# Distributional Effects of Race-Blind Affirmative Action

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**Abstract**

The "Texas Top Ten" law guaranteed admissions to all students ranking in the top decile of their high school class to each public university in the state of Texas, including the state flagship universities. This paper evaluates the effects of Texas Top Ten and associated scholarship programs on the distribution of college applications, admissions, and matriculation and on students' performance in college. I construct a model of students' application portfolios and financial-aid application decisions, colleges' preferences and admissions rules, students' choice of college, and students' grades and persistence in college. I estimate this model using a survey of a cohort of Texas high school seniors, together with administrative records of Texas universities. I find that Texas Top Ten led to a 10% increase in underrepresented minority enrollment at the state flagship universities. Next, I consider a large expansion of the Longhorn Opportunity Scholarship, which provides scholarships at UT Austin. Expanding the program to cover all high schools with poverty rates above 60% would cost an additional $60 per student enrolled at UT Austin and lead to an increase in underrepresented minority enrollment of about 5%. The effects on students from poor high schools are larger than those of purely informational interventions. Relative to Texas Top Ten, a hypothetical race-conscious affirmative action policy that awards points to minority applicants would attract underrepresented minority students with relatively poor class rank from relatively affluent high schools. These students would achieve lower college GPAs at flagship universities than those minority students admitted under Texas Top Ten.

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# 1 Introduction

In the late 1990s and early 2000s, several of the largest US states introduced policies that guarantee admissions to public university systems on the basis of local comparisons of students to their high school peers. Florida's Talented 20 law guaranteed admission to some public university to all students in the top twenty percent of their high school class. The University of California, through its policy of Eligibility in the Local Context, guaranteed admission to some UC campus to students who satisfy course requirements and rank in the top 4% of their high school class.[1] In Texas, the "Texas Top Ten rule", formally Texas House Bill 588, guaranteed admission to all Texas public colleges and universities, including the state flagship universities, to all students who finish in the top decile of their high school class in Texas schools.[2] Moreover, in the years following Texas Top Ten's 1998 introduction, Texas' flagship universities introduced scholarship programs attached to specific low-income high schools that had previously sent few students to those institutions. These race-blind policies, rather than explicitly race-based affirmative action programs, were the primary methods that the state universities used in order to increase racial, economic and geographic diversity.

The purpose of this paper is to assess the consequences of the largest race-blind affirmative action policy in U.S. higher education, the "Texas Top Ten" rule and its associated targeted scholarship programs. To measure the effects on the distribution of college applications, admissions and enrollment, and students' outcomes in college, I estimate a model of the college market in Texas, using survey data on high-school seniors in Texas public high schools together with administrative data from Texas colleges and universities. I ask the following questions. First, what were the effects of Texas Top Ten and associated scholarship programs on the distribution of college attendance and achievement in college, both for intended beneficiaries of these programs and for other students? Second, how do the effects of the policy compare to those of a race-based affirmative action program that does not provide guaranteed admission? Finally, which channels and which frictions in the college market are the most promising targets for future interventions aimed at increasing attendance at selective colleges and persistence at those colleges? What is the value of the provision of information about admissions chances, of automatic completion of financial aid applications, and of the availability of additional financial aid through targeted scholarships?

[1] At the same time, the University of California introduced a policy of "comprehensive review" which considered students' high school and family backgrounds, and their performance relative to the opportunities available to them (e.g. the fraction of their high school's AP courses that they had taken.) In this way also, UC's policy resembled that of the University of Texas. In 1998, together with the introduction of Texas Top Ten, the University of Texas began computing a "personal achievement index" for applicants not automatically admitted, which served a purpose similar to that of comprehensive review.

[2] The policy was adjusted in the mid-2000s to include certain coursework requirements as well as top-decile placement; in 2001 the Texas legislature amended the law to require certain coursework, but these rules first took effect with the 2004-2005 ninth-grade class. The data in this paper predate this change.

Texas Top Ten and other percent plans were responses to a sequence of court cases and ballot propositions that banned race-based affirmative action programs. The University of California overhauled its admissions policies as a response to the 1996 passage of California ballot proposition 209, which outlawed the use of race as a criterion in state universities' admissions policies. The passage of Texas House Bill 588 in 1997 followed a court decision banning the consideration of race in college admissions.[3] At the same time, universities made other changes to their admissions policies which also placed increased weight on local comparisons. The University of California introduced a policy of "comprehensive review" which considered a student's neighborhood and high school characteristics in admissions. The University of Texas at Austin similarly began to calculate a personal score for all applicants not automatically admitted, which used measures of applicants' circumstances and high school characteristics including the average standardized test scores of applicants' high schools.

Texas Top Ten has been the subject of political controversy because of its scope. While the University of California guarantees admission to some campus, but not necessarily one where the applicant applied, Texas Top Ten guarantees admission to every institution including the state flagship universities.[4] In the years after 1997, the University of Texas at Austin expanded in order to meet rising demand caused in part by the program. Nonetheless, In 2009 it saw eighty-one percent of its entering class admitted automatically under Texas Top Ten. The university argued that these automatic admits displaced many applicants that it would have liked to accept. As a result, a legislative compromise limited "Top Ten" automatic admissions to 75% of its entering class beginning in 2010, in practice resulting in a "Top 8%" plan.[5]

To understand the consequences of changes in the program, I construct and estimate a model of colleges' admissions and financial aid rules, students' choice of application portfolios and matriculation decisions, students' probability of applying for financial aid, and students' persistence in college. I then use the model to perform counterfactual experiments, removing Texas Top Ten, providing information about admissions chances and the possibility of financial aid, expanding

[3] In 1996, the Fifth Circuit Court of Appeals ruled in *Hopwood v. Texas* that race could not be used as a factor in admissions decisions at the University of Texas School of Law nor, by extension, at any Texas public universities. In 2004, *Grutter v. Bollinger* allowed Texas universities to again consider race as a factor in admissions, but the Top Ten rule remained in effect. Following *Grutter*, UT Austin began using race as a factor for students not automatically admitted under Texas Top Ten. The data used in this paper predate this change.

[4] In Florida, The Talented Twenty program offers automatic admission to state universities based on high-school GPA cutoffs. Each university uses a different rule in practice. Moreover, the policy is somewhat opaque. The "talented twenty" program therefore does not guarantee admission to all public universities, like Eligibility in the Local Context but unlike Texas Top Ten. See Zimmerman (2013) for an evaluation of the returns to college for students who just cross the lowest "talented twenty" threshold for admission. See Arcidiacono, Aucejo, Coate and Hotz (2014) for an evaluation of the effects of California ballot Proposition 209 on graduation rates.

[5] See the university's announcement, http://www.utexas.edu/news/2009/09/16/top8_percent/ posted on Sept. 16, 2009. More recently, the US supreme court heard a challenge to the University of Texas' admissions policies, in particular challenging the consideration of race for students not automatically admitted.

scholarship programs, and introducing race-based affirmative action at the flagship universities.

The model that I use has the following structure. First, students simultaneously choose application portfolios and complete applications for financial aid. Students face a cost for each college application, which they trade off against the probability of admission and financial aid and the value of the option to attend that school. Students have noisy information about the quality of their applications as perceived by admissions offices. They also face uncertainty about the financial aid offers they will receive, and may fail to complete financial aid applications. Next, each college makes offers of admission to maximize the quality of its entering class subject to a constraint on the expected size of the class and the constraints imposed by the Top Ten law. Colleges simultaneously consider their applicants and students receive offers of admission and financial aid. Third, students observe their offers and choose their preferred colleges, if any. Finally, in each semester that they are enrolled in college, students' grades realize and the students drop out or continue.

I make use of individual-level survey and administrative data together with aggregate data on financial aid. My primary data source is the Texas Higher Education Opportunity Project,[6] which consists of a survey of a cohort of high school seniors in 2002, together with administrative records on all applicants to nine colleges and universities over several years before and after 2002. The 2002 cohort's high school careers took place while Texas Top Ten was in effect, and the survey reveals that students were well informed about Texas Top Ten. In the survey, I observe students' application portfolios, financial aid applications and outcomes, high school characteristics, test scores and class rank.

Additionally, for a subset of these students I observe a followup survey which measures which college(s), if any, they attend during the following year. This data provides information about students' preferences and information, the probability that students complete their financial aid applications, and colleges' admissions rules and probability of giving financial aid. Administrative data from Texas universities provides information on students' GPAs and persistence as a function of their academic characteristics, parents' income and occupation, and high school characteristics. Finally, while the survey reveals from which institutions a student received an offer of financial aid or a scholarship, it does not provide the amount. I use aggregate data from IPEDS on the average award at each institution, together with the choice model, to determine the size of financial aid offers.

In the data I observe specific scholarship programs, attached to some high schools, that target specific state flagship universities. The Longhorn Opportunity Scholarship, introduced in 1999, provides four-year scholarships at UT-Austin for students from certain low-income, low-flagship-attendance high schools. The Century Scholarship program similarly provides scholarships to students attending Texas A&M. In the survey and the administrative records we observe whether each student's high school was a Longhorn or Century school. The data allow me to look at UT-Austin and Texas A&M, the two flagship universities, and examine the effects of specific changes

[6] http://www.texastop10.princeton.edu/

in their admissions guarantees and expansions of their scholarship programs.

I obtain parameter estimates via the method of simulated moments. With estimates in hand, I conduct counterfactual experiments evaluating the removal of Texas Top Ten, the introduction of race-based affirmative action, the expansion of targeted scholarship programs, increasing the probability that students complete financial-aid applications, and provision of information about admissions chances. I solve for the new admissions rules that colleges would choose, the applications that students would submit, and the choices that they would make.

I find that Texas Top Ten led to a large increase in flagship attendance among Black and Latino students and a small increase in first- and second-year college GPA for students attending the state flagship universities. My estimates imply that the removal of the Texas Top Ten admissions guarantee would lead to a 10.0% decrease in state flagship attendance among underrepresented minority students. The effects are more dramatic for minority students in the top decile of their high school class. The removal of Texas Top Ten would cause a 17% increase in state flagship attendance, in contrast, among students from affluent high schools.[7] These students are more likely to attend religious colleges, out-of-state universities, and non-flagship public institutions under Texas Top Ten.

Additionally, I find that expanding the Longhorn scholarship program to cover all schools at which at least 60% of seniors had ever qualified for free lunch would lead to a large increase in minority enrollment at UT Austin. This expansion, which increases by a factor of five the number of students eligible for Longhorn scholarships, would lead to a 5% increase in share of minority students, and a 2% increase in the share of first-generation college students, attending the University of Texas at Austin. These effects are similar to those of a best-case purely informational intervention of automatically completing all financial aid applications and providing information about admissions chances. Moreover, the informational intervention has a large effect on overall college attendance as well as a large percentage effect on the share of students matriculating at highly selective private universities. Accounting for the direct costs of the informational intervention as well as the effects on the amount of financial aid awarded, I show that the informational intervention entails $900 in additional expenditure per poor-high-school student induced to attend a state flagship university. This figure is roughly a third of the cost per additional poor student enrolled at a state flagship university under an expansion of the Longhorn Scholarship program.

Finally, I show that Texas Top Ten would attract stronger students to flagship universities than would a hypothetical race-based affirmative action policy in which the flagship universities' admissions offices award points to Black and Hispanic applicants. The points are chosen to match the same share of Black and Hispanic students matriculating at each flagship university as under Texas Top Ten. This hypothetical policy would attract minority students with relatively poor class rank from relatively affluent high schools who would attain lower college grade point averages than those minority students enrolled under Texas Top Ten. There are two reasons why Texas Top Ten

[7] That is, high schools at which fewer than 15% of students have ever qualified for free or subsidized lunch.

attracts stronger students. First, the preferences of colleges' admissions offices are not perfectly aligned with the predictors of grades. Second, Texas Top Ten has a large effect on students' application decisions, drawing fewer minority applicants from affluent high schools but many more minority applicants with top-decile class rank.

The remainder of the paper proceeds as follows. In section 2 I discuss the paper's relation to the literature and its contributions to literatures on affirmative action and on the sources of "undermatching" of talented students and competitive colleges. Section 3 presents the model. Section 4 introduces the data and argues that my modeling choices are consistent with patterns in the data. In section 5 I discuss identification and estimation. Section 6 presents the results. Section 7 concludes.

# 2 Relation to Literature

This paper presents the first model of supply and demand for higher education under a "percentage plan". Crucially, it allows colleges' admissions rules to respond strategically to students' and other colleges' policies. Because of the size of the Texas Top Ten program, a change in the admissions guarantee would affect the admissions chances of a large share of college applicants. Indeed, the main criticism made by opponents of the plan is that the rule displaces many non-automatically-admitted students from the University of Texas.[8] Therefore, in order to model of the consequences of changes in the Top Ten law, this paper allows for colleges to adjust their admissions policies.

My model allows three frictions that may lead to undermatching: Low-income students may face higher application costs. Some individuals may be unaware of financial aid opportunities. Low-income applicants may be worse-informed about their admissions chances. Because the model allows for several sources of undermatching, and we observe variation in costs (from scholarship programs) and in information about admissions chances (from Texas Top Ten), one can use the model as a laboratory to measure the importance of sources of undermatching or mismatch, and to assess the likely consequences of interventions such as completion of financial aid forms or information provision when they are applied at large scale.

## 2.1 models of college applications and admissions

I build on earlier studies of college applications, admissions and matriculation: especially relevant are Arcidiacono (2005) and Howell (2010), who examine the consequences of race-based affirmative action programs. The programs that those papers consider were much smaller in scope than Texas's rule: Arcidiacono argues that we can ignore their "general equilibrium" effects. That is, he argues

[8] Again see e.g. "New Law in Texas Preserves Racial Mix in State's Colleges", New York Times, November 24 1999.

that a sufficiently small fraction of students were affected by race-based affirmative action that we can ignore the effects on non-minority applicants. His counterfactual, and Howell's, consist of removing the benefit of affirmative action for minority students, and thereby reducing the total number of students admitted.[9] These papers do not allow colleges' admissions rules to change in response to the removal of affirmative action. Because of the scale of Texas Top Ten, in contrast, it is crucial to allow admissions chances to adjust for students outside the top decile after policy changes.

Two other papers estimate equilibrium models of college admissions, including optimal behavior by colleges. Epple, Romano and Sieg (2006) estimate an equilibrium model of college choice in which colleges maximize a "quality" measure subject to a budget constraint. They allow for peer effects, in that a college's quality depends on the average test score and (inverse) income of its students. In their model, however, each college chooses the tuition that makes the marginal student indifferent between their choice and the next-best option, and the market clears via prices. Fu (2014) also estimates colleges' choice of tuition. Fu, and Epple, Romano and Sieg, take a different approach to modeling colleges' preferences and behavior than does this paper.[10] As I consider public institutions, I take tuition as exogenous to the decisions of the admissions office. As I describe later, Texas' flagship universities' admissions offices do not choose among in-state students on the basis of ability to pay.[11] In the year that the surveyed students entered college, Texas public universities were not able to choose tuition levels, as the maximum level was set by the state legislature.[12]

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[9] A student's chance of admission at a set of colleges $J_a$ when applying to a set $J \supset J_a$ is given by:

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

where $\gamma_a$ are parameters to be estimated, and $X_{aj}$ are observable characteristics including demographics $1(black)$. The counterfactual experiment adjusts the admissions policy by setting $\gamma_{a,1(black)} = 0$. Arcidiacono argues convincingly that this counterfactual is reasonable in his setting because of the relatively low numbers of students whose admissions outcomes would change.

[10] See also Epple, Romano and Sieg (2008) and Epple, Romano, Sarpca and Sieg (2014).

[11] In each year, 90% of matriculating students at UT Austin are categorized as "in-state" and pay in-state tuition.

[12] In 2003, Texas House Bill 3015 deregulated tuition in Texas universities. Prior to that year, the state had set maximum tuition levels. See http://www.utexas.edu/tuition/history.html. Deregulation took effect for the 2003-04 class, one year after the surveyed cohort in this paper entered college. After deregulation, each year tuition levels at UT were set by a committee based on budget projections and approved by the board of regents of UT. Deregulation was coupled with a reduction in state funding to universities, so that overall tuition increased, and has continued to increase in the following years. See http://www.dallasnews.com/news/state/headlines/20120922-texas-college-tuition-up-55-percent-since-2003-deregulation-analysis-shows.ece for context.

## 2.2 Effects of costs, admissions chances, and financial aid difficulties on applications and matriculation

This paper also draws on a literature documenting the responsiveness of students' applications and matriculation decisions to financial aid and application costs, and contributes to a literature on policy channels for increasing matriculation at selective colleges among students with good test scores and grades at underserved high schools. Avery and Hoxby (2003) investigate matriculation decisions and their sensitivity to financial aid offers. Two key papers show that students' application portfolios respond to incentives: Using SAT-sending as a proxy for applications, Card and Krueger (2005) provide evidence that students' application portfolios responded in the anticipated way to the removal of affirmative action; Pallais (2009) shows that students' application decisions were highly sensitive to a change in the number of schools to which the ACT could be sent for free.

Texas Top Ten and associated scholarship programs affected students' application decisions. Using a dataset of all SAT takers in Texas in 1996-2004, Andrews, Ranchhod and Sathy (2010) examine the effects of the introduction of Texas Top Ten. Consistent with our model, they show that after the introduction of the Texas Top Ten program, students in the top decile became less likely to send 4 or more applications, suggesting a reduction in uncertainty, and that top-decile students became more likely to apply to UT-Austin. Additionally, they provide evidence that the presence of Longhorn Opportunity Scholarship, which supports students at UT-Austin, greatly increases the probability that top-decile students apply to UT-Austin.[13] Using administrative data from an urban school district, Daugherty, Martorell and McFarlin (2012) show that the Top Ten Percent law has a significant impact on on attendance at Texas flagship universities and increases the total number of semesters enrolled.[14]

A growing literature is examining the "undermatching" of low-income and minority students and selective colleges. Avery and Hoxby (2012) document the existence of a large number of high-achieving, low-income high school students who do not apply to selective colleges.[15] Hoxby and Turner (2014) show that providing information on net costs of college, information about admissions chances, and completed application-fee waivers have large effects on applications.[16]

I contribute to this literature by comparing the best case for interventions in the style of Hoxby and Turner to the benefits and costs of an expansion of scholarship programs. That is, I evaluate the effects of completing financial aid applications for students and providing all students

[13] They find that the Century Scholarship has a similar but smaller effect on the probability of application to Texas A&M.

[14] Interestingly, they do not find a significant increase in college enrollment overall. The authors suggest that the Texas Top Ten law shifted applicants to flagship schools from private and out-of-state universities of similar quality.

[15] See also Bowen, Chingos and McPherson for evidence on "undermatching".

[16] See also Dynarski and Scott-Clayton, and Bettinger et al, for experimental evidence on frictions in college applications.

full information about their unobserved quality as perceived by admissions offices,[17] interventions which the literature estimates to have relatively low costs per student. I compare the effects on the distribution of college applications, attendance and persistence to those of an expansion in the Longhorn Opportunity Scholarship to cover a large set of poor high schools. In the model, I am able to evaluate the effects of greater scholarship provision at scale, accounting for the ways in which it affects students' application decisions and colleges' admissions rules.

