as a density with the same support as the joint distribution of unobservables, $f(\mu,\xi)$, and such that $\frac{L_i(\theta,\mu,\xi)\, f(\mu,\xi)}{g(\mu,\xi)}$ is bounded, smooth in θ, and easy to evaluate given μ and ξ. The unconditional likelihood contribution of individual i

[5] Additional applications to tier $i-1$ colleges have no impact on yield rate estimates for tier i admissions officers because I assume perfectly correlated admissions outcomes.

[6] The small difference that does exist between columns 2 and 3 is due to the fact that $\hat{Q}_i$ includes individuals who only provide information on a single college application. These sample members cannot be used to estimate $\hat{Q}_{ij}$ because truncation only occurs when $j \geq 2$.

was specified as

$$L_i(\theta) = \int_{\Lambda}\int \frac{L_i(\theta, \mu_i, \xi_{ij})\ f(\mu, \xi)}{g(\mu, \xi)}\ g(\mu, \xi)\ d\xi\ d\mu$$

and the importance sampling simulator for $L_i(\theta)$ as

$$L_i^R(\theta) = \frac{1}{R}\sum_{r=1}^{R} \frac{L_i(\theta, \mu_i^r, \xi_{ij}^r)\ f(\mu_i^r, \xi_{ij}^r)}{g(\mu_i^r, \xi_{ij}^r)},$$

where r indexes R draws of μ_i and ξ_{ij}. The specific form of the importance sampler $g(\mu_i^r, \xi_{ij}^r)$ employed is motivated in conjunction by a data limitation discussed earlier in the paper.

Recall that the total number of applications submitted is reported as a categorical variable and, when combined with respondents being asked for only their top two application choices, this results in an application set truncation problem where the extent of the truncation is typically unknown. Let S_{ia} be the true, complete application strategy, which can be divided into the set of college applications that are observed in the data, S_{ia}^o, and the set of unobserved applications, S_{ia}^u, that must be simulated to fill out the true set. The following simulation algorithm is used only for individuals with potentially truncated sets.[7] If n_{ia} is the total (but unobserved) number of applications submitted by individual i, then the range $[\underline{n}_{ia}, \overline{n}_{ia}]$ that contains n_{ia} as well as the number of observed applications, n_{ia}^o, are data. The minimum number of colleges to be simulated is $\underline{n}_{ia} - n_{ia}^o$; the maximum number of applications to be simulated is $\overline{n}_{ia} - n_{ia}^o$. To make these definitions more concrete, consider an example. Suppose that individual i applies to six colleges and lists the University of Pennsylvania as his first choice. The observed set is $S_{ia}^o = \{\text{UPenn}\}$, and the set of unobserved college applications, S_{ia}^u, must contain a minimum of four and a maximum of nine colleges because the total number of applications, which I observe categorically, is $[5, 10]$. Because I have no information regarding the distribution of the number of applications within each categorical range, I randomly draw a number from within the reported range and use this as the simulated number of applications submitted by individual i for simulation r, n_{ia}^r. For each r, $J+3$ standard uniform random variables are then drawn and transformed into $J+2$ values of $\xi_{ij}^r \sim N(\mu_\xi, \sigma_\xi^2)$ and a single $\mu_i^r \sim N(\mu_\mu, \sigma_\mu^2)$, where these distributional parameters are included in the parameter vector θ to be estimated. The simulated μ_i^r and ξ_{ij}^r enable the calculation of marginal value functions like equation (**??**) and thereby determine the order in which i would add applications to any that are already observed in S_{ia}^o. The first $n_{ia}^r - n_{ia}^o$ colleges from this ordered list have the highest marginal values and are selected to be in S_{ia}^u. Finally, the union of S_{ia}^o and S_{ia}^u is defined as one simulated application set for individual i, S_{ia}^r, and this process is repeated R times. The underlying uniform random variates and the simulated application sets are held constant over different values of the parameter vector θ to insure convergence.

[7] The true S_{ia} is completely observed for those individuals who report applying to a single college where the identity of that institution is known, for those who list either a community college or trade school as their first or second choice, and for those who do not apply to college at all. All other individuals have potentially truncated application sets.