## 2.3 Percentage plans and affirmative action bans

The current paper begins with SAT-taking high school seniors considering freshman applications, and ends with outcomes in the first two years of college. Using aggregate match data, Hickman (2014) models students' choice of human capital investment prior to college applications. He uses the model to evaluate the effects affirmative action policies on students' pre-college human capital investments. Cullen, Long and Reback (2013) consider strategic high school choice under the Texas Top Ten law. They focus on the small fraction of students who have multiple available public schools and would stand to increase their chances of guaranteed admission the most by changing schools. A significantly higher than normal fraction of such students indeed change schools..

It is important to place this paper in the context of studies that link college admissions in Texas to later outcomes. Examining the labor market, Andrews, Li and Lovenheim (2012) estimate quantile treatment effects on earnings from attending various Texas colleges. In another paper, these authors document that many students enter the flagship universities via transfer admissions from two-year colleges and non-flagship four-year institutions, and that there are many transfers across colleges within Texas.

A series of papers examine Texas Top Ten using the Texas Higher Education Opportunity Project (THEOP) datasets that I use in this paper. Niu, Tienda and Cortes use the THEOP senior survey to document the ways in which students' reported preferences, and realized admissions outcomes, differ by high school background.[18] Cortes (2010) examines the effects of the end of affirmative action and the introduction of Texas Top Ten on students' persistence and graduation, using a difference-in-differences strategy.[19] Niu and Tienda (2010) use a regression discontinuity

[17]One could provide this information e.g. by hiring college counselors to read students' applications.

[18]Niu, Tienda and Cortes show that students from resource-poor schools are less likely to list selective colleges as their first preferences, but that there are no significant differences in selectivity in enrollment among top-decile graduates.

[19]Cortes finds that persistence and graduation rates for non-top-decile minority students were lower under the percent plan than under race-based affirmative action, while top decile students' persistence was higher, so that graduation rates and early persistence for minority students with low class rank were lower relative to those of top-decile students after the reform. I show, however, that Texas Top Ten increased the share of top-decile minority students, and decreased the share of non-top-decile minority students, relative to race-based affirmative action.

design on the THEOP survey data used in this paper. They do not find a statistically significant effect of Texas Top Ten on flagship enrollment when considering all seniors, but do find a large and significant positive effect for Hispanic students. Using administrative data from THEOP, Fletcher and Mayer (2013) provide evidence that students differ discontinuously across the Top Ten Percent threshold, showing that the law affects application decisions. Importantly, these regression discontinuity designs characterize the effects on the marginal student of gaining automatic admission via Texas Top Ten, but admissions chances for students outside the top decile are different in the presence of Texas Top Ten than in its absence. The effects of "threshold crossing" are the difference of the effects of Texas Top Ten on top decile students, relative to the counterfactual in which it is not present, and the effects of Texas Top Ten on non-top-decile students.[20] This paper extends the analysis of Texas Top Ten's effects to consider the consequences for inframarginal students and measure the indirect effects of the policy through its effects on the college market.

Finally, this paper relates to the literature on race-based affirmative action and its effects on college applications and admissions rules. A series of papers by Antonovics and Backes examines the removal of affirmative action in California; which saw policy changes similar to those in Texas. Antonovics and Backes (2013) argue that, in response to a ban on race-conscious affirmative action, University of California campuses changed the weights they place on SAT scores, grades, and family characteristics.[21] Backes (2012) surveys affirmative action bans across states using institution-level data, finding that Black and Hispanic enrollment dropped at flagship institutions, but failing to find significant effects on graduation rates. Antonovics and Backes (2013b) examine the effects of California's affirmative action ban on minority applications.

# 3 Model

In this section I describe the model of college applications, admissions, enrollment and persistence in detail. The model closely matches the actual admissions rules at UT, and is designed to account for key facts about financial aid applications, application portfolios and the structure of students' and colleges' information. I first discuss the timing of actions and information revelation. I then describe students' utilities given financial aid and admissions offers, colleges' admissions decisions, students' financial aid applications, and students' beliefs at the time of applications. Finally, I

[20] Similarly, when examining application and matriculation patterns a difference-in-differences approach does not separate the effect of the introduction of Texas Top Ten on top-decile students from the effects on non-top-decile students. There is no "control group" whose admissions chances and application patterns do not change. In particular, Texas Top Ten provided information to top-decile students which encouraged them to apply to state flagship universities, and it crowded out some other students. Moreover, because of population changes in Texas it would be difficult to use a neighboring state as a control.

[21] In the current version of the model, colleges may change their admissions cutoffs, but the weights on characteristics such as SAT scores and class rank reflect the colleges' utility functions, which are held constant.

describe college persistence and equilibrium.

### 3.1 Model timing

The model has the following timing structure. First, high-school seniors simultaneously choose which colleges to apply to and whether to apply to financial aid at those colleges. Second, colleges observe which students applied, and their characteristics, and choose which students to accept and whom to offer financial aid. Third, students observe their admissions and financial aid outcomes, as well as matriculation-time preference shocks, and choose where to matriculate among the colleges that admit them. Finally, students' college outcomes (GPA, number of semesters, graduation) are realized. Note that the model begins with SAT-taking (or ACT-taking) high school seniors; I do not model effort in high school or the decision to take a standardized test.[22]

### 3.2 Students' preferences and matriculation decisions

I begin with the third stage of the model and work backwards. At the time of matriculation decisions, student $i \in I$ picks the college $j$ in his admissions set $B_i$ offering the highest value $U_{ij}$, where

$$U_{ij} \equiv u_{ij}(Aid_{ij}) + \epsilon^C_{ij}.$$

$u_{ij}(Aid_{ij})$ is a utility term, defined below, that depends on the financial aid offer $Aid_{ij}$. Each student has the outside option of not attending any college immediately, which gives utility

$$U_{i0} = u_{i0} + \epsilon^C_{i0}.$$

The vector of matriculation-time shocks $\epsilon^C_i = (\{\epsilon^C_{ij}\}_{j\in J}, \epsilon^C_{i0})$ is correlated within an individual's college offers. This correlation allows for common shocks, such as financial shocks, that shift student $i$'s utility for the outside option relative to all colleges. In particular, $(\{\epsilon^C_{ij}\}_{j\in J}, \epsilon^C_{i0})$ have the generalized extreme value distribution that gives a nested logit, with all colleges in a common nest, the outside option in its own nest, and correlation parameter $\lambda$ among the inside choices $j = 1, \ldots, J$.

The utility function $u_{ij}(Aid_{ij})$ is given by

$$\begin{aligned} u_{ij}(Aid_{ij}) =& \delta_j + \beta_i^{SATrank} \cdot \tau_{SAT_j} + \beta_i^{SAT} \cdot \overline{SAT}_{jt} - \beta_i^{p} \cdot p_j(Aid_{ij}) + \beta_i^{dist} Dist_{ij} \\ &+ \beta^{dist\times pov} \cdot Dist_{ij} \cdot hspov_i + \beta_i^{X} X_{jt} + \epsilon^A_{ij}, \end{aligned}$$

[22] In other work ("Effects of Texas Top Ten on High School Achievement") I use administrative data from the Texas Education Agency, the Texas Higher Education Coordinating Board, and the Texas Workforce Commission to estimate the incentive effects of Texas Top Ten and trace the effects of high school human capital changes induced by Texas Top Ten through college and into the labor market.

where

$$\delta_j = \overline{\beta}^{SAT}\overline{SAT}_{jt} + \overline{\beta}^{X} X_{jt} + \xi_j.$$

$\tau_{SAT_{jt}}$ is the rank of $i$'s SAT scores among the entering class at college $j$. $\overline{SAT}_{jt}$ is the average of the 25th and 75th percentile SAT scores among the entering class at college $j$.[23] Together, these terms allow students to care about both the academic quality of their peers and their relative position in their cohort. The term $p_j(Aid_{ij})$ is a measure of net price which I will discuss below. $Dist_{ij}$ is the distance (in miles) between $i$'s high school and college $j$. $X_{jt}$ is the student-faculty ratio at $j$, which proxies for expenditure on educational inputs. $hspov_i$ is the fraction of students at $i$'s high school who have ever received free or reduced-price lunch, which is a common proxy for poverty.

In order to capture substitution patterns, I add two additional terms to the utilities of attending the flagship universities, UT Austin and Texas A&M. I add interactions $1(white) \times 1(j =$ Texas A&M) and $1(white) \times 1(j =$ UT Austin) to capture the racial divide in preferences for flagship colleges, and a random coefficient $\beta^{TAMU}$ which enters with weight 1 when $j =$ Texas A&M and $-1$ when $j =$UT Austin.

The mean utility term $\delta_{jt}$ consists of a school-specific fixed effect $d_j$, the "peer effect" $\overline{\beta}^{SAT}\overline{SAT}_{jt}$, student-faculty ratio, and a year-specific shock for each college. The constant $d_j$ captures elements of the college's quality that are not measured by SAT scores and inputs, such as prestige or the reputation of its athletic teams.

Let 0 denote the outside option, i.e. not attending any four-year college. The utility of the outside option, not including the matriculation-time shock, is given by

$$u_{i0} = \epsilon^{A}_{i0}.$$

where $\epsilon^{A}_{ij}$ is an extreme-value shock that is independent across students and schools. It follows that the value of the outside option at the matriculation stage is

$$U_{i0} = \epsilon^{A}_{i0} + \epsilon^{C}_{i0}.$$

It is important to have shocks $\epsilon^{A}$ at the application stage as well as shocks $\epsilon^{C}$ at the time of final choices. Application-stage shocks are needed to match observed application decisions. As applications are costly, however, if students have full information at the time of applications they will apply to at most one college each. If there is only uncertainty about admissions outcomes, students will attend college with probability 1 if admitted.[24]

[23] As discussed below, the 25th and 75th percentile SAT scores are easily observable; in initial estimation I allowed $\overline{SAT}_{jt}$ to be the average of 25th and 75th percentile scores.

[24] We will see that students also do not know their financial aid offers.

**Random coefficients** Because the mean utility term $\delta_{jt}$ contains a shifter for each variable in $X_{jt}$, we assume without loss that the mean of the random coefficients $\beta_i^X$ is zero; $\beta_i^X$ is independently normally distributed with variance $\sigma_X^2$ and mean $\mu_X$. Other variables, which vary across individuals, have random coefficients that are independently normally distributed with mean and variance to be estimated, e.g. $\beta_i^{dist} \sim N(\mu^{dist}, \sigma^{2dist})$ independently across $i$, and independent of other random coefficients.

**Peer characteristics** In the empirical application, I estimate SAT rank in the following manner: I divide the college's 75th and 25th percentile SAT scores by 1600 so that the maximum possible score is 1. I then fit a beta distribution to these quantiles via GMM. I calculate the quantile of this distribution that student $i$'s SAT score represents.

Two factors motivate this procedure. First, while the 25th and 75th percentiles at each college are easily available to students via college guides and the colleges' websites, the entire distribution is not. Second, at colleges where I have access to the full distribution of SAT scores, the beta distributions fit well.[25]

I assume that at the time of applications, the values of $\overline{SAT}_{jt}$ and other characteristics are precisely known by all potential applicants. That is, students know what the 25th and 75th percentile SAT scores will be at each college after students make matriculation decisions. This perfect foresight assumption is reasonable given the large number of applicants at most of the colleges in the dataset; UT-Austin admitted 13,476 students in 2002, for instance, of whom 7,935 enrolled.[26]Each individual represents a small fraction of the thousands of students who will attend each college, and has a negligible impact on quantiles of SAT scores.

## 3.3 Financial Aid

Federal student aid eligibility in the U.S. is based on a comparison of of two dollar amounts, the estimated cost of attendance at a given college for a particular student, and the student's expected family contribution, which I denote $EFC_i$. The expected family contribution of student $i$ is given by a nonlinear function of the income and assets of $i$'s parents, $i$'s own income if any, and characteristics of $i$'s household.[27] In practice, many universities, including the University of Texas at Austin, determine institutional financial aid awards as well as a function of students' federal $EFC$. As a result, the expected family contribution plays an important role in the model of financial aid.

[25]See figure 3 in the appendix for the graphical fit at UT Austin.

[26]See table S-22 of UT Austin's Office of Institutional Research 2003-04 statistical handbook, http://www.utexas.edu/academic/ima/sites/default/files/SHB03-04Students.pdf.

[27]Each applicant for financial aid calculates her $EFC_i$ as part of the Free Application for Federal Student Aid (FAFSA), a form that is required for applications for need-based financial aid.

### 3.3.1 Probability of receiving financial aid

Students receive financial aid at college $j$ with a probability that depends on household income and differs across colleges. I allow the probability of receiving aid to be discontinuous in income at the point where federal student aid becomes unavailable. Let $p_j^{max}$ denote the list price of college $j$. Once the expected family contribution $EFC_i$ is greater than $p_j^{max}$, the student may receive merit scholarships but not income-based aid.[28] Let $y_i$ denote the income of $i$'s household. The probability of receiving aid at $j$ conditional on applying for aid is

$$\begin{aligned} Pr(Aid_{ij}|\text{i applied for financial aid at j}) =& 1(EFC_i < p_j^{max})\Phi\left(\alpha_j^f + \alpha_y^f y_i\right) + \\ & 1(EFC_i \geq p_j^{max})\Phi(\alpha_j^f \alpha_j^{schol} + \alpha_y^f y_i). \end{aligned}$$

### 3.3.2 Financial aid amounts

$p_j(Aid_{ij})$ is the net cost of attending college $j$ with the financial aid offer $Aid_{ij}$. I assume that conditional on receiving nonzero aid at $j$, the amount of aid $\Delta p_{ij}$ is a deterministic function of $i$'s expected family contribution $EFC_i$ at each school. Importantly, colleges may fail to provide sufficient aid to match the student's need as specified by the federal formula. I assume that if a student receives financial aid, the amount varies across colleges and decreases to zero as the student's income increases: total financial aid is given by $\Delta p_{ij}$ below:

$$\begin{aligned} I_{aid} &= \alpha_j^{aid} + \alpha_y^{aid} \cdot EFC_i \\ \Delta p_{ij} &= \frac{(c^m + p_j^{max})}{1 + \exp(I_{aid})} \end{aligned}$$

The net cost is given by

$$p_j(Aid_{ij}) = c^m + p_j^{max} - Aid_{ij}\Delta p_{ij},\ Aid_{ij} \in \{0, 1\},$$

where $c^m$ is a parameter that captures additional costs relative to the outside option, including the cost of moving, books and supplies, and foregone wages. The functional form is designed to allow the amount of aid received to decrease to zero as income increases. $c^m$, $\{\alpha_j^{aid}\}_{j\in J}$, and $\alpha_y^{aid}$ are parameters that are estimated jointly with all other parameters.

### 3.3.3 Targeted scholarships

Recall that the Longhorn Opportunity Scholarship and the Century Scholarship program provide financial aid and mentorship at the University of Texas at Austin and Texas A&M, respectively,

[28] This assumption is motivated by the fact that institutional need-based aid at UT Austin is a function of federal EFC only.

and are associated to certain high schools. I make the following adjustments for students whose high schools participate in the Longhorn Opportunity Scholarship program. First, if a student graduates in the top 10% of his class, he faces no uncertainty about whether he will receive aid at UT-Austin. If he completes an application for aid at UT Austin and chooses to attend that university, he receives the Longhorn scholarship with probability 1. Second, if a student receives the Longhorn scholarship and matriculates at UT Austin, he pays at most the extra cost $c^m$, regardless of his income. (If $p_j(Aid_{ij})$ is less than this extra cost, he pays $p_j(Aid_{ij})$.) If he is aware of aid at UT Austin, he is fully aware that he will pay at most $c^m$. His probability of completing an application for financial aid, however, is exactly the same as if he were not at a Longhorn high school. I model the Century scholarship at Texas A&M analogously.

#### 3.3.4 Random coefficients

The coefficient on price is given by:

$$\beta_i^p = \beta_0^p + \beta_y^p / \max(y_i, \$10000).$$

That is, disutility from paying for college[29] varies with income, among incomes that may reasonably come from full-time work. For sufficiently low incomes, $\beta_i^p$ does not depend on income. The main purpose of this functional form is to prevent distaste for price from increasing unboundedly as income approaches zero. We estimate $\beta_0^p$ and $\beta_y^p$ jointly with the full model.

#### 3.3.5 Financial aid applications

We will see in the descriptive analysis that many students fail to complete financial aid applications, even where it appears that those applications would be likely to succeed and to have large effects on net price. There is a great deal of evidence in the literature that households have difficulty completing financial aid applications. In my model, students fail to complete financial-aid applications with some probability, either because of unawareness or because of difficulties or frictions in completing and submitting the forms. Applicants may not complete financial-aid applications although the implied benefits may be very large.

In the model, conditional on applying to $j$ a student completes an application for financial aid at $j$ if and only if $Aware_{ij} = 1$. That is, $Aware_{ij}$ is a latent variable which determines whether $i$ is able to apply for financial aid at college $j$. If $Aware_{ij} = 1$ I will say that $i$ is *aware* of financial aid at college $j$. $Aware_{ij}$ need not be taken literally as awareness, but may reflect difficulty in completing the FAFSA, unawareness of deadlines, or other frictions.

Students are aware of financial aid at college $j$ with probability

$$Pr(Aware_{ij}) = \Phi(\gamma^{finaidA} z_i^{finaidA} + \eta_i^{aware}) 1(EFC_i < p_j) + \Phi(\gamma^{scholA} z_i^{finaidA} + \eta_i^{aware}) 1(EFC_i \geq p_j).$$

[29] i.e. marginal utility from consumption of the numeraire good, if utility is a function of college and a numeraire.

Observed financial aid application terms $z_i^{finaidA}$ are a constant, $i$'s SAT composite score, and the fraction of students at $i$'s high school who have ever qualified for free or subsidized lunch. The coefficients may change discontinuously as students' income rises and they become ineligible for federal aid. For such students, applying for financial support entails finding particular scholarship or aid programs rather than simply completing the FAFSA. $\eta_i^{aware}$ is an unobserved shock which allows for correlation in $i$'s awareness across colleges. I assume that $\eta_i^{aware}$ is normally distributed, with mean zero and a variance $\sigma_i^{aware}$.

A student's awareness of financial aid at $j$ means that he understands that the college's list price is not necessarily the price he will pay if he matriculates, and that he correctly calculates his aid amount $Aid_{ij}$ conditional on receiving aid as well as $Pr(Aid_{ij} > 0)$, his chances of receiving financial aid at $j$ conditional on admission. Students who are not aware of financial aid at college $j$, in contrast, assume that they will pay list price when calculating the expected value of application portfolios.

There is an important difference between my treatment of financial aid applications and the model of applications for admission. Students calculate the expected value of each portfolio given their characteristics (including what they expect to pay) and weigh the benefits against application costs, but they do not trade off the benefits of financial aid against an analogous financial-aid application cost because they do not calculate the benefits of financial aid at schools where they fail to complete applications for aid. My model says that before an applicant completes the FAFSA and applies for aid he does not know what amount of financial aid he should expect to receive; we allow for the possibility that talented low-income students underapply because, failing to account for financial aid, they assume that colleges are unaffordable, although they stand to pay much less than the list price.

The model of financial aid applications is similar in some ways to the concept of consideration sets. A student may fail to "consider" aid at college $j$, and therefore considers $j$ expensive and may be less likely to apply. I could, in addition to application costs, allow students to be unaware of some colleges. One would be able to estimate the model similarly, allowing each student to apply only to schools within his "consideration set," using high-school characteristics as shifters of the probability that student $i$ considers college $j$.[30] A crucial difference is that I partially observe the financial aid "consideration" set, as we see whether the student applied for aid at every school in his application portfolio.

[30]Goeree (2008) estimates a model of demand for personal computers in which individuals can choose only products within a "consideration set" that the econometrician does not observe. There, advertising exposure serves as a shifter of consideration sets that is excluded from utility conditional on consideration.

## 3.4 Colleges' admissions policies

Each college maximizes the expected quality of its entering class subject to the constraint that its expected enrollment is less than its capacity. In this section I define the expected quality of a class and show that colleges' optimal admissions policies are cutoff rules.

From the perspective of college $j$, the quality of student $i$ is given by

$$\tilde{\pi}_{ij} = \pi_j^0 + z_{ij}\gamma + q_i + \mu_{ij}$$

where $\pi_j^0$ is a college-specific constant term, $z_{ij}$ is a vector of observable student characteristics, $\mu_{ij}$ is an idiosyncratic match term, and $q_i \in R$ consists of components of student $i$'s application, such as the quality of his essays or special talents not measured by test scores and class rank, that affect the quality of his application at all colleges. In particular, college $j$ observes

$$z_{ij} = (testscore_i, classrank_i \overline{classrank_{s(i)}})$$

as well as the residual quality $q_i$ of each student who applies, and the match term $\mu_{ij}$. I assume

$$\mu_{ij} \sim N(0, 1)$$

independently across $i$ and $j$. Importantly, $\mu_{ij}$ is orthogonal to $q_i, z_{ij}$.

From each college's point of view, the quality of a class is the sum of the quality of students. Let

$$\pi_{ij} = \tilde{\pi}_{ij} - \pi_j^0$$

The quality of a class $C(j) \subset I$ is given by:

$$\Pi_{jt}(C(j)) = \sum_{i \in C(j)} \left(\pi_{ij} + \pi_j^0\right).$$

This separability assumption[31] implies that colleges do not engage in "class balancing". Indeed, it does not appear that any public institutions in the sample engaged in explicit class balancing.[32]

[31] i.e. the assumption that utility is additive over students; put differently, colleges' preferences are responsive in the sense of Roth and Sotomayor (1990).

[32] This model is designed to conform to UT Austin's admissions policies as described by its admissions office. In short, since the end of affirmative action in 1997, the university has computed two scores for each applicant. The first, the "academic index", is a linear function of grades and class rank, with parameters that depend on the applicant's intended major. The second score, the "personal achievement index", reflects personal characteristics including the extent to which the applicant took advantage of opportunities, and includes the student's essays as well as factors including the ratio of the applicant's SAT scores to his high school's mean score, combined according to an unspecified formula. After admitting top-decile students, the university assigns the remaining positions using (up to discretization into "cells") a cutoff in a weighted sum of the two indices. See 570 U.S. ___ (2013) page 4, for a brief discussion. (The court's decision is available at http://www.supremecourt.gov/opinions/12pdf/11-345_l5gm.pdf).

Under my assumptions, UT-Austin may have preferences that result in a class that is half male and half female given the observed distribution of applications, for instance, but the marginal value of a male applicant is not decreasing in the fraction of admits who are male. If more males with characteristics similar to those of current admitted students were to apply, my model predicts that the distribution of admissions offers would change proportionally.[33]

College $j$ does not observe $\mu_{ij'}$ for $j' \neq j$. I assume that college $j$ observes $(z_i, q_i, \mu_{ij})$ for all applicants before choosing who to admit.[34] Given any set of admitted students, the set of matriculating students $C(j)$ is random from $j's$ perspective because it depends on students' preferences and on their other offers of admission and financial aid which in turn depend on shocks that are not observed by $j$.

Taking expectations over these unknowns conditional on its application set $A(j)$, college $j$ chooses a (possibly random) admission rule, solving

$$\max_{B\{j\}\in[0,1]^{A(j)}} E\Pi_j(C(j)|A(j)) \text{ s.t. } E(C(j)|A(j)) \leq K_j,$$

where $K_j \in R_+$ is college $j$'s capacity, $C(j) \subseteq I$ is the set of students matriculating at $j$, and $A(j) \subseteq I$ is the set of students submitting an application to $I$. I assume that colleges cannot commit to an admission rule that is not optimal given applications.[35]

### 3.4.1 Texas Top Ten

I model Texas Top Ten as a constraint on admissions: if student $i$ applies to $j$, and $i$ is in the top decile of his class, then $j$'s admission set must include $i \in B(j)$.

[33] In principle, one could allow for class balancing via "assignment preferences" (see Hatfield and Milgrom 2005). College $j$ has $R_j$ roles, each with capacity $K_{jr}, r = 1, \ldots, R_j$. The college sets cutoffs $\underline{\pi}_{jr}$ in each role $r$ such that the capacity constraints are satisfied for each $r$, with equality whenever $\underline{\pi}_{jr} > 0$. A student is admitted whenever $\max_r \left(\pi_{ijr} - \underline{\pi}_{jr}\right) > 0$. This preference structure allows a college to engage in class balancing. For example, it can hold a fraction of seats in which underrepresented minority applicants receive a bonus to their admissions score. Suppose the fraction of minority applicants changes greatly across cohorts while the fraction of minority admits does not, holding SATs and class rank equal; this pattern would constitute evidence of class balancing.

[34] With a continuum of applicants, as in Chade, Lewis and Smith it does not matter whether the college chooses an admissions cutoff before or after it observes who applied and what their characteristics are. With a finite number of students, if a college has sufficient applications from students that it would like to enroll, the college will admit some students, and not admit others, so that the expected attendance shares of admitted students sum to just less than the capacity. If the college knows the quality of each applicant, there is an interval in which the cutoff may lie in which the admissions decisions of that college are identical. This interval shrinks to a point as the number of applicants increases.

[35] A college might want to publicly commit to favoring certain applicants in order to affect application behavior. In their model of early admissions, Avery and Levin similarly assume that admissions offices cannot commit to rules that are suboptimal given some realization of students' applications.

## 3.5 Beliefs and information

### 3.5.1 Admissions quality and admissions chances

While colleges observe students' admissions quality parameters $(z_i, q_i)$, each student knows her $z_i$ but observes only a noisy signal of her residual "caliber" $q_i$. That is, colleges observe an econometrician-unobserved characteristic of each student, but students observe only a potentially uninformative signal. I assume that each applicant $i$ observes a signal $s_i \in R$ which is distributed jointly normally with $q_i$ for each applicant and is independent across applicants:

$$\begin{pmatrix} q \\ s \end{pmatrix} \sim N\left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{q(i)} & \rho_{(i)}\sigma_{q(i)} \\ \rho_{(i)}\sigma_{q(i)} & 1 \end{pmatrix} \right).$$

Here $\sigma^2_q$ is the variance of unobserved quality $q$, and $\rho$ is the coefficient of correlation between $q$ and $s$. Without loss of generality the variance of the signal $s$ is 1.

Importantly, the quality of students' information, as well as the importance of unobserved quality relative to the information provided by SAT scores and grades, may vary across students' high schools. For instance, students from some schools may have worse information about admissions chances, as represented by a lower value of $\rho$. I therefore allow the variance parameters to vary with the fraction of students at $i$'s high school who have ever received free or subsidized school lunch, a common proxy for poverty which I denote $Econdisadv_{s(i)}$:

$$\begin{aligned} \sigma_{q(i)} &= \exp(\beta^\sigma_0 + \beta^\sigma_1 Econdisadv_{s(i)}) \\ \rho_{(i)} &= \frac{\exp(\beta^\rho_0 + \beta^\rho_1 Econdisadv_{s(i)})}{1 + \exp(\beta^\rho_0 + \beta^\rho_1 Econdisadv_{s(i)})}, \end{aligned}$$

This information structure is new to the literature on college choice. It allows for correlation in admissions conditional on observed characteristics and, through the signal, it allows for selection on an unobservable admissions-relevant characteristic in the application decision. We will see that students' admissions calibers matter for their college grades as well as for their admissions outcomes. Relatedly, Arcidiacono, Aucejo, Fang and Spenner (2012) test whether applicants to Duke University possess private information about their first-year grades, unknown to the university at the time of admissions. They conclude that the university possesses private information unknown to the students, but fail to reject the hypothesis that students have no private information. My modeling assumptions are consistent with this finding.

## 3.6 Portfolio choice

At the time of applications, students know the functions $u_{ij}(Aid_{ij})$ that will determine their utilities from attending each college, but do not know their financial aid offers or matriculation-time shocks.

Given a choice set $B \subseteq \mathcal{J}$, let $Aid_{iB}$ denote a vector of financial aid offers $\{Aid_{ij}\}_{j \in B}$. The value of a choice set $B \subseteq \mathcal{J}$ before the student's shocks $\epsilon^c_{ij}$ are known[36] is given by

$$U_B \equiv k + \sum_{Aid_{iB} \in 2^{|B|}} Pr(Aid_i) \cdot \log\left(1 + \left(\sum_{j \in B} \exp(u_{ij}(Aid_{ij})/\lambda)\right)^{\lambda}\right).$$

In the model, students trade off the gain in expected utility from college applications against the applications' cost. I assume that the cost of applications depends on the number of colleges to which a student applies. Let

$$C(n; w_{s(i)}) = c^{fixed}_{w(s_i)} + c^{var}_{w(s_i)} n$$

be the cost of applying to $n$ schools for a student from high school $s_i$ with characteristics $s_i$.

In estimation, I assume

$$\begin{aligned} c^{fixed}_{w(s_i)} &= \beta^{fixed}_0 + \beta^{fixed}_{econdisadv} Econdisadv_{s(i)} \\ c^{var}_{w(s_i)} &= \beta^{var}_0 + \beta^{var}_{econdisadv} Econdisadv_{s(i).} \end{aligned}$$

That is, there is a fixed cost of submitting any applications, plus a constant marginal cost per application. To capture heterogeneity in access to college counselors or other resources, I allow the fixed and marginal costs to vary with the fraction of students at $i$'s school who have ever qualified for free or subsidized lunch. Here, application costs include not just application fees, but the costs of time and effort in acquiring information and preparing applications. I hypothesize that these costs are higher at poorer schools, where the families may have less familiarity with college applications and offer less support and the schools are likely to provide less college counseling service.

Students are expected utility maximizers. The value of an application portfolio $A \subseteq \mathcal{J}$ to an applicant with admissions chances $\{P_i(B|A)\}_{B \subseteq A}$ is given by

$$V_i(A) \equiv \sum_{B \subseteq A} P_i(B; A) E_{aid}\left[\log\left(1 + \left(\sum_{j \in B} \exp(u_{ij}/\lambda)\right)^{\lambda}\right)\right] + k - C(|A|, w_{s(i)}).$$

Students choose a portfolio to maximize $V_i(A)$.

Importantly, the marginal gain from an additional application decreases as the portfolio grows. The value of the first application to a regional Texas public university may be high. In contrast, the fifth such application is less valuable, as the student can be enrolled in at most one college.

[36] The expression for $U_B$ follows from the nested logit error specification. See e.g. Train, "Discrete Choice Methods with Simulation" (2009), chapter 4.

Students may submit multiple applications because of admissions risk, because of the value of multiple draws of matriculation-time shocks, and because of the value of multiple financial aid draws.

In the model, students have rational expectations and therefore calculate their admissions chances correctly. They do not observe their residual quality $q_i$ or match-specific shocks $\mu_{ij}$, but integrate over the conditional distribution of $q_i$ given their signals. From the student's perspective, the chance of admission to a set $B \subseteq A \subseteq \mathcal{J}$ is:

$$P_i(B; A) = \int_q \prod_{j \in B} \left( \Phi(z_{ij}\gamma_j + q_i) \right) \prod_{j' \in A \setminus B} \left(1 - \Phi(z_{ij}\gamma_j + q_i)\right) \phi(q_i; \rho s_i, 1 - \rho^2) dq_i,$$

where $\Phi(\cdot)$ is the standard normal CDF, and$\phi(\cdot; \mu, \sigma^2)$ the density of a normal random variable with mean $\mu$ and variance $\sigma^2$, so that the conditional density of $q_i | s_i$ is $\phi(q_i; \rho s_i, 1 - \rho^2)$.

## 3.7 Equilibrium

### 3.7.1 Cutoffs

My first result shows that colleges' strategies consist of cutoff rules. Note that since colleges observe $q_i$ and $z_{ij}$, colleges have private values.[37]If college $j$ could observe the decisions of college $j'$, it would gain additional information about its applicants' probability of matriculation, but it would not learn any information that affects its best estimate of the value of its applicants. Moreover, since students submit applications before colleges choose admissions rules, colleges do not affect applications through their choice of admissions rule.

**Proposition 1.** *Colleges' optimal admissions rules consist of cutoffs* $\{\underline{\pi}_j\}_{j \in \mathcal{J}}$ *such that an applicant is admitted to* $j$ *if and only if* $\pi_{ij} > \underline{\pi}_j$*, and either* $\sum_{i:\pi_{ij} > \underline{\pi}_j, j \in A_i} Pr(C_i = j) = k_j$ *or* $\underline{\pi}_j = \pi_j^0$*.*

*Proof.* Let $Admit\{j\}$ be an admissions rule that satisfies the expected capacity constraint, and suppose it is not a cutoff rule. Then there are two applicants $i$ and $i'$ such that $\pi_{ij} < \pi_{i'j}$ but $Admit\{j\}(i) > 0$ and $Admit\{j\}(i') < 1$. If admitted, $i$ attends $j$ with probability $P_{ij}$ and $i'$ attends with probability $P_{i'j}$, for some $P_{ij}, P_{i'j} \in (0, 1)$. It is feasible and profitable for $j$ to reduce $Admit\{j\}(i)$ by $\frac{\epsilon}{P_{ij}}$ and increase $Admit\{j\}(i')$ by $\frac{\epsilon}{P_{i'j}}$ for some $\epsilon$.

If $\underline{\pi}_j > \pi_j^0$ then college $j$ can profitably increase expected enrollment by lowering $\underline{\pi}_j$. $\square$

[37]That is, the information observed by college $j$ is sufficient for its valuation $\pi_{ij}$, and hence sufficient for the expected valuation of $i$ conditional on other colleges' information and $i$ matriculating at $j$. Colleges' valuations of a given student are not statistically independent. Indeed they are highly correlated, as they depend jointly on the student's caliber, SAT scores, and grades.

The proposition says that the college chooses a cutoff $\underline{\pi}_j \geq \pi_j^0$. Either the college admits every applicant whom it finds acceptable, in which case $\underline{\pi}_j = \pi_j^0$, or its capacity constraint binds. If $\underline{\pi}_j > \pi_j^0$ then the sum of attendance probabilities of students above the cutoff is equal to the college's capacity. Given this result, for the remainder of the paper I describe colleges' strategies as cutoffs $\underline{\pi}_j \in R_+$ for $j \in \mathcal{J}$.

### 3.7.2 Equilibrium Definition

A rational-expectations equilibrium is a tuple

$$\left\{\{A_i\}_{i\in I}, \{B\{j\}\}_{i\in J}, \{C_i\}_{i\in I}, \{X_j^{peer}\}_{j\in J}\right\}$$

that satisfies the following properties:

1. $A_i \in \mathcal{A}$ solves $i$'s application problem
$$\max_{A\in\mathcal{A}} V_i(A)$$
given admissions rules $B\{j\}$, peer characteristics $X^{peer}$, and $i$'s characteristics.

2. For each admission set $B_i$, $C_i : 2^{B_i} \times \mathcal{X}^{peer} \to \Delta J$ maximizes $i$'s utility within $B_i$, i.e.
$$C_i\left(B_i, \hat{X}^{peer}\right)[j] = \mathbf{1}\left\{U_{ij}(\hat{X}_j^{peer}) > U_{ik}(\hat{X}_k^{peer})\ \forall k \in B_i\right\}.$$

3. For each college $j$, $\underline{\pi}_j$ maximizes $\mathbb{E}\left(\Pi_j | x_i, z_i, q_i\right)$ subject to $\sum_{i\in Admit(j)} Pr(C_i = j|x_i, z_i, q_i) \leq k_j$, where $Pr(C_i = j|x_i, z_i, q_i)$ are the matriculation probabilities induced by $A$ and $X^{peer}$, integrating over the distribution of the student's other applications and admissions offers given the characteristics $x_i, z_i, q_i$ observed by college $j$.

4. $\forall j :\ X_j^{peer} = X^{peer}(C(j))$, where $X^{peer}(C(j))$ are characteristics of the entering class $C(j)$.

For the purposes of (4), $X_j^{peer} = (SAT_j^{25}, SAT_j^{75})$ are the quantiles of the SAT distribution at $j$, from which student $i$ calculates $\overline{SAT}_j$ and $\tau_i^{SAT_j}$.

Because optimal admissions rules are cutoffs, we will identify admissions rules with the corresponding cutoffs and consider equilibria[38] of the form:

[38] If there were a continuum of potential applicants, together with a measure, then we could define equilibrium as a BNE of the game with the same timing structure, in which college $j$ receives a large negative payoff if the measure of students enrolled at $j$ exceeds $k_j$, and obtain the same properties and predictions. In the data, there is only a large finite number of applicants, not a continuum; hence colleges cannot perfectly predict their actual enrollment. To adapt the model to the finite dataset, I do not specify what colleges' payoffs would be if their enrollment were to exceed their expected capacity, but constrain colleges to admit a class that has an expected number of enrollees not greater than the expected capacity. Given the large number of students, one could attain very similar predictions with a BNE in which each college pays a steep and increasing cost for exceeding its capacity, rather than a hard constraint.

$$\left\{\{A_i\}_{i\in I}, \{\underline{\pi}_j\}_{j\in J}, \{C_i\}_{i\in I}, \{X_j^{peer}\}_{j\in J}\right\}.$$

### 3.7.3 Limited multiplicity of equilibria

In general, there is no guarantee that equilibrium is unique, for reasons similar to those in Chade, Lewis and Smith. In this section, I show that given fixed distribution of application portfolio choices, there is a unique mutual best response by colleges. That is, there is precisely one vector of cutoffs $\underline{\pi}$ such that each $\underline{\pi}_j$ is optimal given $\underline{\pi}_{-j}$ and applications.

To show these results, I show that holding applications, financial aid, and peer characteristics fixed, students' matriculation probabilities are isotone in $\underline{\pi}$. As a result, market-clearing cutoffs $\underline{\pi}$ form a complete lattice. As a corollary, for any set of applications, cutoffs exist that satisfy the colleges' problems. Letting $\underline{\pi}_L$ denote the lowest cutoff and $\underline{\pi}_H$ denote the highest, When students' choice probabilities satisfy a substitutes property, I show that $\underline{\pi}_L \neq \underline{\pi}_H$ leads to a contradiction, as the share of students attending the outside option and/or nonselective colleges must be strictly higher under $\underline{\pi}_H$ than under $\underline{\pi}_L$, but the share at each selective college cannot decrease.

Let $Pr(C_i = j|B)$ denote the probability that student $i$ enrolls in college $j$ given admission to a set of colleges $B \subseteq \mathcal{A}$, holding financial-aid offers and peer characteristics fixed. Let $Pr(C_i = 0|B)$ denote the probability that $i$ chooses the outside option.

**Condition** (Substitutes)**.** For each individual, the following condition holds:

$$B \subseteq B' \implies Pr(C_i = 0|B') < Pr(C_i = 0|B).$$

This condition holds generally whenever the outside option is a possible substitute for each college.[39] In particular it is satisfied for the nested logit specification of utility in this model conditional on random coefficients, and hence for the mixed nested logit specification.