Once values of μ_i^r and ξ_{ij}^r are drawn and the simulated application set S_{ia}^r is determined, the only source of randomness left in the application stage is associated with the draw of n_{ia}^r from within $[\underline{n}_{ia}, \overline{n}_{ia}]$. The lack of smoothness in $L_i^R(\theta)$ stems from the fact that the number of applications submitted is discrete, so it is natural for the importance sampler to utilize the randomness inherent in drawing a discrete value of n_{ia}^r. The probability of drawing n_{ia}^r equals $\frac{1}{\overline{n}_{ia}-\underline{n}_{ia}}$, which is continuous in the parameters and meets the other importance sampler criteria discussed above. Thus, $g\left(\mu_i^r, \xi_{ij}^r\right)$ is defined as $\frac{1}{\overline{n}_{ia}-\underline{n}_{ia}}$ and the importance sampling simulator becomes

$$L_i^R(\theta) = \frac{\left(\overline{n}_{ia} - \underline{n}_{ia}\right)}{R} \sum_{r=1}^{R} L_i\left(\theta, \mu_i^r, \xi_{ij}^r, n_{ia}^r\right).$$

Note that the value of the importance sampler is constant over simulations even though the simulated number of applications, n_{ia}^r, is not.

Table 1
Summary Statistics of Individual Characteristics

	All Seniors in 1992	**Subset of Applicants†**	**Subset of Enrollees†**
*Proportion**			
Female	.511	.528	.531
White	.691	.697	.717
Black	.100	.099	.095
Hispanic	.120	.091	.082
Asian	.079	.105	.100
Native American/Other	.009	.008	.006
With Father's Highest Degree:			
Less than HS Diploma	.125	.073	.062
HS Diploma	.265	.212	.196
Some College	.168	.182	.187
College or Advanced Degree	.265	.388	.424
Attending:			
Public HS	.867	.800	.779
Catholic HS	.072	.102	.110
Non-Catholic Private HS	.061	.097	.111
Applying to any 2-year college	.288	.159	.033
Applying to any 4-year college	.550	1.000	1.000
Submitting 1 total application†	.225	.409	.360
Submitting 2-4 total applications†	.249	.452	.470
Submitting 5+ total applications†	.076	.139	.170
Enrolling in 2-year college	.240	.120	.000
Enrolling in 4-year college	.426	.774	1.000
Entering the labor force	.333	.105	.000
Average Family Income (1987$)	$41,898	$51,239	$54,583
Average NELS Std. Test Score	51.7	56.0	57.2
(standard deviations)	(9.71)	(8.45)	(7.89)
N	9,482	5,217	4,040

† Refers to individuals applying/enrolling in four-year colleges or universities.

* Proportion refers to the proportion of the group indicated by the column heading. Categories may not sum to one due to rounding or non-exhaustive category choice.

Source: Author's calculations using NELS:88.

Table 2

Characteristics of 1st and 2nd Application Choices for Applicants and Enrollees†

	Application Choices of Applicants		Application Choices of Enrollees		Enrollment Choices
Barron's Selectivity	1st	2nd	1st	2nd	
Number (N) choosing:					
Most competitive colleges	903	615	786	558	678
Very competitive colleges	943	615	758	520	730
Somewhat comp. colleges	2179	1246	1611	1021	1671
Less/Non-competitive colleges	1192	504	885	412	961
College identity unobserved*	0	103	0	75	0
N	5,217	3,083	4,040	2,585	4,040
Proportion of N choosing:					
Most competitive colleges	.173	.199	.195	.216	.168
Very competitive colleges	.181	.199	.188	.201	.181
Somewhat comp. colleges	.418	.404	.399	.395	.414
Less/Non-competitive colleges	.228	.163	.219	.159	.238
College identity unobserved*	.000	.033	.000	.029	.000
Distance From Home					
Number (N) choosing:					
Less than 100 miles	3719	1981	2879	1684	2972
Between 100 and 300 miles	987	651	770	542	725
Between 300 and 600 miles	232	163	179	132	168
More than 600 miles	279	185	212	153	175
College identity unobserved*	0	103	0	75	0
N					
Proportion of N choosing:					
Less than 100 miles	.713	.643	.713	.651	.736
Between 100 and 300 miles	.189	.211	.191	.210	.180
Between 300 and 600 miles	.045	.053	.044	.051	.042
More than 600 miles	.054	.060	.053	.059	.043
College identity unobserved*	.000	.033	.000	.029	.000

† Refers to individuals applying/enrolling in four-year colleges or universities.

* Some individuals indicated that they applied to multiple institutions, however, the identity of the second institution was missing data.

Source: Author's calculations using NELS:88, IPEDS, and Barron's.

Table 3
Distribution of the Number of Applications Submitted by Individual Characteristics

	Number of Applications Submitted			
	0	1	2-4	5+
Proportion*				
Male	.463	.218	.249	.071
Female	.423	.244	.252	.081
White	.438	.236	.251	.075
Black	.444	.238	.256	.061
Hispanic	.573	.203	.186	.039
Asian	.264	.215	.353	.169
Native American	.579	.284	.105	.032
Low Income ($\leq$\$30K)	.548	.226	.195	.032
High Income (>\$100K)	.085	.225	.352	.338
N	4,194	2,190	2,375	723

$*$ Refers to the proportion of individuals with each characteristic that submit a given number of applications.

Source: Author's calculations using NELS:88.

Table 4
Distribution of Admission Offers by College Application

	1^{st} Application		2^{nd} Application	
	Number	Proportion	Number	Proportion
All Applicants	5217	1.000	2980	1.000
Admitted	4267	.818	2020	.678
Denied	406	.078	494	.166
Unknown	544	.104	466	.156
By Total Number of Applications Reported				
1 Application	2136	1.000	–	–
Admitted	1807	.846	–	–
Denied	146	.068	–	–
Unknown	183	.086	–	–
*2-4 Applications**	2358	1.000	2280	1.000
Admitted	1905	.808	1550	.680
Denied	198	.084	401	.176
Unknown	255	.108	329	.144
*5+ Applications**	723	1.000	700	1.000
Admitted	555	.768	470	.671
Denied	62	.086	93	.133
Unknown	106	.147	137	.196

* For 394 applicants, the colleges in which they enrolled were different from the first and second application choices provided. There is no "3^{rd} Application" column because I only observe this additional information when individuals are admitted to their third choice.

Source: Author's calculations using NELS:88.

Table 5

Determinants of Admission to Four-Year College by College Selectivity†

	Marginal Effect on Adm. Probability by Degree of College Selectivity				**All Selectivity Categories**
	Most	**Very**	**Some**	**Less**	
1^{st} Choice					
Male	**-.060**	.024	-.015	-.018	-.017
Black	**.130**	-.053	-.015	-.030	-.017
Hispanic	.064	-.076	-.020	-.044	-.026
Asian	.033	-.043	**-.092**	.008	-.029
Test score	**.018**	**.009**	**.011**	**.007**	**.011**
Med. college SAT	**-.164**	.025	-.014	.000	**-.061**
Probability of admission for average applicant	.751	.838	.846	.867	.833
N	901	943	2,179	1,191	5,217
2^{nd} Choice					
Male	.016	-.012	.020	-.072	-.004
Black	**.127**	.014	-.020	-.061	-.015
Hispanic	-.024	-.063	-.096	-.046	**-.080**
Asian	-.037	-.021	-.012	-.105	-.045
Test Score	.002	.003	**.007**	**.007**	**.011**
Med. college SAT	.000	-.002	.007	-.009	**-.080**
Probability of admission for average applicant	.821	.622	.732	.746	.685
N^*	615	615	1,246	504	2,980

† Outcome is admission to the college listed as first choice. Probabilities reported are marginal effects from a probit model.

* According to Table 3, the number of applicants providing a second choice is 3,083. The identity of the second choice college is missing for 103 of these individuals, however, so a sample of 2,980 applicants is available for the admission probits at the second choice college.

Note: Marginal effects in bold are statistically significant at the 95% level.

Source: Author's calculations using NELS:88, IPEDS, and Barron's.