**Proposition 2.** *If the substitutes condition holds, then conditional on applications and expected peer characteristics there is a unique cutoff vector $\underline{\pi}$ that satisfies equilibrium condition (3).*

*Proof.* For each set $B \subseteq \mathcal{A}$ and and $B' \subseteq A$ with $B \subseteq B'$, each agent's choice probabilities must satisfy[40]

$$Pr(C_i = j|B') \leq Pr(C_i = j|B). \tag{*}$$

[39] The condition is related to the "connected substitutes" condition of Berry, Gandhi and Haile with continuous prices. In my setting, what is needed is that when a capacity-constrained college is removed from the choice set, the probability of not attending any capacity-constrained college strictly increases.

[40] This result is due to Block and Marschak (1960) and Falmagne (1978). See also Haile, Hortacsu and Kosenok (2008). In particular, a direct application of Theorem 1 of Falmagne (1978) gives that for any sets $B_0, B_1 \subseteq \mathcal{A}$, we have $Pr(C_i = j|B_0) - Pr(C_i = j|B_0 \cup B_1) \geq 0$.

Define $\underline{\pi}^*(\underline{\pi}) : R^{|J|} \rightarrow R^{|J|}$ by $\underline{\pi}_j^*(\underline{\pi}) = \underline{\pi}_j^*(\underline{\pi}_{-j})$. That is, the $j$th component of $\underline{\pi}^*$ is the cutoff that college $j$ optimally chooses given (fixed) applications and student preferences, and the cutoffs of other colleges. By (*), the function $\underline{\pi}^*$ is isotone in $R^{|J|}$. Its fixed points therefore form a complete lattice.

Let $\underline{\pi}_L^*$ be the lowest equilibrium cutoffs, and $\underline{\pi}_H^*$ be the highest. Let $\mathcal{J}_u \subseteq \mathcal{J}$ denote the set of schools that are not selective at $\underline{\pi}_L$, i.e. the union of the outside option and the set of schools for which $\underline{\pi}_{Lj}^* = \pi_j^0$. For a contradiction, suppose $B_i(\underline{\pi}_H^*) \neq B_i(\underline{\pi}_L^*)$ for some student $i$.

The share of students attending the outside option must strictly increase. Moreover, in any random utility model the the share of students attending other colleges in $\mathcal{J}_u$ must also weakly increase.[41] Therefore the share of students attending colleges in $\mathcal{J}_u$ must strictly increase:

$$\sum_i Pr(C_i \in \mathcal{J}_u | \underline{\pi}_H^*) > \sum_i Pr(C_i \in \mathcal{J}_u | \underline{\pi}_L^*).$$

Cutoffs of college in $\mathcal{J} \backslash \mathcal{J}_u$ are weakly higher under $\underline{\pi}_H^*$, however, implying that they are at full capacity in both $\underline{\pi}_L^*$ and $\underline{\pi}_H^*$, i.e.

$$\sum_i Pr(C_i \notin \mathcal{J}_u | \underline{\pi}_H^*) = \sum_i Pr(C_i \notin \mathcal{J}_u | \underline{\pi}_L^*),$$

which is a contradiction. □

This "limited multiplicity" result is helpful in evaluating counterfactuals. It shows that interaction among colleges is not itself a source of multiplicity. In the appendix I prove that an equilibrium exists.

## 3.8 College outcomes

I model persistence in college as an outcome of interest. In each semester $t$, student $i$ at college $j$ obtains grades that depend on his pre-college academic characteristics including unobserved caliber, the college that he attends, and whether he receives a targeted scholarship program. We allow the slope of grades with respect to SAT scores to differ across colleges, reflecting the possibility that colleges differ in the ability to educate students across the distribution of academic preparation.

[41] For $j \in \mathcal{J}_u$, if $\underline{\pi}_{Hj}^* = \underline{\pi}_{Lj}^*$ then the share must weakly increase by (*). Alternatively, $\underline{\pi}_{Hj}^* > \underline{\pi}_{Lj}^*$ if and only if college $j$ has filled its capacity under $\underline{\pi}_H^*$.

Semester grades are given as follows:

$$
\begin{aligned}
gpa^*_{ijt} =& \beta^{gpa}_j + \beta^{gpa}_{sat} sat_i + \beta^{gpa}_{rank} classrank_i + \beta^{gpa}_q q_i + \beta^{gpa}_{los} los_i \cdot 1(j = UTA) \\
&+ \beta^{gpa}_{satXuta} \cdot sat_i \cdot 1(j = UTA) + \epsilon^{GPA}_i
\end{aligned}
$$

$$
gpa_{ijt} = \begin{cases} 0 & \text{if } gpa^*_{ijt} < 0 \\ gpa^*_{ijt} & \text{if } gpa^*_{ijt} \in [0,4] \\ 4 & \text{if } gpa^*_{ijt} > 4 \end{cases}
$$

Cumulative GPA is given by

$$
\overline{gpa}_{ijt} = \frac{1}{t} \sum_{r \leq t} gpa_{ijt}.
$$

In each semester, student $i$ continues with probability

$$
Pr(continue_{ij}) = \Phi(\beta^{continue}_{GPA} \overline{GPA}_{ijt} + \beta^{continue}_{firstyear} \cdot (t \leq 2) + \beta^{continue}_y y_i + \beta^{continue}_j)
$$

and drops out with complementary probability.

I focus on UT Austin and Texas A&M because access to state flagship schools is a primary goal of the Texas Top Ten program and because these institutions offer the most detailed administrative data.

# 4 Data and Descriptive Analysis

I rely on the administrative records of Texas colleges and universities, and a set of surveys of high school students, conducted by the Texas Higher Education Opportunity Project. The administrative data consist of 629,388 applications to nine Texas colleges in the years 1990-2004. They include admissions and enrollment decisions, test scores, grades and demographics of applicants, as well as transcript data (major, grades, time to graduation) of enrollees at those institutions. In addition, the dataset contains a survey of students in the spring of 2002, 13,803 seniors and 19,969 sophomores in total from Texas public high schools. There are also two follow-up surveys with the seniors, in 2003 and 2006, and one with the sophomores.

## 4.1 THEOP survey

THEOP selected 105 Texas public high schools at random in the spring of 2002. Of these, 86 high schools gave permission for in-class surveys; all seniors and sophomores who were present in school on "survey" day filled out a paper-and-pencil survey. These "survey days" took place between March 4, 2002 and May 27, 2002. At 12 additional schools, students completed surveys by mail in May 2002.

| | 2002 | 2003 | 2004 | 2006 |
|---|---|---|---|---|
| Senior cohort | Wave 1: N=13,803 | Wave 2: N=5,836 | | Wave 3: N~5,800 |
| Sophomore cohort | Wave 1: N=19,969 | | Wave 2: N=3,092 | |

Source: http://www.texastop10.princeton.edu/survey_overview.html

Table 1: Survey

The initial wave surveyed 13,803 seniors: for cost reasons, the survey designers followed up with a randomly selected subsample, interviewing 5,836 of the original seniors the following year in the survey's second wave.[42]

The data include the year and term an applicant desired to enroll, demographics including gender, ethnicity, citizenship and Texas residency, and many academic characteristics: high school class rank (by decile), SAT/ACT score, and AP classes taken. We also observe high school characteristics including mean SAT scores, fraction of students receiving free or reduced-price lunch, and fraction of SAT-takers.

Most importantly, I see up to five college applications, together with indicators for financial aid applications, admissions and financial aid outcomes at each college. I do not see the student's matriculation choice in wave one, but if a student appears in wave two I see which institution, if any, she is currently attending, as well as any college or university the student attended within the past year.

### 4.1.1 Final dataset

In estimation, I restrict the dataset to students who have taken the SAT or ACT and are not missing class rank or standardized test scores; the final dataset consists of 4144 high school seniors. Of these, 1975 were tracked in wave two of the survey and hence have observable college choices.

### 4.1.2 ACT scores

Some students take the ACT instead of the SAT; if a student took both exams, I keep that student's SAT scores. Otherwise, I convert ACT composite scores to SAT combined scores using the College board's 1999 ACT-SAT concordance tables.[43]

[42] The survey designers included in wave two all Black and Asian students in the original sample, as well as random samples of Hispanics and non-Hispanic whites. The 5836 students who completed the wave two survey represent a 70 percent response rate. See the "Senior Wave 2 Survey Methodology Report" at http://theop.princeton.edu/surveys/senior_w2/senior_w2_methods_pu.pdf for details.

[43] http://research.collegeboard.org/sites/default/files/publications/2012/7/researchnote-1999-7-concordance-sat-act-students.pdf

#### 4.1.3 Income

The data do not provide $i$'s household income; I do, however, observe the education and occupational category of each of $i$'s parents. I draw incomes from the March CPS. To do so, for each household I construct the household head's education and occupational category. For each simulation draw, I then draw from incomes in the 2002 and 2003 March CPS samples of Texas residents with the same occupational category and education. Because the THEOP dataset uses a different encoding of occupations, I convert the CPS sample occupation codes to 1990 CPS codes as described in the data appendix. If either parents' occupation category or education is missing in the THEOP data, but one variable is present, I draw from the March CPS conditional on the variable that is present.

#### 4.1.4 Expected family contribution

In estimation, I use the family's expected family contribution (EFC) as a measure of the amount of financial aid the student is likely to receive. I use the federal government's "simplified EFC formula worksheet A" from the 2002-2003 FAFSA, using parents' income, the number of parents/guardians who live with the applicant, and the number who work full-time, if the applicant lives with two parents. In practice, I draw a large number of income draws for each student from the CPS, and for each draw calculate the EFC using the formula. In estimation I integrate over these draws when calculating the likelihood and moments.

### 4.2 Comparison to administrative data

In addition to the survey, THEOP provides admissions, enrollment, and demographic data for applicants to the nine colleges/universities in table 2.

I observe the year and term an applicant desired to enroll. I also see demographics: gender, ethnicity, citizenship, TX residency; and academic characteristics: high school class rank, SAT/ACT score, AP classes taken, as well as characteristics of the student's school including high school mean SAT scores and fraction eligible for free/reduced lunch. By semester, for enrolled students, I observe credit hours earned, semester GPA, department and field of study.

At UT Austin and Texas A&M there is additional detail. These datasets provide the exact class rank as well as the student's first- and second-choice majors and the major for which the applicant was considered. I make use of the enrollment data for the state flagship universities, UT Austin and Texas A&M, together with characteristics of the students including class rank, SAT/ACT scores, and high school characteristics, students' semester grades, and whether they are present for all semesters.

A good description of the data can be found in Tienda and Niu (2010). That paper documents regression discontinuity effects, showing that variation in top-decile status indeed appears to affect

| | Application Data | | College Transcript Data | |
|---|---|---|---|---|
| Institution | N | Years | N | Years |
| Texas A&M | 163,027 | 1992-2002 | 637,018 | 1992-2007 |
| Texas A&M Kingsville* | 18,872 | 1992-2002 | 91,106 | 1992-2004 |
| UT Arlington | 29,844 | 1994-2002 | 51,315 | 1994-2002 |
| UT Austin | 210,006 | 1991-2003 | 659,102 | 1991-2004 |
| UT Pan American** | 44,747 | 1995-2002 | 115,812 | 1995-2005 |
| UT San Antonio# | 61,221 | 1990-2004 | 160,604 | 1990-2004 |
| Texas Tech | 81,153 | 1995-2003 | 211,771 | 1995-2004 |
| Rice | 36,190 | 2000-2004 | 18,149 | 2000-2005 |
| SMU | 45,549 | 1998-2005 | 60,607 | 1998-2005 |

* Applicant data for enrollees only: 1992-1994

** Limited variables provided

# Applicant data for enrollees only, 1990-1997

http://www.texastop10.princeton.edu/admin_overview.html

Table 2: Administrative dataset

students' application decisions and the type of college that they attend. Andrews, Ranchhod and Sathy (2010) show that the introduction of Texas Top Ten affected matriculation decisions.

The THEOP survey is based on a stratified sampling design that placed unequal weights on different types of high schools. Using the population weights, however, one obtains patterns very similar to those in the administrative data. A sequence of papers by Marta Tienda and coauthors describes the survey design and findings. I have confirmed that population-weighted mean SAT scores, class rank, and high school characteristics (poverty, SAT scores) of students in the survey who attend flagship universities closely match the actual numbers in the administrative data.

## 4.3 Descriptive Analysis

In this section, I provide evidence that the modeling choices are reasonable. It is necessary to allow for matriculation-time shocks and to allow students to fail to apply for financial aid, as well as to allow for correlation and private information in admissions outcomes.

### 4.3.1 Variation over time in applications, admissions, and enrollment shares

I begin with a description of the time-series variation in applications, admissions and enrollment at the University of Texas at Austin. While I obtain the main results using a survey of a single cohort, the relative changes that the model predicts from the removal of Texas Ten are close to these numbers. Table 37 shows the raw number of applications, offers of admission, and matriculation at UT Austin over the years 1992-2003 among all Texas public high school students, and among Black, Hispanic and Native American Texas public high school students.

In 1996 and previous years, the university admitted students on the basis of predicted first-year grades, together with a race-based affirmative action policy. In 1997, there was no official affirmative action policy, although UT Austin essentially admitted all top-decile applicants. In 1998, Texas Top Ten began, together with the university's policy of computing academic and personal indices for each applicant outside the top decile. The survey cohort entered college in the fall of 2002 as first-time freshmen.

Table 38 shows Black, Hispanic and Native American applications, admissions and matriculation as a share of the totals at UT Austin listed in table 37. Minorities' enrollment as a share of the total was 14% lower in 1997 than in 2002. We will see that the model predicts that minorities' enrollment would be 10% lower in 2002 if Texas Top Ten were not in effect. The difference may in part reflect population changes, in particular the increasing share of Hispanic students in Texas high schools, as well as other changes in demand for colleges and in UT Austin's admissions policies.

The administrative data shows also that the share of applications and enrollment of top-decile students increased following the introduction of the Texas Top Ten policy. Tables 39 and 40 show changes at UT Austin in the share of students in the top decile of their high school class and of minority students in the top decile respectively. Table 40 shows that in 2002, 10.3% of applications to UT came from top-decile minority students, while in 1997 the share was 7.3%, a 31% decrease relative to 2002. I will show that Texas Top Ten led minority students with high class rank to apply to the University of Texas at Austin by providing a guarantee of admission. This finding is consistent with the difference in shares across years.

#### 4.3.2 Matriculation-time shocks

1574 out of the 1975 SAT-taking students in the estimation sample who appear in "wave 2" of the dataset were admitted to at least one college. Of these, 297 students did not matriculate at any four-year college. Using the survey's population weights, 14.01% of SAT- or ACT-taking students were admitted to some four-year college but did not matriculate at any four-year college. Allowing for this fact is important, and for this reason the model contains matriculation-time preference shocks and uncertainty about financial aid.

#### 4.3.3 Financial aid

In the survey data, while 69% of students submit financial aid with all applications (or submit no applications), 19% submit at least one application for admissions but no financial aid applications, and 11% apply for aid from some but not all colleges to which they applied. Table 32 shows a descriptive probit regression of financial aid application conditional on submitting an application for admission. An observation is an application to a school by an individual. We include individual-level random effects.

The probability of submitting an application for aid is decreasing in the average income of the household head's occupation, measured in units of $10000 2002 dollars. Other factors that affect the expected family contribution correlate with application probabilities in the expected way. The number of parents or guardians appears in the FAFSA formula, with single-parent households having a lower EFC. Indeed, two-parent households are less likely to apply for aid. Higher high school poverty correlates with additional aid applications. Finally, the individual random effects are highly significant. This pattern is consistent with a common source of difficulty in financial aid applications across colleges, such as a difficulty in completing the FAFSA.

#### 4.3.4 Admissions

It is empirically true that students' outcomes are correlated within portfolios. To provide descriptive evidence I estimate random-effects probit estimates of admissions chances using the survey data. Table 33 in the appendix displays the results. The analysis is descriptive only because it does not use the full model to control for selection on application decisions.[44] We can obtain the implied admissions cutoffs by multiplying the coefficient on each college dummy by -1. These results show reasonable values for admissions cutoffs. Most importantly, the residual covariance of admissions outcomes within a portfolio is significant. That is, there is strong evidence for the existence of individual-level unobservables which affect admissions chances at all colleges. I find a variance of "caliber" of approximately 1. (As in the full model, the variance of match terms $\mu_{ij}$ is normalized to 1.) A likelihood-ratio test of $\sigma_u = 0$ is massively rejected, with a $p$-value of less than .0001.

Without allowing correlation within applications, one may overestimate application costs. All else equal, higher correlation implies smaller application portfolios because a rejection is "bad news" about other outcomes.[45] (In the extreme case, imagine that the only uncertainty a student faces is about admissions. If all outcomes are perfectly correlated, there is no sense in applying to more than one college.) Hence if I did not allow for correlation in admissions outcomes via students' caliber, I might incorrectly ascribe "undermatching" to application costs rather than information.

Turning to the signal of caliber, and its sources of identification in the data, I demonstrate that higher selectivity of an application portfolio correlates with increased admissions chances

[44] For simplicity we also do not vary the variance of caliber with high school poverty, i.e. we impose $\sigma_q = exp(\sigma_q^{const})$. If in the model we imposed $\rho = 0$ for all students, so that no student had any signal of his/her caliber, then the first column of this table would give us exactly the model estimates of admissions parameters.

[45] See Naygpal (2004)

conditional on observables. In the second column of table 33 I estimate admissions chances via probit, adding a proxy for the aggressiveness of application portfolios. I use the average selectivity of colleges in each individual's portfolio as ranked by Barron's guide to colleges in 2002. I also add an interaction of this selectivity measure and high school poverty to see if patterns of selection vary. Having highly selective schools in the portfolio will predict better admissions outcomes if and only if students have some signal of their caliber; if students are informed about caliber, then those with better signals will apply more aggressively. Indeed I find that selectivity of portfolios predicts admissions outcomes. In this descriptive regression I do not see any pattern with changes in high school poverty.

### 4.3.5 College Outcomes

In the model I assume that scholarship programs affect grades but conditional on grades do not affect dropout rates. The descriptive evidence is consistent with this assumption. Two regressions provide descriptive evidence on grades and dropout rates using the administrative datasets. In the first specification, GPA is a linear function of academic and high-school characteristics with individual random effects, i.e. grade-point average in term $t$ is given by:

$$GPA_{ijt} = X_i\beta_j + \tilde{\mu}_{ij} + \tilde{e}_{ijt}.$$

The sample is the population of all Texas public high school students entering the flagship universities as freshmen in the fall of 2002. In the second specification, dropout rates are given as a probit on grades, characteristics, and time dummies for the population of students who entered state flagship universities in the spring of 2002.

I display the results in tables 34 and 35 in the appendix. I find that, conditional on grades, the relation between persistence and participation in the LOS and Century scholarship programs is not significant. In particular, the LOS program includes a mentoring component as well as financial support; nonetheless, coming from a Longhorn Opportunity Scholars high school correlates with higher grades, but conditional on grades there is no apparent association between the program and persistence in college.

### 4.3.6 In-state applicants

I will assume in counterfactuals that colleges do not adjust the fraction of out-of-state students that they admit. The data support this assumption. In the administrative data, both before and after the introduction of Texas Top Ten, 90% of enrolled students at UT Austin came from within Texas, suggesting that the university targets a specific percentage of in-state students. There is little support in the UT Austin admissions office's decisions for the hypothesis that the university has changed the fraction of students paying in-state tuition as a means of controlling its budget.[46] At Texas A&M and regional campuses, a larger fraction of students come from within Texas, and there is less reason to worry about changes in apparent capacity for in-state students in counterfactuals.