Table 6

Enrollment of First-Time Freshman in Selective Texas Public Universities†

	Academic Year					
	1995	1996	1997	1998	1999	2000
Number						
White	7529	7528	7887	8498	9757	10675
Black	563	528	439	340	404	565
Hispanic	1581	1683	1468	1340	1570	1795
Asian	993	959	942	1192	1372	1586
Native American	30	41	47	58	70	57
Total	10,696	10,739	10,783	11,428	13,173	14,678
Proportion						
White	.704	.701	.731	.744	.742	.727
Black	.053	.049	.041	.030	.031	.038
Hispanic	.148	.157	.136	.117	.119	.122
Asian	.093	.089	.087	.104	.104	.108
Native American	.003	.004	.004	.005	.005	.004
Total	1.000	1.000	1.000	1.000	1.000	1.000

† Selective Texas public universities include UT-Austin, Texas A&M, and UT-Dallas.

Notes: Race-neutral policies were implemented for the class entering in the Fall of 1997. Policy guaranteeing admission to a Texas public campus for top 10 percent of graduates in every public Texas high school began in the Fall of 1998.

Source: Author's calculations based on Kain and O'Brien (2001).

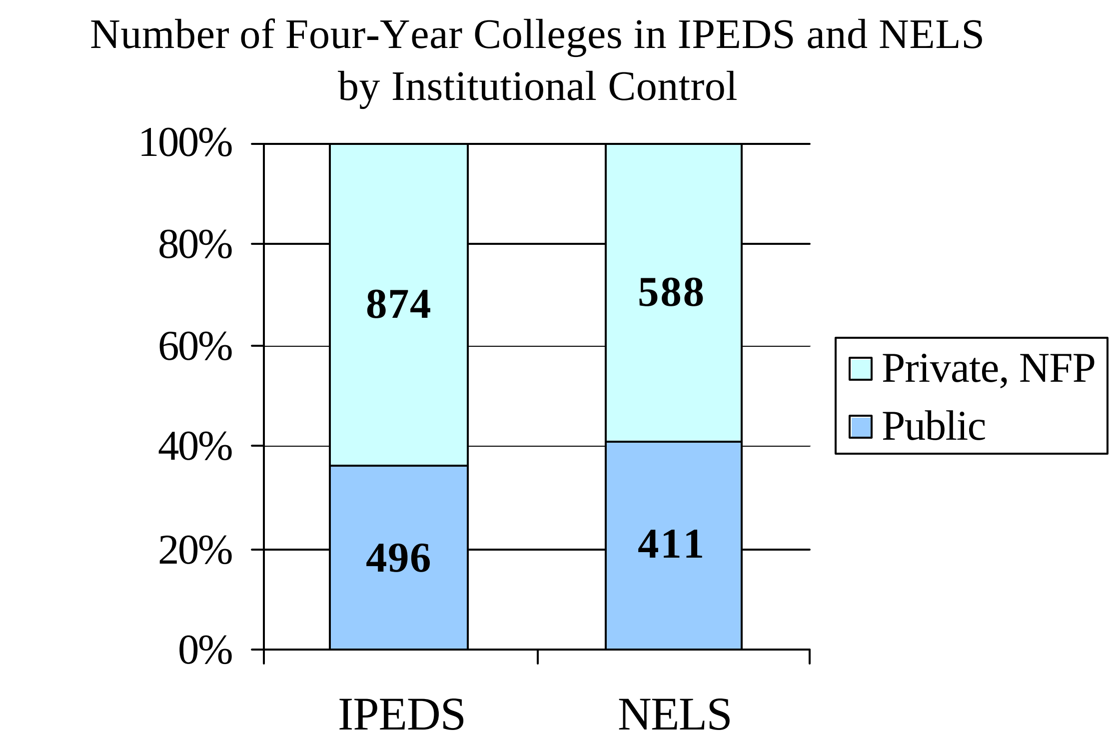
Table 7
Enrollment of First-Time Freshman in University of California – Berkeley

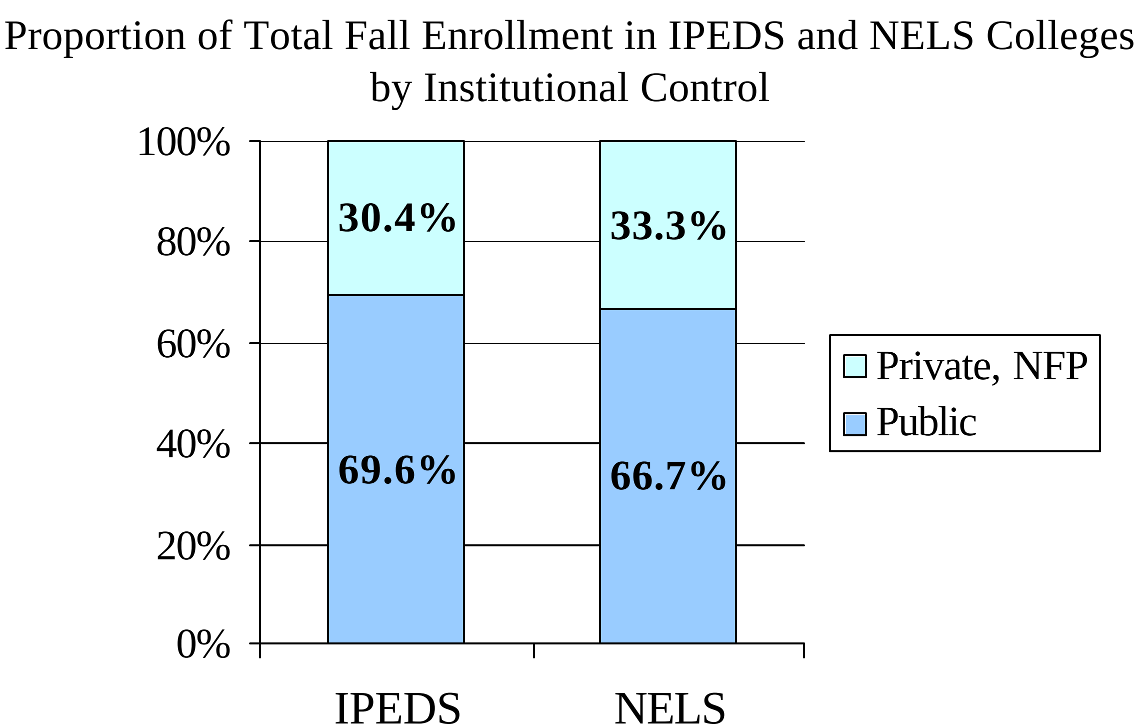
	Academic Year					
	1995	1996	1997	1998	1999	2000
Number						
White	1018	1090	1018	1090	1138	1122
Black	222	233	257	126	130	148
Hispanic	531	549	472	271	335	320
Asian	1268	1432	1468	1565	1595	1630
Other	215	208	171	143	186	444
Total	3,254	3,512	3,386	3,195	3,384	3,664
Proportion						
White	.313	.310	.301	.341	.336	.295
Black	.068	.066	.076	.039	.038	.037
Hispanic	.163	.156	.139	.085	.099	.100
Asian	.390	.408	.434	.490	.471	.443
Other	.066	.059	.051	.045	.055	.125
Total	1.000	1.000	1.000	1.000	1.000	1.000

Note: Race-neutral policies first implemented for the class entering in the Fall of 1998. Policy guaranteeing admission to a UC campus for top 4 percent of graduates in every public California high school began in the Fall of 2001.

Source: Chan and Eyster (1999) and Common Core of Data.