# 5 Estimation and Simulation

I estimate cutoffs $\{\underline{\pi}_j\}_{j\in\mathcal{J}}$ and all parameters except the "peer characteristics" $\overline{\beta}_j$ via the method of simulated moments.

## 5.1 Overview

I use three sets of moments in the simulated GMM procedure. The first set of moments is the score of the likelihood of all observables in the THEOP survey. Each student has an application portfolio $A_i$, a set of schools $B_i$ offering admission, financial aid applications and offers $(A_i^{finaid}, Aid_i)$, a matriculation decision $C_i$, and college outcomes if he attends college. For students in the first wave of the survey only, we see $A_i, B_i$ and financial aid applications and offers, whose likelihood we compute. For students who are in both waves of the survey, we observe matriculation decisions as well, which appear in the likelihood for these students. The second set of moments matches average financial aid awards in IPEDS to those predicted by the model at each school. In the administrative data, we observe admissions to $j$, matriculation at $j$, and grades and the decision to drop out each semester. The third set of moments requires that grade point averages and dropout rates of surveyed students as predicted by the model match the observed grades and dropout rates in the administrative data. This final set of moments makes use of an "indirect inference" strategy.

## 5.2 Identification in practice

Although the model is estimated via simulated GMM, there are clear sources of identification of particular components of the model.

[46] Table 36 in the appendix provides statistics on admissions and matriculations by in-state and out-of-state applicants at UT Austin over the years 1991 through 2003 as given in the administrative data. The fraction of the enrolled students whom the university classified as in-state applicants remained slightly above 90% in each year with the exception of 1997, where 89.9% of first-time freshmen were in-state. This lack of change tells us that despite changes in policy – the removal of affirmative action, the introduction of Texas Top Ten – the university did not greatly adjust the fraction of out-of-state students. The share of students from in-state public high schools is also nearly constant.

**Information structure** We first turn to the identification of the information structure. To identify the importance of the unobserved caliber $q$, it is crucial to see application portfolios. The importance of caliber $q$ is identified from correlation in admissions outcomes within an individual's application portfolio. If, fixing observables, admission to school $j$ for student $i$ does not predict a higher chance of admission to school $k$ for student $i$, then there is no role for a common "caliber" that affects both admissions chances. In the language of the model, if admissions outcomes are nearly uncorrelated after conditioning on the observable variables $z_i$ that affect admissions, then we conclude that the variance of $q$ is small.

Observing application portfolios together with admissions outcomes allows me to estimate the quality of students' signals $s$. If students have private information about their admissions chances, students with aggressive application portfolios will have relatively high probabilities of admission conditional on observables. For example, consider two students with identical test scores, grades and high schools, one of whom applies to a more selective portfolio (Rice and UT Austin, for example, rather than UT Austin and a regional UT campus). Students may apply to different portfolios because of differences in application costs, varying preferences, or differences in beliefs about admissions chances. Only in the latter case, however, should we see that the student who applies to the riskier portfolio is more likely to gain admission to schools that are common to both portfolios.

The covariance term $\rho$, therefore, can be backed out from the correlation between application decisions and admissions outcomes. Conditional on observables, students with high signals will apply as if likely to be admitted, e.g. to schools with high cutoffs, or to few schools, and will be likely to gain admission. Students with low signals may send more applications to lower-ranked schools. If, in contrast, all variation in portfolios conditional on observables is driven by preferences, unusually aggressive portfolios should not predict higher admissions chances.

Additionally, the relation between application decisions and matriculation choices provides information about beliefs. For intuition, consider a student considering applying to a college at which the econometrician predicts that he has a very low chance of admission. If $\rho \approx 0$ then the student has no additional information about the econometrician-unobserved admissions quality term $q_i$. The student must therefore have a very strong taste for the "long-shot" college in order to submit such an application. Therefore, students who submit "long-shot" applications are a selected sample; if admitted, they should be highly likely to attend. In contrast, if $\rho$ is high, then the extent of selection is lower for students with low admissions indices $z_{ij}\gamma_j$; students can submit applications that appear to the econometrician to have low probabilities of success, because the students have high signals of $q_i$.

**Admissions Parameters** The admissions parameters $\gamma$ and cutoffs $\underline{\pi}$ are identified via the distribution of admissions outcomes conditional on applications. I observe the probability of offers of admission to sets $B \subseteq A$ conditional on characteristics $z_i$ and applications to all colleges in $A$.

For intuition, suppose there were no signal, i.e. $cov(q, s) = 0$ for all students. In this case, we would know the probability of admission to colleges conditional on $z_i$, and it would be possible to estimate admissions parameters $\sigma^q, \gamma, \underline{\pi}$ separately using only the admissions data. In the model, if $cov(q, s) = 0$ we could obtain consistent estimates of $(\sigma^q, \gamma, \underline{\pi})$ via a standard random-effects probit regression.[47]

When students have private information about admissions chances, there is a selection problem in the above regression. The admissions model is linked to students' choices through the unobserved caliber $q$ and its signal. We observe admissions outcomes at $j$ only for students who apply to $j$, but these students have different admissions chances at $j$ conditional on observables because students' signals affect their application decisions. To solve this problem, the estimation procedure makes use of variation in characteristics, such as distance, that shift applications but are excluded from admissions. Distance to the college appears in the utility function, and therefore affects application probabilities, but does not affect admissions outcomes.

**Utility functions** To identify choice parameters, I use the matriculation decisions of students as well as the choice of application portfolios. I observe the distribution of matriculation decisions conditional on observables application sets, and admissions outcomes. In addition, the initial choice of application portfolios reveals information about students' utilities, as an application portfolio is a lottery over admissions sets. If college $j$ has high mean utility, there will be many applications to $j$ and a high probability of matriculation among admitted students. If students with particular characteristics, such as low distance to $j$, have high utility from attending $j$ we will see the same pattern among such students.

In addition, in order to identify the parameters that affect substitution patterns, it is especially useful to observe application portfolios, as I do, rather than top choices only. If a particular form of unobserved heterogeneity is important, there will be correlation in the relevant characteristic within portfolios. For instance, if there is heterogeneity in the utility that students obtain from peers' SAT scores, we will see that applying to a college with high SAT scores correlates with high SAT scores in other colleges within an applicant's portfolio.[48]

[47] Let the unit of observation be an application $A_{ij}$. Regress the admissions outcomes $B_{ij}$ on covariates and college dummies with individual-level random effects.

[48] As with admissions, there is a selection problem, as a student's signal and caliber affect his applications and admissions outcomes. Fortunately, there is random variation in admissions outcomes, admissions chances, and financial aid offers that is independent of students' utilities, and that leads students who apply to a particular portfolio to face different choice sets. There are shifters of admissions chances which are excluded from utility. For example, part of the variation in $i$'s class rank comes from sampling error in tests and random noise in grading, and another part of the variation comes from variation in $i$'s peers. These sources of variation are unrelated to $i$'s utility function. In the model, shocks $\mu_{ij}$ are excluded from $i$'s utility, as is $q_i$, $s_i$, and $i$'s class rank.

**Financial aid** The probability of receiving a financial aid offer conditional on application is observed, as is the distribution of income $y_i$ for each student. Using variation in parents' education and occupation as a shifter of income, we can identify the distribution of financial aid offers conditional on income and observables, and hence the parameters governing financial aid offers. The size financial aid awards is not observed in the survey, but the average amount disbursed at each college must match known numbers from IPEDS.

To identify the joint distribution of financial aid awareness and other characteristics, I make use of the fact that financial aid awareness is partially observed. In the standard consideration set model, an instrument is needed that is excluded from utility but shifts the probability that a particular alternative is in the consideration set. Here, in contrast, we observe a set of applications to colleges, some of which may be without applications for financial aid. There is still selection, as being unaware of financial aid at college $j$ will make a student less likely to submit an application to $j$. If I simply estimated probit regressions of financial aid application on covariates, conditional on application to $j$, I would overestimate the probability of financial aid awareness. If an application is sufficiently attractive, however, then a student may apply even without being aware of financial aid. Observable characteristics such as distance, and unobservables such as $s$ about which it is possible to make inferences, will shift application probabilities but do not affect awareness of financial aid.

**Outcomes** If I observed $q$ and income in the administrative data, I could directly observe the joint distribution of college grades, persistence, and all relevant individual characteristics. Hence, I could identify the parameters governing grades and persistence. The administrative data does not provide these variables, however. I use a set of instruments, including high school characteristics and parents' education, that are present in both datasets and correlate with $q$ and with income but do not directly affect students' outcomes conditional on the students' characteristics.

## 5.3 Choice set

I restrict portfolios to contain a maximum of five colleges. In the final survey dataset, most individuals apply to no more than five colleges; among students in our final dataset, 97.9% submit five or fewer applications. To further speed computation, I restrict the possible set of portfolios: while we allow all portfolios of up to three colleges, we restrict the set of possible large portfolios. Among portfolios containing five applications, I allow only those that some applicant in the data was observed to have chosen. We allow portfolios of four colleges that are subsets of the allowed 5-college portfolios as well as all portfolios of four colleges which appeared in the data. This restriction reduces the choice set from $|A| = 4480$ to $|A| = 817$ possible portfolios. It rules out certain unlikely combinations of colleges; for instance a student cannot apply to three highly selective private institutions and two of the smaller regional non-flagship public colleges.

## 5.4 Likelihood

I observe $\{x_{ij}, z_{ij}, A_{ij}, B_{ij}, Aware_{ij}^{obs}, Aid_{ij}C_{ij}\}_{i\in I^{sample}, j\in J}$, where $Aware_{ij}^{obs} \in \{0,1\}$ is an indicator for completing an application for financial aid at college $j$ and is observed only for $j \in B_i$. Let $\theta \in \Theta \subset R^N$ be a vector of parameters, where $\Theta$ is the set of allowed parameter values. Recall that $A_{ij}, B_{ij}, C_{ij}$ denote applications, admission, and matriculation respectively for student $i$ and college $j$. $Aware_{ij}^{obs} = 1$(i applied for financial aid at j) is generally not the full vector of financial-aid awareness, because we do not observe whether $i$ would have completed an application for aid at colleges outside his application set.

Let $\omega_i$ denote the vector of random coefficients $\beta_i$ of individual $i$ as well as income $y_i$.

The likelihood of applications $\ell_i^{Ap}$ is the measure of the set of preference and signal draws such that the observed application portfolio maximizes expected utility among all application portfolios:

$$\ell_i^A(\theta, \omega_i, q^s) = Pr\{A_i = \arg\max_{A\in\mathcal{A}} V_i(Apply_i|\omega_i, \theta)\}.$$

The following expression is the likelihood of admissions:

$$\ell_i^{B|A}(\theta, q^s) = \int \prod_{j\in B} \left(\Phi(z_{ij}\gamma_j + q_i - \underline{\pi}_j)\right) \prod_{j\in A\setminus B} \left(1 - \Phi(z_{ij'}\gamma_{j'} + q_i - \underline{\pi}_{j'})\right) dF_i(q|q^s).$$

Note that admissions chances do not depend on students' random coefficients. The likelihood of financial aid awareness is the probability that the applicant completes financial aid applications where he is observed to have applied:

$$\ell_i^{F|A,B}(\theta, \omega_i) = \left[\sum_{\tilde{A}:\tilde{A}\cap A_i = Aware_i^{obs}} \prod_{j\in\tilde{A}} Pr(Aware_{ij}|z_i^{finaidA}, \eta_i^{aware}, EFC_i) \prod_{j\notin\tilde{A}} \left(1 - Pr(Aware_{ij}|z_i^{finaidA}, \eta_i^{aware}, EFC_i)\right)\right]$$
$$* \prod_{j\in Aid_i} \Phi\left(\alpha_j^f + \alpha_y^f y_i + \alpha_i^f\right) \prod_{j\in B_i\setminus Aid_i} \left(1 - \Phi\left(\alpha_j^f + \alpha_y^f y_i + \alpha_i^f\right)\right).$$

The likelihood of matriculation is the nested-logit choice probability of school $j$ conditional on $i$'s characteristics:

$$\ell_i^{C|B,Aid}(\theta, \omega_i) = \frac{\exp(u_{ij}(\omega_i, Aid_{ij})/\lambda)\left(\sum_{j'\in B}\exp(u_{ij'}(\omega_i, Aid_{ij'})/\lambda)\right)^{\lambda-1}}{1 + \left(\sum_{j'\in B}\exp(u_{ij'}(\omega_i, Aid_{ij'})/\lambda)\right)^{\lambda}}.$$

For students who appear in wave 1 of the survey, we set $\ell_i^{C|B,Aid} = 1$, as we do not observe matriculation decisions. The likelihood of all observables in the data is given by

$$\ell_i(\theta) = \int_s \int_q \int_{\omega_i} \ell_i^A(\theta, \omega_i, q^s)\ell_i^{B|A}(\theta, s, q)\ell_i^{F|A,B}(\theta, \omega_i)\ell_i^{C|B,Aid}(\theta, \omega_i)\ell_i^{Outcome|C}(\theta, \omega_i, s)dF_i(q, |s, \theta)\phi(s)dsdG_i(\omega_i|\theta).$$

Let $N_{survey}$ denote the number of surveyed students. The first set of moment conditions is given by the score of the likelihood of all data in the survey:

$$g^{surv}(\theta) = \frac{1}{N_{survey}} \nabla_\theta \sum_i \log \ell_i(\theta)$$

## 5.5 IPEDS moments

Expected aid conditional on enrollment is

$$\mathbb{E}_i(Aid_{ij}(\theta)|C_i = j) = \int_{\omega_i} E(Aid_{ij}|\omega_i, \theta) dPr(\omega_i|A_i, B_i, C_i = j).$$

Because students' decisions to apply depend on characteristics, including income, that affect the amount of aid received, we need to integrate over the posterior distribution of unobservables including income given that the student has submitted his observed application portfolio, gained admission to his observed admission set, and chosen to enroll at $j$. We estimate this posterior distribution via simulation, following the computation of the likelihood. The distribution is given by

$$Pr(\omega|A, B, C) = \frac{pr(A, B, C, \omega)}{\int Pr(A, B, C, \omega) dF(\omega)}.$$
$$pr(\omega_m|A, B, C) \approx \frac{Pr(A, B, C, \omega)}{\sum_m Pr(A, B, C, \omega_m)}$$

for a particular draw $\omega_m$.

At each university, the model-predicted average financial aid award must match the average award from IPEDS:

$$g^{aid} = \frac{1}{N_{survey}} \sum_i popwt_i \cdot 1(C_i = j) \cdot \mathbb{E}_i(Aid_{ij}(\theta)|C_i = j) - \overline{Aid}_j^{IPEDS},$$

with $g^{aid}(\theta) = 0$ as $\theta = \theta_0$.

## 5.6 College persistence moments

I estimate the parameters that affect college grades and persistence via moments which match regression coefficients in the following specifications in the administrative data to coefficients obtained from simulated data. To define these moments, I first define the following auxiliary regression specifications.

$$\begin{aligned} outcome_{ij}^{(k)} &= z_i^{outcome}\tilde{\gamma}_j^{(k)} + \epsilon_{ij}^{(k)} \\ gpa_{ij1} &= z_i^{outcome}\tilde{\gamma}_j^{(2)} + \epsilon_{ij}^{(1)} \\ semesters_{ij} &= (gpa_{ij1}, \overline{gpa}_{ij}, z_i^{outcome})\tilde{\gamma}_j^{(3)} + \epsilon_{ij}^{(3)} \\ \log(semesters_{ij}) &= (gpa_{ij1}, \overline{gpa}_{ij}, z_i^{outcome})\tilde{\gamma}_j^{(4)} + \epsilon_{ij}^{(4)}. \end{aligned}$$

$z_i^{outcome}$ = (1, SAT, class rank, HS average SAT, HS % free/reduced price lunch, SAT x poverty, longhorn, century, parents' education) is a set of variables including every variable present in both datasets that affects grades and persistence in the model, as well as high school characteristics and parents' education (UT Austin data only), which correlate with students' caliber and income.

I simulate grades and semesters enrolled in survey using the model. The moments require that the coefficients of the auxiliary model estimated in administrative data, satisfy the OLS orthogonality conditions in the simulated data:

Let $Pr(m, q|i)$ denote the posterior probability of caliber $q$ and random coefficients and income draw $\omega_m$, given $i$'s observed characteristics, applications, admissions and matriculation, calculated via Bayes' rule. The distribution of $q_i, y_i$ conditional on matriculation to UT Austin is not the same as the population distribution. For instance, the choice set depends on admissions outcomes which are more likely to be positive when $q_i$ is high.

The moment condition requires that the coefficients $\tilde{\gamma}$ obtained from the administrative datasets satisfy the OLS conditions on the simulated data:

$$g^{outcome}(\theta) = \sum_{i \in Survey,} popwt_i \cdot \sum_{m,q} Pr(\omega_m, q|i) \cdot \left(outcome_{ijmq}^{(k)}(\theta) - z_i'\tilde{\gamma}^{(k)}\right) \cdot \tilde{\gamma}^{(k)}.$$

## 5.7 Computation

To compute the moments, I approximate the distribution of the caliber $q$ and signal $s$ with a discrete grid, integrate over random coefficients via simulation, and simulate financial-aid awareness at schools to which $i$ does not apply. I provide details in the computational appendix. In that appendix I also state and prove a result that simplifies the computation of the expected value of application sets.

Computing the value of an application set $A \subset \mathcal{A}$ requires integrating over all possible outcomes $B \subseteq A$, as the value depends on the probabilities and utilities of each admissions set $B$ that is possible given application to $A$. In principle, and dropping $i$ subscripts, computing $V(A)$ for all $A$ requires computing $|\mathcal{A}|$ utility terms $\{U(B)\}_{B \in \mathcal{A}}$, and $\mathcal{O}(|\mathcal{A}|^2)$ multivariate normal CDF evaluations $\{P(B|A)\}_{B \subseteq A, A \in \mathcal{A}}$. With over 800 portfolios, it would be expensive to compute all of these probabilities directly for each draw for each individual at each trial parameter value. I show that one needs only evaluate $|\mathcal{A}|$ multivariate normal CDFs and perform some matrix multiplication. In particular, it is necessary to evaluate only the multivariate CDFs of the form $P(A|A)$, i.e. the probability of a student's being admitted to all schools in her application set, for each possible application set $A \in \mathcal{A}$. I show that an application of the inclusion-exclusion principle gives the probabilities $P(B|A)$ via a linear transformation of these probabilities, that is via multiplication with known sparse matrices.

## 5.8 Selective and unselective colleges

In evaluating counterfactual policies, it will be important to determine which colleges' capacity constraints bind, as these colleges' cutoffs will adjust to hold the total size of the entering class fixed, while other colleges' class sizes may adjust. The following definition formalizes the notion that a selective college is one whose capacity constraint binds.

**Definition 3.** A college $j$ is *selective* at a set of cutoffs $\underline{\pi}$ if $\underline{\pi}_j = \pi_j^0$.

That is, a college is selective in a particular equilibrium if it turns away qualified applicants because of limited capacity. If a college is not selective, it does not follow that it admits all applicants. Rather, the college sets its cutoff such that the least-preferred student that it would admit has value 0. It may reject some candidates who apply because it prefers to keep their seats empty.