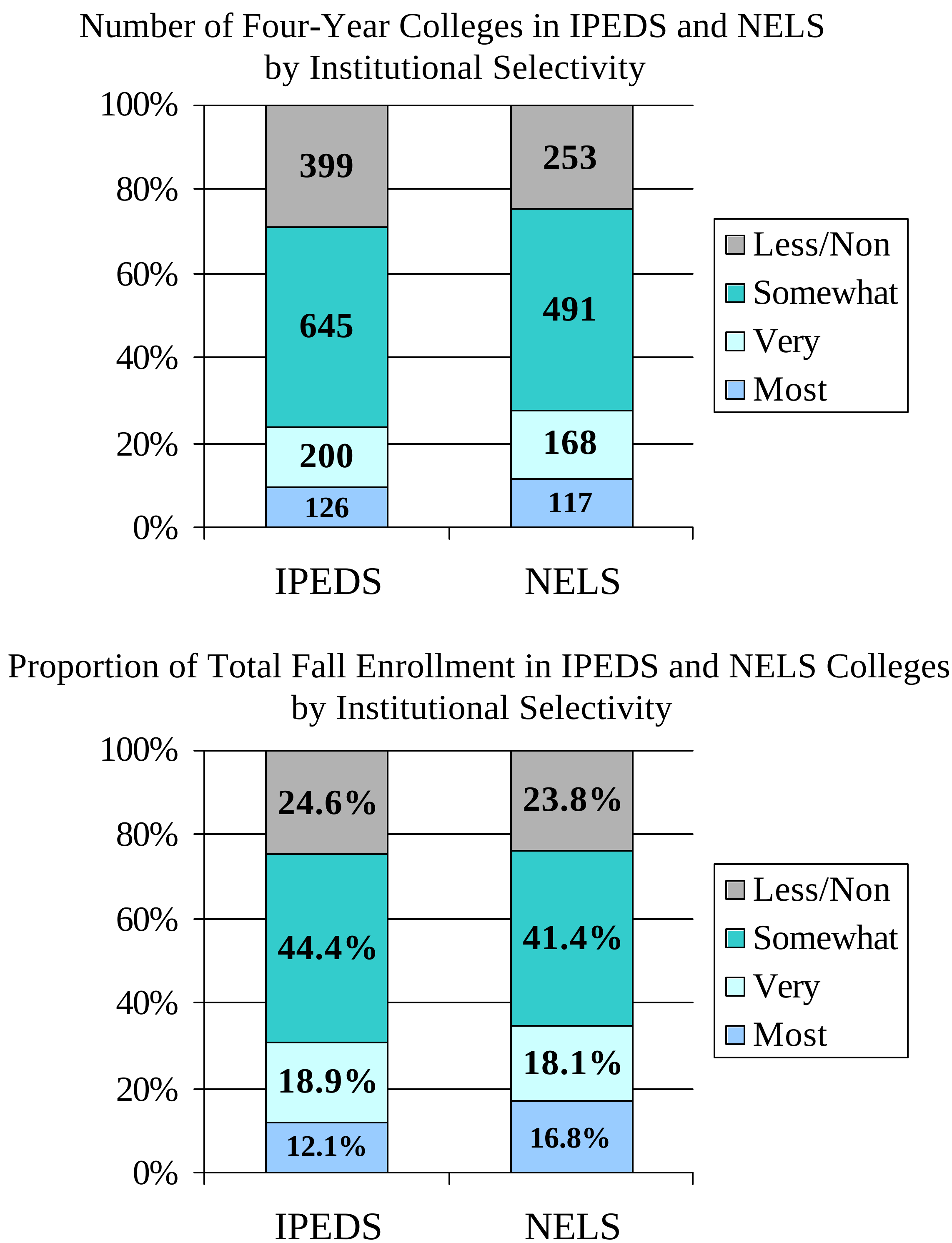
Figure 1





Source: Author's calculations using NELS:88 and IPEDS.