It is not possible to identify $\pi_j^0$ from the data and model. In particular, while we observe the college's actual enrollment and can estimate its cutoff, there is no way to observe directly whether its capacity constraint binds. We see that a college rejects a student, but admissions data alone cannot tell us whether the college would have liked to admit that student if space permitted or if it would always reject him in favor of an empty seat. Nonetheless, reputation, and college guides such as Barron's, give a good indication of which colleges' capacity constraints bind. If a college is known to be selective, we infer its expected capacity from the number of students who enroll, and in this case we hold its capacity fixed in counterfactuals. If it is not selective, its total enrollment may change. My key assumption is that colleges that are selective in the baseline remain selective under the counterfactuals that we consider, and colleges that are not selective remain so. This assumption is reasonable for the policies that we consider, which hold students' preferences fixed and are unlikely to cause sufficiently drastic changes.

I will assume throughout out counterfactual experiments that the state flagship universities, in-state private colleges and universities, and Texas Tech University are selective. Moreover, as discussed in section 4, I assume that these colleges have a fixed capacity for in-state students. I will assume that the marginal seats at a Christian college and at the marginal public four-year college are such that the aggregate Christian college and the aggregate other four-year Texas college are not selective. In addition to the assumptions on selectivity, I assume that out-of-state universities and aggregate private institutions do not change cutoffs under counterfactuals, as Texas public school students make up relatively small fractions of the current and counterfactual sets of matriculating students at those universities.

# 6 Results

All of the parameters in this section are estimated jointly. As there are 103 estimated parameters, I split the maximum-likelihood parameter estimates into several tables for readability. The full set of parameter estimates is given in the appendix. Table 3 shows estimation results for admissions cutoffs $\underline{\pi}$, college preference parameters $\gamma$, and college-specific financial aid parameters. Tables 4, 5, 6 and 7 show the remaining results. I first describe the estimated parameters and model fit. The main results begin in section 6.2.

## 6.1 Parameter estimates

We first focus on informational parameters, which are displayed in table 5 on page 59. These estimates lead to three immediate findings. First, variation in unobserved caliber $q$ is an important source of variation in students' admissions chances. An increase of one standard deviation in $q$ is worth three and a half times more than a standard-deviation increase in SAT scores.[49] Second, the variance of unobserved caliber is larger at poorer high schools. That is, $\sigma^q_{econdisadv} < 0$. The higher the poverty rate of the student's high school, the more important is $q$, relative to observables such as SAT scores and class rank, in predicting college admissions for students who are not automatically admitted via Texas Top Ten. Third, the covariance term $\rho$ is decreasing in high school poverty rates, ($\rho_{econdisadv} < 0$). That is, students from poorer schools have a noisier signal of their unobserved caliber $q$. It follows from the second and third findings that students at poorer high schools have worse information about their admissions chances.

The cutoffs $\underline{\pi}$ and admissions parameters are such that the average student has high admissions chances at all colleges except highly selective private universities. Importantly, admissions chances

[49] Among students the median value of $econdisadv_{s(i)}$ is equal to .2788. That is, the median student's high school has just over a quarter of seniors receiving free or reduced-price lunch. For this student, at the point estimates,

$$\sigma^q_i = \exp(\sigma^q_{const} + \sigma^q_{econdisadv}) \approx \exp(\sigma_{const} + \sigma_{econdisadv} * .2788) \approx 1.66$$
$$\rho^q_i = \exp(\rho_{const} + \rho_{econdisadv})/(1 + \exp(\rho_{const} + \rho_{econdisadv} * .2788)) \approx 0.764.$$

I rescale SAT scores to have a minimum of zero and a maximum of 1. Within the sample used for estimation, the standard deviation in SAT scores is 0.1190, so that a one-standard-deviation increase increases $i$'s admissions index by approximately $\gamma_1 * .1190 \approx .48$ points. Admissions indices are measured in "probit units", i.e. relative to an independent error term $\mu_{ij}$ which has a standard normal distribution.

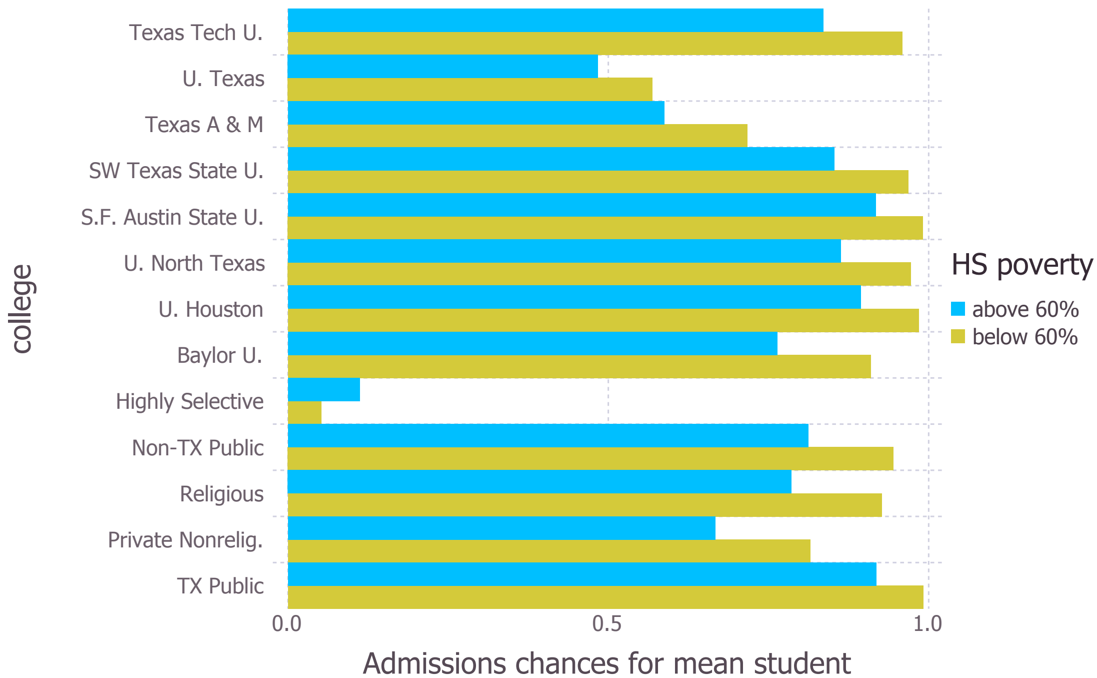


Figure 1: Admission chances for mean non-top-decile student

at most colleges are close to one for the average student as well as for students with caliber $q$ that is above average, but decrease as $q$ decreases. This nonlinearity means that greater uncertainty about $q$ given a signal $s$ results in lower perceived admissions chances from the applicant's point of view conditional on $s$. Recall that Texas Top Ten provides certainty about admissions chances for top-decile students. Because perceived chances are lower at poorer high schools, this certainty has a larger effect on the perceived admissions chances of students from those schools.

Figure 1 shows average students' perceived admissions chances at all colleges for students outside the top decile of class rank. The chances are calculated for a student with a signal of caliber $s = 0$. Within each college, the upper bar shows the chances for students with mean SAT scores, class rank, and high school characteristics among non-top-decile students at schools with rates of free/reduced lunch above 60%. The lower bars show the chances for average students at high schools with rates below 60%. The mean student at affluent high schools is essentially guaranteed admission everywhere except private colleges and flagship institutions. Students from poorer high schools face lower perceived chances everywhere except at highly selective private colleges. (At highly selective colleges, having a caliber of 0 will lead to rejection with probability near 1, so that greater uncertainty, i.e. greater variance in caliber given one's information, leads to higher admissions chances conditional on $s$). As a result, the guarantee provided by Texas Top Ten may be especially valuable for students from less affluent schools.

Admissions chances are high for these average students. They are even higher for students who "barely miss" the cutoff for automatic admissions. Figure 4 in the appendix shows model-predicted admissions chances for a student with a signal $s$ that is one standard deviation above the average, in the 12th percentile of his high school class at an affluent high school. I assign this student the average SAT scores and information structure for students outside the top decile at schools with less than 15% poverty rates. Despite claims that such students are displaced from the flagship universities, this hypothetical student is very likely to be admitted everywhere except highly selective private colleges. (His chance of admission to the University of Texas at Austin is 95%.)

The full set of estimates is given in table 3. The order of cutoffs makes sense. Selective private universities have the highest cutoffs, followed by UT Austin and Texas A&M. The regional four-year Texas public institutions (Stephen F Austin State University, and Other TX Public 4-year colleges and universities) have the lowest cutoffs, and therefore offer the best chances of admission. SAT and class rank (normalized to a maximum of 1, for bottom decile students) move admissions chances in the expected direction.

We now turn to the parameters of the utility function. As with cutoffs, the pattern of mean utilities makes sense. Selective private universities have the highest mean utility term $\delta_j$, followed by UT-Austin and then by Texas A&M. I find that students' utility is decreasing in distance, but that there is no additional effect of distance when interacted with income $y_i$. Utility is increasing in students' expected rank $\tau_{SAT}$ among their peers at college $j$, but the effect is not enormous given the range of SAT scores within each college; the difference in mean utilities between Texas A&M and "Other Texas Public Four-year Institutions" is nearly equal to the value of moving from the very bottom of the SAT distribution at a college to the very top; in practice, a student who has the lowest SAT score at Texas A&M would not have the highest score at a non-flagship school.

To help interpret the utility parameters, figure 2 shows the share of students who would choose to attend each college if offered admission to all of the colleges.[50] The top bar for each college shows tastes, taking financial aid awareness and the probability of receiving financial aid as estimated. Here we find that 70% of students would choose to attend a four-year college, the most popular being UT Austin, with 12% of students preferring the flagship school. Nine percent of students would choose to attend a selective private school. This low number raises the question of whether students' distaste for the most selective schools is based on the perceived expense of attending them, especially given that some students fail to complete financial aid forms and treat the list price as the true price. I therefore calculate preference shares under the assumption that every

[50] The student is offered admission at exactly one college within each aggregate group; for instance, he gets exactly one draw of $\epsilon^M$ for "other Texas public universities".

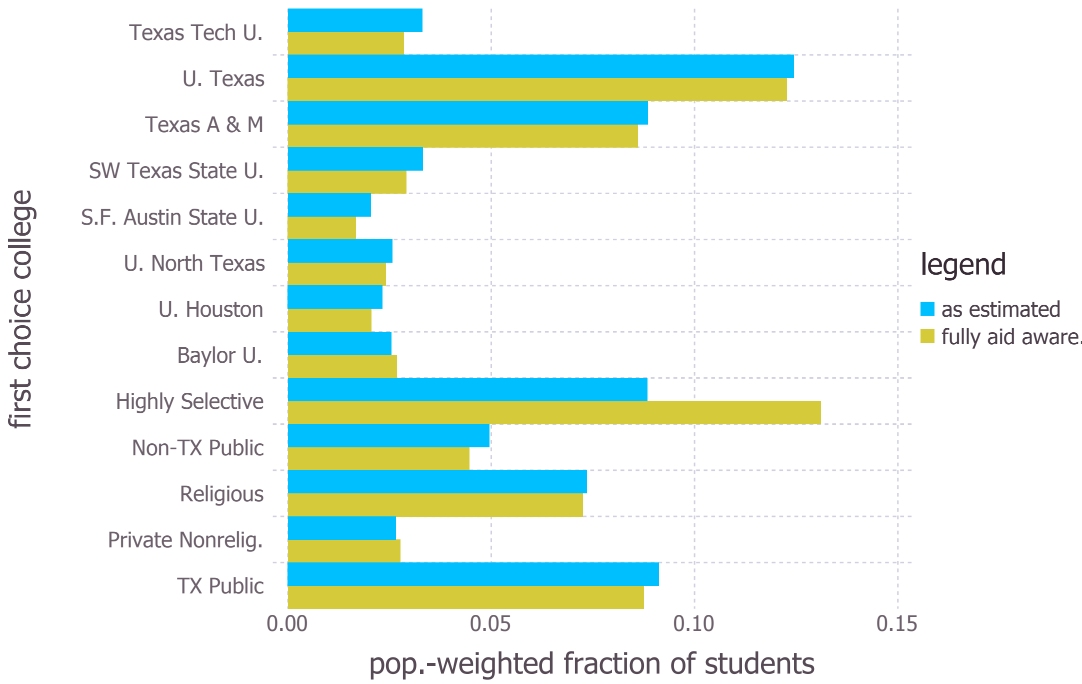


Figure 2: Preference shares if admitted everywhere

student completes financial aid applications at each school, and that each student whose expected family contribution is less than the list price receives financial aid, but without changing size of the financial aid offer as a function of income. Presumably, failure to receive need-based aid comes from failing to list the school or properly complete the FAFSA. In this calculation I remove this friction. I find that the share of students preferring highly selective private colleges increases to 13% of the total population. This result suggests that difficulty with financial aid applications may be especially important at the margin of applications to highly selective private colleges.

The cost parameters are reasonable as well. We see that the disutility of cost is declining in $y_i$. To aid interpretation, costs are measured in units of 10000 2002 dollars. There is an additional cost $c^m = \$2790$ of attending college, beyond the list price. The probability of consideration of financial aid is increasing in the student's SAT score and in the school's poverty, and decreasing in income. While financial aid amounts differ across schools, the colleges have similar probabilities of giving financial aid, with the exception of Baylor University, other religious colleges, and non-flagship colleges, which are unlikely to give awards.

Turning to application costs, we see that the first application is more costly than additional applications, but only by a factor of roughly 1.5. (Recall the cost of submitting one application is $C_0 + C_1$, with $C_0 = c0_{const} + c0_{econdisadv} econdisadv_i$ and $C_1$ defined similarly.) That is, the cost of applying to two schools is less than twice the cost of applying to one. Application costs are not increasing in economic disadvantage of the student's high school: $c1_{econdisadv}$ is close to zero, with a small standard deviation relative to the magnitude of $c1_{const}$, and $c0_{econdisadv}$ is also small. Students from poorer schools have worse information, and preferences differ when students are made aware of financial aid, but I do not find that application costs differ. As a result, I consider interventions targeted at information and financial aid.

### 6.1.1 Model fit

In the appendix, I discuss model fit in detail. The distribution of applications, admissions, and matriculation decisions generated by the model closely matches the population-weighted distribution given by the survey. I examine the number of applications, admissions offers, and matriculations at each college within several subpopulations: Black, Hispanic and American Indian ("underrepresented minority") students, first-generation college students, students from affluent high schools with less than 15% free/reduced price lunch eligibility,[51] and minority students at affluent high schools. I did not use moments designed to match shares within these populations. Nonetheless the model fits well within each of these groups.

I show also that the model produces estimates of policy-relevant effects that are consistent with the literature. Niu and Tienda (2010)[35], however, use the same THEOP dataset to examine the effects of threshold crossing on state flagship university attendance. (The THEOP dataset, which this paper uses, was collected by Marta Tienda.) That is, they compute the difference between matriculation probabilities of top decile students under Texas Top Ten and matriculation probabilities of marginal non-top-decile students under the same policy, using a regression discontinuity design. As I describe in the appendix, I replicate this difference within the model. I first evaluate matriculation probabilities under automatic admissions, within a group of marginal applicants. I then disable automatic admissions, holding $\underline{\pi}$ fixed, and reestimate matriculation probabilities. My estimates imply that 27.7% of top decile students would attend a flagship university under Texas Top Ten, but only 16.5% would do so in the counterfactual where there is no Texas Top Ten law. As a result, I find a threshold-crossing effect on flagship attendance of 11.2 percentage points, which is slightly above the point estimates of Niu and Tienda but well within their confidence intervals.

[51] I use a working definition of an affluent high school as one where fewer than fifteen percent of students have ever qualified for subsidized lunch.

### 6.1.2 Peer characteristics

We will see that the policy experiments that we consider have small effects on 25th- and 75th-percentile SAT scores. As a result, we are able to ignore the utility effects of changes in peer SAT scores when we calculate new equilibria. Nonetheless, as I discuss in the appendix, we can obtain bounds on the effect of peer SAT scores under the assumption that students prefer higher SAT scores and that these are positively correlated with the unobservable qualities of colleges.

## 6.2 Impact of Texas Top Ten

We now move on to the main results of the paper. In the first policy experiment, I evaluate the effects of removing Texas Top Ten, holding the population of Texas high school students fixed. Colleges use the admissions preferences that they had used to evaluate students who were not guaranteed admissions under Texas Top Ten. The colleges find new equilibrium cutoffs.[52] I allow Baylor University, University of Houston, University of Texas at Austin, Texas A&M and Texas Tech to adjust admissions policies, as these are the institutions that are selective and draw most of their students from Texas.

While Texas Top Ten had negligible effects on the total number of students attending each four-year college, it had large effects on the demographics within each college's entering class. Consider table 10 on page 63, which displays the number of college matriculations per 100 students in the population, as predicted by the model.[53] The first column, labeled "benchmark", shows the number of matriculating students at each college. The column labeled "no TTT" shows the percentage changes in these numbers when Texas Top Ten is removed and colleges' cutoffs adjust. Under Texas Top Ten, slightly more than half of the sample matriculates at some four-year college. Non-flagship Texas public universities are the most popular, enrolling nearly 13 students per 100 SAT-taking high school seniors. The University of Texas at Austin is the second most popular. In the counterfactual, the number of students attending non-flagship schools decreases by a small amount (0.4% at the point estimates). Overall, removing Texas Top Ten would lead to a small decrease in four-year college matriculation.

Increased matriculation at flagship universities under Texas Top Ten by underrepresented groups offsets decreased matriculation by students from affluent high schools. Table 11 on page 64 shows enrollment changes for Black and Hispanic students.[54] Again, we focus on the benchmark and the TTT column. Under the benchmark, 48 out of every 100 minority students attend a four-year college, with 11 out of this hundred attending the University of Texas at Austin. The

[52] In the computational routine I was able to find only one set of equilibrium cutoffs.

[53] That is, for each student in the survey, I use the model to generate the probability that that student will attend college $j$. I then aggregate using population weights.

[54] See also table 14, which provides results for first-generation college students.

removal of Texas Top Ten would lead to an ten-percent decrease in matriculations at UT Austin, and an overall decline of 1.4 percent, or one student per 150, in four-year college attendance.

In contrast, we see large increases in attendance by students from relatively affluent high schools. We restrict attention to students in whose high school cohorts fewer than 15% of students have ever received subsidized lunch. Table 13 on page 66 shows that roughly 1 out of every 6 such students attends a flagship university in the benchmark. The share of students attending UT Austin would increase by 16.6%, or 1.2 students per 100, if Texas Top Ten is removed. Texas Top Ten lowers flagship attendance especially for minority students at these high schools. In table 16 we see that the share of students attending UT Austin increases by a large amount, 30% of a base of 7.2 students per hundred, when Texas Top Ten is removed.

One may worry that Texas Top Ten came at a cost of increased financial aid expenditures and lower academic quality at flagship schools. I find that it did not. Table 21 on page 75 shows average financial aid amounts under the benchmark and counterfactuals, in 2002 dollars, holding fixed financial aid awareness and the distribution of financial aid offers and amounts. We see that the selective private schools offer the greatest average aid package or reduction in list price, followed by other private schools. Per-capita expenditures at public universities change little with the removal of the Top 10% plan. At our point estimates, removing Texas Top Ten causes Texas A&M to spend one additional dollar per student per year; The University of Texas at Austin spends an additional 20 dollars per student per year. The effect of Texas Top Ten on the distribution of SAT scores is negligible.[55]

Given that the entering cohort's scores do not change, it is not surprising that Texas Top Ten does not decrease students' grades. Table 20 shows the effects of Texas Top Ten on the distribution of grade point averages at the flagship universities. I consider grades in the first two years of college only. Each table displays a different subpopulation: the full sample, underrepresented minority students, first-generation college students, affluent high schools, and underrepresented minorities at affluent high schools. Again, we focus on the "benchmark" and "no TTT" columns. In all cases, average grades are higher under Texas Top Ten. Texas Top Ten attracts a population of students who attain higher grade point averages in college than the population that would attend without the policy.