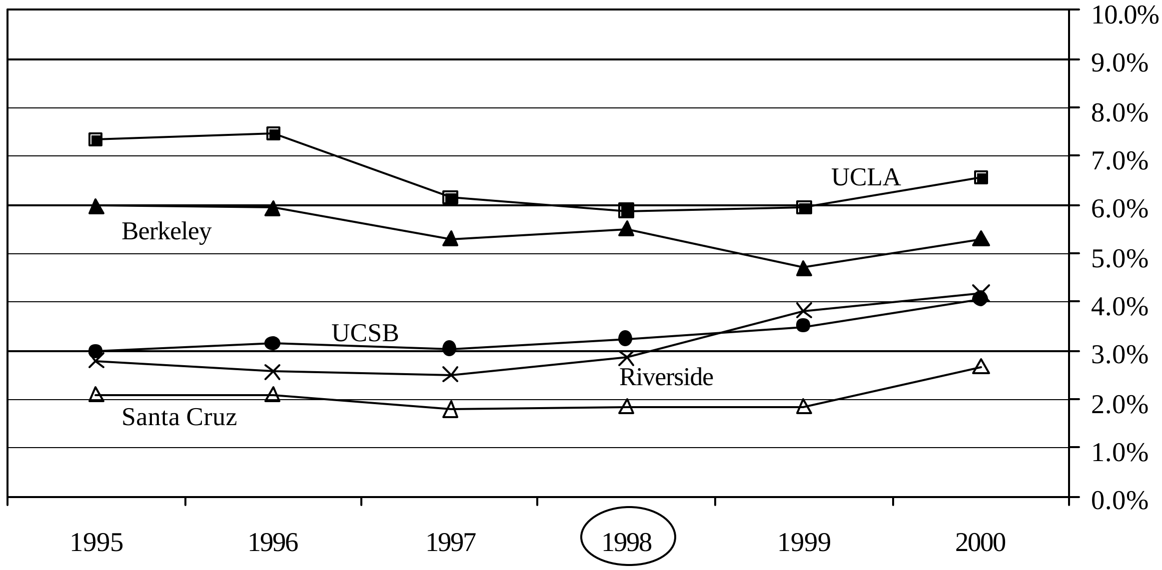
Figure 2



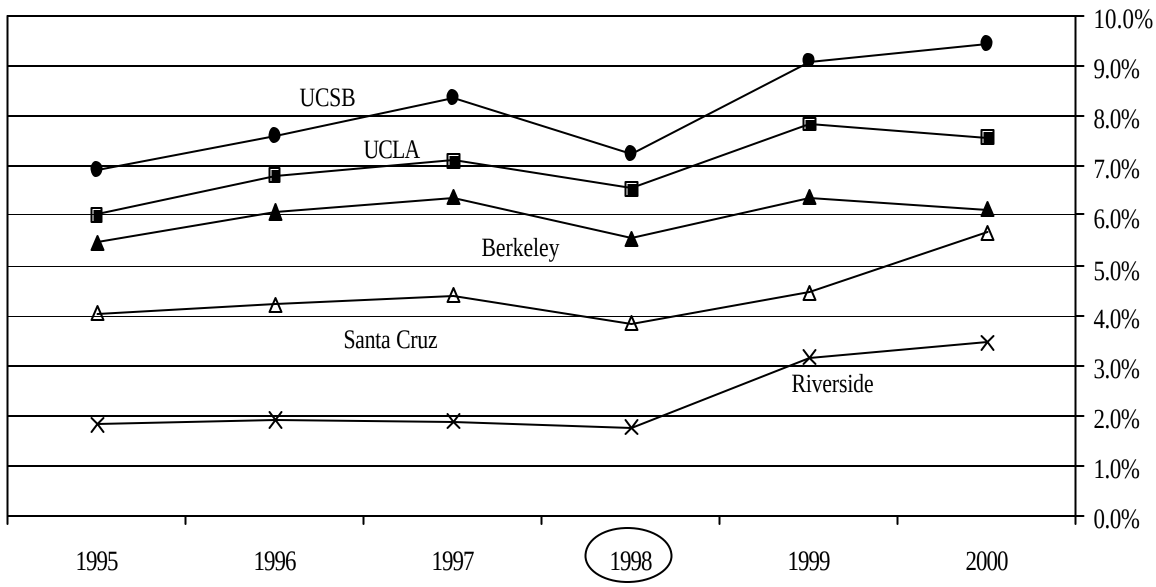
Source: Author's calculations using NELS:88, IPEDS, and Barron's.

Figure 3

Proportion of Black High School Graduates in California
Applying to Various UC Campuses