There are two reasons why Texas Top Ten improves outcomes. First, colleges' preferences are not perfectly aligned with the grade production function. The parameter estimates in table 7 and 4 show that better SAT scores and better class rank are better in grades as well as admissions, but the weights are not the same. More importantly, in the grade equation$\beta_q^g$ is insignificant but negative

[55]Table 22 on page 76 shows 10th, 25th, 75th, and 90th percentiles of SAT scores in the benchmark and without Texas Top Ten. At UT Austin, the 25th-percentile SAT composite score in the entering cohort would fall from 0.644, or 1030 out of 1600, to 0.638, or 1020 out of 1600, with the removal of Texas Top Ten. The 75th percentile SAT score would similarly fall by 10 points out of 1600. The effects at Texas A&M are negligible at the 25th and 75th percentiles.

at the point estimate. That is, colleges overweight unobservables in admissions, among students not automatically admitted, relative to their contributions to grade point averages. Texas Top Ten specifically targets students with high class rank, who in turn earn high grade point averages.

Second, because Texas Top Ten affected colleges' admissions policies, it affected the distribution of applications. Under Texas Top Ten, colleges had a larger pool of applicants with high class rank, who had relatively high predicted grades, and whom they were required to admit. The removal of Texas Top Ten would decrease applications to UT Austin from students in the top decile by 22.2%, and increase applications to the aggregate non-flagship public college by 24.2%.[56] These effects are large. Moreover, Texas Top Ten's removal would decrease underrepresented minority students' applications to UT slightly, as shown in table 11, but there is substantial heterogeneity within the population of minority students. In particular, the number of minority applicants to flagship schools who were in the top decile of their high school class would fall dramatically (by 32% at UT Austin and 10% at Texas A&M, respectively) in the absence of Texas Top Ten.[57]

Admissions chances change for students outside the top decile as well. Table 8 shows that colleges' cutoffs change in response to the removal of Texas Top Ten. At Baylor and the University of Houston, the effects on admissions chances are small. In contrast, it becomes significantly easier to gain admission to the flagship universities and to Texas Tech University. The change in the cutoff at UT Austin is equivalent to an increase of more than one standard deviation in SAT score for applicants.[58]We have seen that total college enrollment falls slightly at the point estimate when Texas Top Ten is removed. Table 10 shows that the total number of applications per 100 students increases by 1.5% when Texas Top Ten is removed. Applications to flagship university campuses increase as well.

The parameter estimates imply, however, that admissions chances do not change by a large amount for students just across the threshold at affluent high schools. These students have very high admissions chances even under Texas Top Ten. For instance, consider a student with $s$ one standard deviation above the average, class rank of .12, and the average SAT score for a non-top-decile student at an affluent ($<$15% poverty rate) high school. If anything, by using the average SAT score for all non-top-decile students I underestimate this student's chances. Nonetheless, this student has a greater than 95% chance of admission at the state flagship universities.

[56]See the bottom panel of table 15. Applications to Texas A&M would have fallen as well.

[57]See table 17. This percentage change is close to the percentage change that was observed at UT Austin, comparing the years 1997 (in which there was no Texas Top Ten) and 2002. See table 40, which shows that the share of applications to UT Austin from in-state public high school students that were submitted by top-decile minorities was 31% lower in 1997 than in 2002.

[58]The cutoff at UT changes from .60 to -0.05 when Texas Top Ten is removed. As discussed previously, an increase of one standard deviation in SAT composite score is worth .470 points relative to the variance of the idiosyncratic admissions shock, which is normalized to 1.

## 6.3 Race-conscious affirmative action

Recall that Texas Top Ten replaced race-based affirmative action after 1996. My results imply that Texas Top Ten would outperform a more conventional race-based affirmative action policy. In particular, Texas Top Ten compares favorably to a policy that provides points to minority applicants at flagship universities to enroll the same number of minority students, as Texas Top Ten would admit students who would have better academic achievement in college. Precisely, I consider a policy consisting of cutoffs $\{\underline{\pi}_j\}_{j\in J}$ for all applicants to non-flagship universities and non-minority applicants to the flagship universities, and four specific cutoffs$\{\underline{\pi}^{Black}_{UTA}, \underline{\pi}^{Hispanic}_{UTA}, \underline{\pi}^{Black}_{TAMU}, \underline{\pi}^{Hispanic}_{TAMU}\}$for minority applicants at flagship universities.[59] As in the model, students are admitted if their admissions score $\pi_{ij}$ is above the relevant cutoff. I solve for the cutoffs that ensure that the shares of black students and other minorities at each flagship university are the same as those under Texas Top Ten. In its effects on college matriculation and grades this policy closely resembles the absence of Texas Top Ten for non-minority students, but it greatly changes the distribution of minority students at flagship universities.

Relative to Texas Top Ten, The race-based affirmative action program would enroll minority students from relatively affluent high schools with relatively poor class rank. Table 16 shows that within affluent high schools, the number of minority students enrolling at UT Austin would be 44% higher than under Texas Top Ten. The remaining rows of the table show that these students are less likely to attend all non-flagship colleges. In contrast, at high schools with greater than 60% poverty, the number of minority students matriculating at UT Austin would fall by 18%.[60] Relative to Texas Top Ten, the number of minority students in the top decile of their high school cohort who attend UT Austin falls by 38%, from a base of one student out of every four to roughly one student out of every seven.[61]

As a result, the students admitted under affirmative action have worse academic performance than the students admitted under Texas Top Ten. We turn again to table 20 to see predicted first- and second-year grade point averages at flagship universities. In the top panel, we see that overall grades are lower under affirmative action than under Texas Top Ten, falling from an average of 2.81 to 2.78 at UT Austin. The difference at Texas A&M is smaller. The second panel shows the change within the population of underrepresented minority students. GPAs fall from 2.69 out of 4 to 2.64 at UT Austin. The bottom panel shows that minority students who were in the top decile

[59] The cutoff for Hispanic students applies also to Native American and pacific islander applicants. Table 9 displays the simulated cutoffs.

[60] Table 12 gives the distribution of matriculation, admissions and applications on students from high schools at which at least 60% of students have ever qualified for free or subsidized school lunch. The number of such students (of all races) attending UT Austin would fall by 26%. Table 18 gives the distribution of matriculation, admissions and applications for minority students at these high schools.

[61] These figures come from the top panel of table 17, which displays matriculation shares for minority students in the top decile of their high school class.

of their high school class perform relatively well. Under Texas Top Ten, these students achieved a GPA of 2.75 at UT Austin, which is higher than that of other minority students.[62] Top-decile minority students are much less likely to apply, however, under race-based affirmative action than under Texas Top Ten.[63]

Unlike Texas Top Ten, however, race-based affirmative action has small effects on non-minority students' admissions chances. For this reason, majority students at affluent high schools might favor race-based affirmative action over Texas Top Ten. Table 9 displays the cutoffs that colleges would choose under this affirmative action policy. Non-minority students' cutoffs under affirmative action are very close to those under the absence of Texas Top Ten. Matriculation, admissions, and applications figures for students from affluent high schools, and for non-minority students generally, are very close to those in the absence of any affirmative action program. The overall effects on grade point averages are also very similar. Table 20 shows that grade point averages at UT Austin and Texas A&M among non-minority students are nearly identical in the absence of Texas Top Ten with or without race-based affirmative action.

## 6.4 Undermatching

We now turn to the consequences of policies designed to increase access to flagship universities and reduce undermatching. There is a large literature documenting the effects of informational interventions and of assistance in applying for aid. Because of the expense, however, there is less evidence on the effects of changes in financial aid policy.

In 2002, the Longhorn Opportunity Scholarship was present at high schools that enrolled 2.5% of surveyed students. The average student at a Longhorn-eligible school attended a school in which 74.7% of students had at one time qualified for reduced price or free lunch, which I take as a measure of poverty. If the University of Texas at Austin were to extend the program to cover all schools with greater than 60% poverty, it would cover 14.7 percent of surveyed students (by population weight), resulting in a 4.8x expansion in the share of students covered.

An expansion in the availability of aid, however, would not necessarily affect all students' incentives, as students may be unaware of the program or otherwise fail to complete an application for financial aid. In addition to evaluating this expansion of financial aid holding awareness fixed, I consider a combined intervention in which all students at high schools with above 60% poverty rates have all aid applications completed automatically, in addition to the expansion of the Longhorn Opportunity Scholarship. That is, all students at these high schools are made aware of financial aid at all colleges. This policy experiment represents the effects of an expansion in aid together with the best-case scenario for financial aid informational interventions.

[62] Non-top-decile minority students had an average GPA of 2.57 under the benchmark at UT Austin.

[63] Returning to the bottom panel of 17, we see that applications to UT Austin from such students would fall by 22 percent under race-based affirmative action, from a base of 34 applications per 100 students.

An expansion of the Longhorn opportunity scholarship would have large effects on the distribution of students at flagship universities. Table 11 shows the effects on minority students. The column labeled "LOS" shows the effects of the expansion of the scholarship program. The next column, labeled "LOS+", shows the effects of scholarship expansion together with automatic completion of financial aid applications. The number of minority students at UT Austin would increase by 4% under an expansion in the scholarship program, and by 5.5% when combined with the financial aid intervention. The number of students from poor (>60% free/reduced-price lunch) high schools would increase by 12.7%, relative to the benchmark, under the expansion of the scholarship program, and by 16.5% under the combined intervention, as shown in table 12.

Because of the increased demand for seats at UT Austin, UT Austin's admission standard would increase.[64] As a result, the number of students at UT Austin from affluent high schools would decrease by 5% from a base of 6 per 100 under an expansion of the Longhorn scholarship program and aid application completion.[65]

These distributional effects at flagship universities are similar to those of an upper bound on the effects of information provision. The column labeled "Info" shows the results of an experiment in which all students at all high schools automatically learn their caliber $q_i$ and are aware of financial aid at all colleges. This policy would increase demand for seats at the University of Texas, at Texas A&M, and at Baylor University, leading those colleges to increase their admissions standards, but would lead to lower admissions standards at Texas Tech, as shown in table 8. At UT Austin, the increase in the cutoff for a given applicant is the equivalent of a .7 standard deviation decrease in that applicant's SAT total score. The number of minority students attending UT Austin would increase by 5.3 percent, while the number of students from affluent high schools would decrease by 7.1%. The increase in first-generation college enrollment that would follow from the informational intervention is larger than the effect that would follow from the Longhorn scholarship expansion, but unsurprisingly the targeted scholarship expansion has a larger effect on enrollment of students from poor high schools.[66]

The informational intervention has the largest effects, in percentage terms, on matriculation at highly selective colleges. In the benchmark, the number of students attending such colleges is small, but the information intervention would increase the number of matriculating students by 61% at highly selective colleges, and increases offers of admissions by 46%. Table 10 shows that there would be large effects on attendance at private and religious colleges. It is consistent with Hoxby and Turner that there are large effects on the margin of applications to highly competitive colleges. I do not find large effects in absolute terms, as few students in my data would attend highly selective private universities under any of the interventions that I consider. A crucial difference is

[64] See table 8. UT Austin's cutoff would increase from .60 to .73, the equivalent of a quarter standard deviation increase in SAT scores.

[65] See table 13 for the effects on affluent students.

[66] See tables 14 and 12.

that Hoxby and Turner consider a population of students with high exam scores, whereas I use a representative sample of Texas high school students who have taken a college entrance exam.

The estimates imply that, unlike an expansion in aid at UT Austin, the informational intervention has large effects on overall four-year college enrollment. Information provision and financial aid application completion would increase overall college attendance by 1.8%, or by about one matriculation per hundred high school students, as shown in table 10. Most of this increase occurs at private, religious and out-of-state public university campuses. By assumption, enrollment at the flagship campuses cannot increase, although increased admissions standards can lead students to substitute to non-flagship universities.

These effects are smaller than they would have been had admissions standards not responded to changes in demand. That is, universities undo a large fraction of the immediate effects of financial aid expansion by increasing their admissions standards. In table 24 I show the effects of aid expansion and informational interventions on the number of students matriculating at each college, holding admissions cutoffs fixed. Table 25 shows the effects on minority students, and table 26 shows the effects on students from poor high schools. In the interventions in which the Longhorn Scholarship program expands, the UT Austin admissions office undoes a large share of the gains in underrepresented minority enrollment, as shown in columns (3) through (6) of table 25. Holding admissions chances fixed, expanding the Longhorn scholarship and providing financial aid awareness would make underrepresented minority students 9.1 percent more likely to attend UT Austin on average. Because the intervention increases demand for seats at UT Austin, however, the admissions cutoff would increase in equilibrium. After cutoffs adjust, the gain in minority enrollment falls to 5.5 percent. The effects are similar but larger for students from poor high schools. In contrast, under the best-case informational intervention, admissions offices' responses augment the effects on matriculation at highly selective private universities. Table 24 shows that matriculation at private colleges and religious colleges is higher after cutoffs adjust. This result is perhaps unsurprising given that the model holds cutoffs at out-of-state private colleges fixed, as Texans are a relatively small share of these colleges' entering classes.

I find that the informational intervention has greater cost-effectiveness than an expansion in financial aid in promoting flagship attendance by students from poor high schools. It is limited, however, in the number of students it can induce to attend flagship colleges. Importantly, in these counterfactuals I hold financial aid formulas fixed, and do not distinguish forms of aid.[67] Table 21 shows total per-capita expenditures at each university. Taking the estimate from Hoxby and Turner of \$6 per student reached by an informational intervention, I find that my best-case informational intervention would cost \$600 per 100 students and deliver .65 additional minority students at flagship universities per 100 minority students, and 1.36 additional students per 100 from schools with poverty above 60%. Ignoring the effects on financial aid expenditures, this

[67] If aid formulas adjusted we would presumably see smaller effects on both expenditure and the number of students induced to move.

amounts to $2986 per additional matriculation by a student from a poor high school. Including the resulting decrease in financial aid expenditure of $419 per 100 students,[68] the cost decreases to $901 per additional student from a poor high school.

The informational intervention, however, is not precisely targeted. Indeed it reaches every student. It would presumably be more cost-effective with better targeting. Note, however, that even holding admissions cutoffs fixed the intervention would have a smaller effect on flagship attendance by students from poor high schools than would the scholarship expansion. In contrast, expanding the Longhorn scholarship would increase financial aid expenditures at UT Austin by $545 per 100 Texas high school students.[69] Under an expansion of the Longhorn scholarship, enrollment at UT Austin by students from poor high schools increases by 1.16 students per 100 such students, who represent 14.7% of the total population of SAT-taking high school seniors. As a result, the financial aid expansion costs $2998 per additional student from a poor high school, despite the more precise focus of the intervention.

# 7 Conclusions

I find that Texas Top Ten has large effects on the distribution of attendance at state flagship universities and in particular at the University of Texas at Austin. It increases racial diversity at the flagship universities and draws more students from relatively poor high schools. At the same time, I do not find evidence that Texas Top Ten leads to mismatch of students and colleges. Rather, Texas Top Ten results in a student body that achieves high grade point averages at flagship universities. In its absence, GPAs at the flagship universities would decrease.

In contrast to Texas Top Ten, a race-based affirmative action policy that awards admissions "points" to minority applicants would attract relatively weak students. The policy would admit more students from affluent high schools and fewer with top high-school grades. These students would achieve lower grades in the state flagship universities than those students admitted under Texas Top Ten. My findings suggest that Texas Top Ten dominates a race-based affirmative action policy if the policymaker wants to increase diversity but avoid "undermatching" or admitting students who will achieve low grades.

It is important to understand why Texas Top Ten enrolls better students at flagship universities while race-based affirmative action would underperform. How can Texas Top Ten improve outcomes if it acts as a constraint on colleges? I find two reasons. First, my estimates imply admissions offices are not optimizing the academic quality of cohort as measured by early college

[68] Average aid expenditures are $50 dollars lower at UT Austin after the informational intervention. According to my estimates, UT Austin enrolls 8.4 out of every 100 exam-taking Texas high school seniors.

[69] Average aid expenditures are $64 dollars higher at UT Austin after the aid expansion. UT Austin enrolls 9.4 out of every 100 exam-taking Texas high school seniors.

grades. They overweight unobservables in admissions and underweight class rank relative to these factors' respective importance for college GPA. Texas Top Ten forces colleges to admit students with high class rank, who then achieve high college GPAs.

Additionally, the Texas Top Ten law is a credible promise. It may be valuable generally for universities or university systems to commit to admissions policies that are not optimal conditional on applications if these policies affect application decisions. I find that guaranteed admission leads to large increases in applications to selective colleges among top-decile students, many of whom have noisy information about their admissions chances. Because Texas Top Ten allows colleges to commit to an admissions policy and publicizes this fact, it induces strong students with poor information to apply to the state flagship universities.

With Texas Top Ten in place, I find that expanding the Longhorn scholarship has large effects on enrollment at a cost of \$60 per student at UT, or \$3000 per additional student from a poor high school. We would see larger effects on enrollment, but strategic response of colleges leads to tougher admissions standards. That is, because capacity is limited at the flagship universities, their admissions offices undo part of the effect of scholarship expansion. As a result, we may overestimate the effects of large-scale interventions if we simply extrapolate from the effects of interventions on small groups. My counterfactual explicitly assumes, however that selective colleges cannot increase their capacity. In practice, UT Austin expanded rapidly after the introduction of Texas Top Ten in 1998, but stopped expanding in the early 2000s. It would be an interesting extension to consider universities' choice to expand when demand increases.

I find that an expansion of the Longhorn scholarship program to cover all schools with above 60% free/subsidized lunch status[70] would enroll more more students from these poor high schools than would a best-case informational intervention. A back-of-the-envelope cost comparison shows that the best-case informational intervention achieves a lower cost per additional student from a poor high school enrolled in a state flagship university than that of an expansion of the Longhorn scholarship program. While providing information is roughly one third as expensive as per student induced to enroll, however, the informational intervention is limited in its effects on the distribution of state flagship university matriculation, while further scholarship expansions are possible. One limitation of this comparison, however, is that it holds colleges' financial aid rules fixed for students not targeted by the scholarship.

We have seen that expanding the Longhorn scholarship has a large effect on minority and first-generation college enrollment when combined with a financial aid awareness intervention. The effects on minority enrollment are similar in size to those of introducing Texas Top Ten. The counterfactuals that I consider, however, hold the universities' financial aid rules fixed for students not covered by the additional Longhorn scholarships. This assumption is reasonable if the funding for the additional scholarships comes from an outside source, such as the state. Because the model holds financial aid rules fixed, however, it does not allow the econometrician to talk about the

[70] That is, schools at which at least 60% of students have ever qualified for free or reduced-price lunch.

design of financial aid packages. It is important to know the extent to which institutions respond to an increase in one form of aid with reductions in other subsidies.