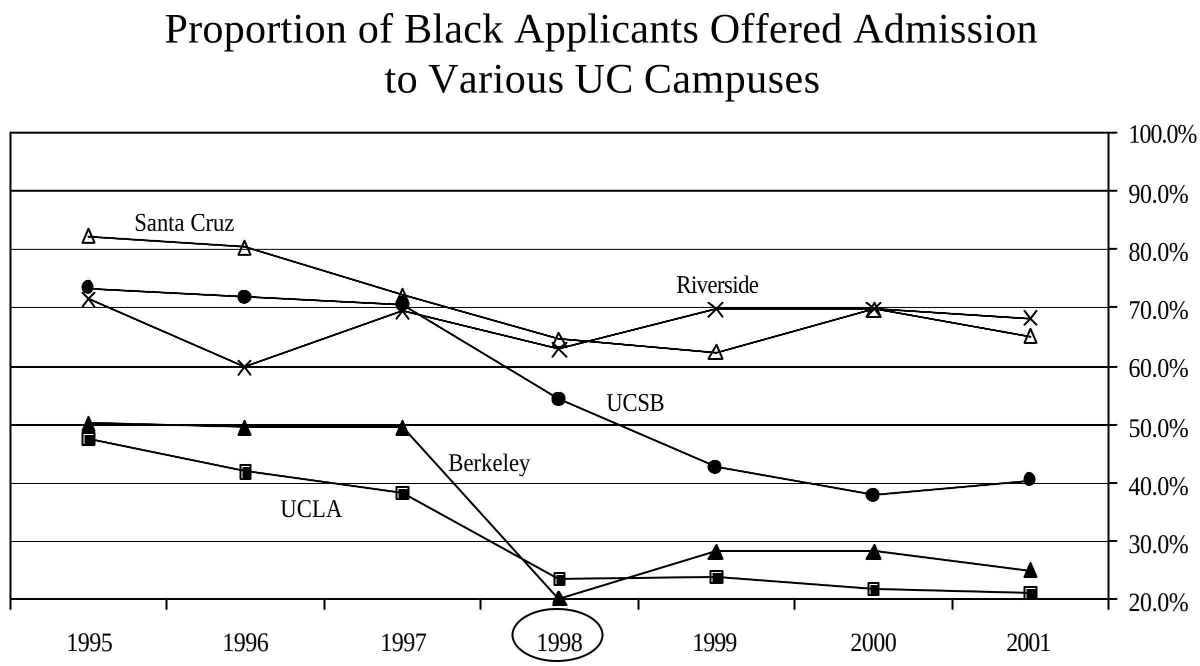


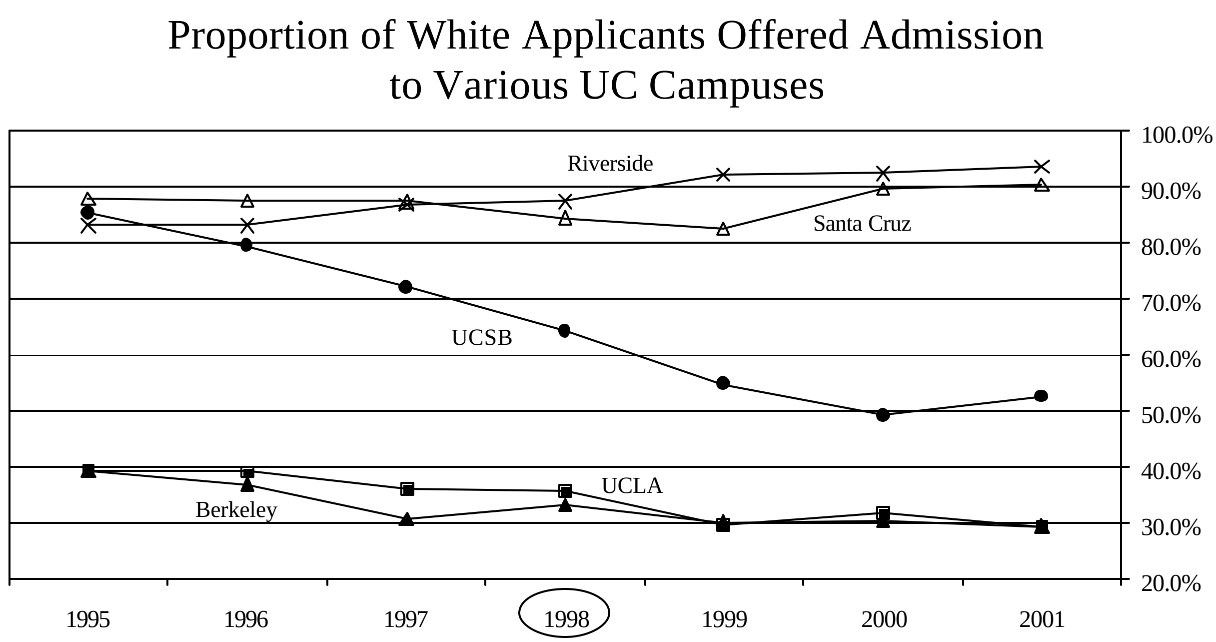
Proportion of White High School Graduates in California
Applying to Various UC Campuses



Source: Author's calculations based on HS graduation figures from the California Department of Education and application statistics from the University of California Office of the President (http://www.ucop.edu/).

Figure 4





Source: Author's calculations based on application and admissions statistics from the University of California Office of the President (http://www.ucop.edu/).