An important limitation of this paper is that I estimate colleges' preferences off of applicants who are not guaranteed admissions via Texas Top Ten. In practice, the University of Texas at Austin uses a combination of predicted first-year grades and a personal score to evaluate applicants who are not automatically admitted. In the absence of Texas Top Ten, the universities could place greater weight on academic characteristics and less weight on personal characteristics. Indeed, there is evidence that the University of California changed the relative weights on academic characteristics after the end of affirmative action.[71] The model here rules out the kind of concern for class composition that would lead admissions offices to change these weights.[72] The affirmative policy that I consider is a minimal modification of colleges' admissions rules to satisfy a racial diversity constraint, taking colleges' preferences as given. I do not evaluate an affirmative action policy that seeks to maximize college GPAs subject to a diversity constraint.

Relatedly, I do not take a stand on what it is that admissions offices maximize. It would be valuable to know whether colleges do a good job of admitting students who benefit from their educations, or go on to high achievement, but do not achieve high college grades.

An additional limitation of this paper is that it begins with SAT-taking high school seniors and ends after the first years of college. The model ignores the effects of Texas Top Ten on the environment within high schools and on which high school each student attends. The effects of Texas Top Ten on students' incentives to achieve high grades may be especially important. In this paper, I find that Texas Top Ten increases diversity in college and early college grades. To fully assess the policy, however, it is important to understand how universities' admissions rules affect the distribution of human capital, wages and employment. In related work, I am using the administrative records of high school students and college students in Texas, together with wage and unemployment data from the Texas Workforce Commission to measure the effects of Texas Top Ten on the distribution of student achievement in high school and to trace the effects of these changes in achievement through college and into the labor market.

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Table 3: Parameter Estimates: cutoffs, school-specific aid and utility terms

| **College** | **Cutoff** ($\overline{\pi}$) | **(se)** | **Utility** ($\delta$) | **(se)** | ($\alpha_j^{finaid}$) | **(se)** | **Pr. Finaid** ($\gamma_j^{finaidB}$) | **(se)** |
|---|---|---|---|---|---|---|---|---|
| *TX Public* | −2.418 | *(0.733)* | −0.279 | *(0.201)* | −0.35 | *(0.915)* | −0.322 | *(0.635)* |
| *Private Nonrelig.* | −0.401 | *(0.733)* | 0.431 | *(0.229)* | 1.813 | *(0.93)* | −0.574 | *(0.791)* |
| *Religious* | −1.161 | *(0.729)* | 0.278 | *(0.185)* | 1.086 | *(0.65)* | −0.984 | *(1.174)* |
| *Non-TX Public* | −1.359 | *(0.738)* | 0.655 | *(0.186)* | 2.025 | *(0.812)* | −0.661 | *(0.86)* |
| *Highly Selective* | 3.075 | *(0.765)* | 2.086 | *(0.228)* | 0.642 | *(0.723)* | 0.61 | *(1.083)* |
| *Baylor U.* | −1.007 | *(0.786)* | −0.368 | *(0.221)* | 0.022 | *(0.674)* | −1.009 | *(1.208)* |
| *U. Houston* | −2.113 | *(0.734)* | −0.663 | *(0.207)* | 0.706 | *(0.995)* | 0.077 | *(0.645)* |
| *U. North Texas* | −1.791 | *(0.744)* | −0.535 | *(0.206)* | 0.412 | *(0.637)* | 0.361 | *(0.856)* |
| *S.F. Austin State U.* | −2.405 | *(0.744)* | −0.728 | *(0.224)* | 2.378 | *(0.86)* | −1.208 | *(1.421)* |
| *SW Texas State U.* | −1.7 | *(0.755)* | −0.353 | *(0.226)* | 1.186 | *(0.761)* | −0.113 | *(0.607)* |
| *Texas A & M* | 0.045 | *(0.729)* | 0.234 | *(0.187)* | −0.26 | *(0.92)* | −0.072 | *(0.596)* |
| *U. Texas* | 0.598 | *(0.732)* | 1.221 | *(0.171)* | −0.396 | *(1.12)* | 0.169 | *(0.695)* |
| *Texas Tech U.* | −1.549 | *(0.747)* | 0.344 | *(0.192)* | 1.946 | *(0.921)* | −0.218 | *(0.601)* |

# A Results tables

## A.1 Parameter Estimates

Table 4: Parameter Estimates: information and application costs

| **parameter** | **estimate** | **SE** | **comment** |
|---|---|---|---|
| $\sigma^q$ ($constant$) | −0.083 | (0.18) | variance of caliber |
| $\sigma^q$ (HS poverty) | 2.12 | (0.293) | |
| $\rho^{corr.caliberandsignal}$ ($constant$) | 1.433 | (0.439) | |
| $\rho^{corr.caliberandsignal}$ (HS poverty) | −0.918 | (0.825) | |
| $\gamma$ ($SAT$) | 4.019 | (0.424) | admissions parameters |
| $\gamma$ ($classrank$) | −4.193 | (0.281) | |
| $\gamma$ ($\overline{SAT}_s$) | −0.49 | (1.108) | |
| $c0$ ($constant$) | 0.154 | (0.022) | application fixed costs |
| $c0$ (HS poverty) | −0.007 | (0.032) | |
| $c1$ ($constant$) | 0.39 | (0.007) | application costs: per app |
| $c1$ (HS poverty) | −0.03 | (0.008) | |

Table 5: Parameter Estimates: financial aid

| **parameter** | **estimate** | **SE** | **comment** |
|---|---|---|---|
| $\gamma^{finaidA}$ ($constant$) | 0.041 | (0.229) | finaid app. probability |
| $\gamma^{finaidA}$ (HS poverty) | 0.606 | (0.126) | |
| $\gamma^{finaidA}$ ($SAT$) | 1.345 | (0.305) | |
| $\gamma^{scholA}$ ($constant$) | −1.2 | (0.25) | finaid app. probability if $EFC_i > p_j$ |
| $\gamma^{scholA}$ (HS poverty) | 2.937 | (0.184) | |
| $\gamma^{scholA}$ ($SAT$) | 1.067 | (0.329) | |
| $\gamma^{finaidB}$ ($y$) | −1.52 | (1.099) | pr. receive finaid |
| $\gamma^{scholB}$ ($constant$) | −0.208 | (0.593) | |
| $\gamma^{scholB}$ ($SAT$) | −1.473 | (0.116) | |
| $\gamma^{scholB}$ ($j$) | −0.979 | (1.172) | |
| $\sigma$ ($aware$) | 0.834 | (0.032) | covariance in financial-aid awareness indices |

Table 6: Parameter Estimates: preferences

| **parameter** | **estimate** | **SE** | **comment** |
|---|---|---|---|
| $c^m$ | 0.279 | (0.193) | additional matriculation cost |
| $\overline{\beta}$ $(\tau_{SAT})$ | 0.264 | (0.157) | mean utility terms |
| $\overline{\beta}$ $(distance)$ | $-0.795$ | (0.055) | |
| $\overline{\beta}^{const}$ $(price)$ | 0.296 | (0.075) | |
| $\overline{\beta}^{y}$ $(price)$ | 0.844 | (0.235) | |
| $\overline{\beta}$ (TAMU X White) | 0.673 | (0.1) | |
| $\overline{\beta}$ (UTA X White) | $-0.239$ | (0.074) | |
| $\overline{\beta}$ (distance X income) | 0.029 | (0.003) | |
| $\sigma^{rc}$ $(\tau_{SAT})$ | 0.312 | (0.265) | random coefficient variances |
| $\sigma^{rc}$ $(distance)$ | 0.319 | (0.025) | |
| $\sigma^{rc}$ $(\overline{SAT})$ | 2.666 | (0.232) | |
| $\sigma^{rc}$ $(S/F)$ | 1.256 | (0.221) | |
| $\sigma$ $(\epsilon_0)$ | 0.16 | (0.027) | sd of application-stage shocks |
| $\lambda$ | 0.363 | (0.009) | matric. stage correlation parameter |
| $log(\sigma)^{UTA_TAMU}$ | $-2.315$ | (1.295) | RC: +1 for TAMU, -1 for UTA |

Note: $\lambda \approx .363$ implies that there is correlation in matriculation-time preference shocks to the "inside" colleges. (As $\lambda \to 0$ the inside options' shocks become perfectly correlated.)

Table 7: Parameter Estimates: college GPA and persistence

| **parameter** | **estimate** | **SE** | **comment** |
|---|---|---|---|
| $\beta^g$ $(constant)$ | 1.885 | (1.987) | college GPA parameters |
| $\beta^g$ $(SAT)$ | 0.304 | (2.313) | |
| $\beta^g$ $(classrank)$ | $-0.058$ | (1.914) | |
| $\beta^g$ $(y)$ | 0.192 | (0.12) | |
| $\beta^g$ $(q)$ | $-0.052$ | (0.539) | |
| $\beta^g$ $(UTA)$ | $-0.348$ | (1.816) | GPA: UT Austin dummy |
| $\beta^g$ $(SATxUTA)$ | 0.832 | (2.323) | GPA: UT Austin x SAT |
| $\beta^g$ $(LOSxUTA)$ | 0.078 | (0.294) | GPA: UT Austin x LOS |
| $log(\sigma)$ $(GPA)$ | 0.292 | (0.641) | GPA: standard deviation of shock |
| $\beta^{persist}$ $(cons)$ | $-0.649$ | (0.782) | Persistence: constant |
| $\beta^{persist}$ $(gpa)$ | 0.711 | (0.496) | Persistence: college GPA |
| $\beta^{persist}$ $(y)$ | 0.281 | (0.321) | Persistence: income |
| $\beta^{persist}$ $(UTA)$ | $-0.057$ | (0.214) | Persistence: UTA dummy |

Table 8: Admissions cutoffs $\underline{\pi}$ under benchmark and counterfactuals

| **College** | $\underline{\pi}$ **(baseline)** | **(no TTT)** | **(LOS)** | **(LOS+)** | **(Info)** |
|---|---|---|---|---|---|
| TX Public | −2.418 | | | | |
| Private Nonrelig. | −0.401 | | | | |
| Religious | −1.161 | | | | |
| Non-TX Public | −1.359 | | | | |
| Highly Selective | 3.075 | | | | |
| Baylor U. | −1.007 | −1.017 | −1.003 | −0.989 | −0.725 |
| U. Houston | −2.113 | −2.133 | −2.117 | −2.122 | −2.275 |
| U. North Texas | −1.791 | | | | |
| S.F. Austin State U. | −2.405 | | | | |
| SW Texas State U. | −1.7 | | | | |
| Texas A & M | 0.045 | −0.3 | 0.045 | 0.048 | 0.312 |
| U. Texas | 0.598 | −0.054 | 0.701 | 0.733 | 0.938 |
| Texas Tech U. | −1.549 | −1.621 | −1.547 | −1.547 | −1.645 |

## A.2 Counterfactuals

### A.2.1 Admissions cutoffs

Table 9: Admissions cutoffs $\underline{\pi}$ under benchmark and affirmative action

| **college** | $\underline{\pi}$ **(baseline)** | **AA (majority)** | **(Black)** | **(Hispanic/Other)** |
|---|---|---|---|---|
| TX Public | −2.418 | | | |
| Private Nonrelig. | −0.401 | | | |
| Religious | −1.161 | | | |
| Non-TX Public | −1.359 | | | |
| Highly Selective | 3.075 | | | |
| Baylor U. | −1.007 | −1.011 | | |
| U. Houston | −2.113 | −2.133 | | |
| U. North Texas | −1.791 | | | |
| S.F. Austin State U. | −2.405 | | | |
| SW Texas State U. | −1.7 | | | |
| Texas A & M | 0.045 | −0.274 | −0.304 | −0.481 |
| U. Texas | 0.598 | 0.043 | −0.047 | −0.343 |
| Texas Tech U. | −1.549 | −1.618 | | |

### A.2.2 Applications, admissions, matriculation

Table 10: Main Results: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 13.182 | -0.7% | -0.4% | -0.2% | -0.1% | -3.1% |
| Private Nonrelig. | 1.839 | -0.1% | -0.3% | +0.0% | +0.2% | +14.2% |
| Religious | 6.806 | -1.4% | -1.6% | +0.5% | +0.9% | +11.0% |
| Non-TX Public | 4.826 | -0.2% | -0.5% | +0.3% | +0.4% | +5.3% |
| Highly Selective | 0.507 | -0.4% | -0.4% | -0.5% | -0.5% | +61.1% |
| Baylor U. | 1.051 | | | | | |
| U. Houston | 1.693 | | | | | |
| U. North Texas | 1.499 | -0.8% | -1.0% | +0.2% | +0.1% | -4.0% |
| S.F. Austin State U. | 1.41 | +1.3% | +1.1% | +0.1% | +0.0% | -9.0% |
| SW Texas State U. | 2.171 | -3.6% | -3.4% | +0.5% | +0.4% | -1.7% |
| Texas A & M | 6.512 | | | | | |
| U. Texas | 8.418 | | | | | |
| Texas Tech U. | 2.851 | | | | | |
| Total | 52.763 | -0.5% | -0.5% | +0.1% | +0.1% | +1.8% |

Population: all Texas public high school students

Offers of admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 28.486 | +0.5% | +0.7% | -0.2% | -0.1% | -4.0% |
| Private Nonrelig. | 5.659 | +0.4% | +0.3% | -0.0% | +0.1% | +8.8% |
| Religious | 16.008 | -0.2% | -0.3% | +0.3% | +0.6% | +7.8% |
| Non-TX Public | 12.017 | +0.8% | +0.5% | +0.2% | +0.2% | +2.9% |
| Highly Selective | 1.194 | -0.3% | -0.3% | -0.3% | -0.3% | +46.2% |
| Baylor U. | 4.855 | +1.4% | +1.5% | -0.1% | -0.2% | -1.9% |
| U. Houston | 6.469 | +2.0% | +1.9% | -0.0% | +0.1% | -1.7% |
| U. North Texas | 6.115 | +0.8% | +0.7% | +0.0% | +0.0% | -3.2% |
| S.F. Austin State U. | 6.213 | +2.4% | +2.3% | +0.0% | -0.0% | -6.9% |
| SW Texas State U. | 7.223 | -0.3% | -0.2% | +0.1% | +0.1% | -2.4% |
| Texas A & M | 12.246 | +1.7% | +1.6% | -0.1% | -0.0% | -0.9% |
| U. Texas | 14.191 | +3.0% | +3.2% | -0.7% | -1.0% | -1.0% |
| Texas Tech U. | 7.707 | +1.3% | +1.3% | -0.0% | -0.1% | -0.6% |
| Total | 128.382 | +1.0% | +1.1% | -0.1% | -0.0% | +0.2% |

Population: all Texas public high school students

Applications for admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 30.556 | +0.9% | +1.1% | -0.1% | -0.1% | -3.8% |
| Private Nonrelig. | 6.627 | +0.3% | +0.2% | -0.0% | +0.1% | +6.0% |
| Religious | 17.393 | -0.1% | -0.2% | +0.3% | +0.6% | +5.9% |
| Non-TX Public | 13.097 | +0.8% | +0.6% | +0.1% | +0.2% | +1.1% |
| Highly Selective | 3.899 | -0.8% | -0.8% | -0.1% | -0.1% | +14.2% |
| Baylor U. | 5.444 | +1.4% | +1.4% | -0.1% | -0.1% | -1.6% |
| U. Houston | 6.875 | +2.3% | +2.3% | -0.0% | +0.1% | -2.5% |
| U. North Texas | 6.539 | +1.3% | +1.2% | +0.0% | +0.0% | -4.0% |
| S.F. Austin State U. | 6.605 | +2.6% | +2.5% | +0.0% | -0.0% | -7.0% |
| SW Texas State U. | 7.759 | +0.3% | +0.5% | +0.1% | +0.1% | -3.6% |
| Texas A & M | 13.854 | +2.5% | +2.4% | -0.0% | +0.0% | -1.8% |
| U. Texas | 16.303 | +5.1% | +5.1% | -0.3% | -0.4% | -2.5% |
| Texas Tech U. | 8.28 | +1.8% | +1.9% | -0.0% | -0.1% | -2.1% |
| Total | 143.229 | +1.5% | +1.5% | -0.0% | +0.0% | -0.8% |

Population: all Texas public high school students

Benchmark model-simulated outcomes vs. counterfactuals:

TTT: remove Texas Top Ten.

LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.

LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.

Info: automatic financial aid application and perfect signal of $q$, all students.

AA: race-based points system at flagship universities.

Table 11: Black and Hispanic Students: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 16.171 | -1.3% | +1.4% | -1.0% | -1.2% | -4.7% |
| Private Nonrelig. | 1.073 | -1.0% | +1.0% | -1.3% | -0.7% | +17.7% |
| Religious | 4.901 | -3.9% | +0.1% | +0.3% | +1.0% | +15.2% |
| Non-TX Public | 3.992 | +0.1% | +1.9% | -0.3% | -0.1% | +10.5% |
| Highly Selective | 0.318 | -1.3% | -0.9% | -2.8% | -2.7% | +87.9% |
| Baylor U. | 0.783 | -1.0% | +2.9% | -0.9% | -0.4% | -0.1% |
| U. Houston | 1.732 | +0.1% | +2.8% | -1.1% | -1.5% | +0.2% |
| U. North Texas | 1.036 | -1.5% | +0.9% | -0.2% | -0.8% | -6.2% |
| S.F. Austin State U. | 1.246 | +2.6% | +4.5% | -0.2% | -0.7% | -12.6% |
| SW Texas State U. | 2.24 | -6.4% | -1.5% | -0.2% | -1.0% | -1.7% |
| Texas A & M | 2.01 | | -2.7% | -3.3% | -3.6% | +3.8% |
| U. Texas | 10.716 | | -10.0% | +4.1% | +5.5% | +5.3% |
| Texas Tech U. | 2.073 | -1.8% | +1.3% | -0.8% | -1.4% | +1.1% |
| Total | 48.289 | -1.2% | -1.4% | +0.3% | +0.5% | +2.7% |

Population: underrepresented minority students only

Offers of admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 34.019 | +0.3% | +2.4% | -0.8% | -0.9% | -5.4% |
| Private Nonrelig. | 4.106 | -0.1% | +0.8% | -0.6% | -0.2% | +11.1% |
| Religious | 12.423 | -1.4% | +1.5% | +0.1% | +0.7% | +11.0% |
| Non-TX Public | 10.17 | +1.3% | +2.5% | -0.2% | -0.1% | +7.0% |
| Highly Selective | 0.924 | -0.9% | -0.9% | -1.2% | -1.1% | +55.2% |
| Baylor U. | 4.09 | +1.4% | +3.0% | -0.4% | -0.2% | -1.4% |
| U. Houston | 6.482 | +2.5% | +3.7% | -0.5% | -0.5% | -1.5% |
| U. North Texas | 5.093 | +0.6% | +1.5% | -0.2% | -0.3% | -3.7% |
| S.F. Austin State U. | 5.861 | +3.8% | +4.4% | -0.1% | -0.3% | -9.0% |
| SW Texas State U. | 7.279 | -1.7% | +0.8% | -0.2% | -0.6% | -2.2% |
| Texas A & M | 5.794 | +2.4% | -1.1% | -1.7% | -1.8% | +1.7% |
| U. Texas | 16.77 | +2.8% | -6.7% | +2.8% | +3.8% | +4.1% |
| Texas Tech U. | 6.473 | +0.4% | +2.0% | -0.5% | -0.8% | +0.2% |
| Total | 119.485 | +0.9% | +0.8% | -0.0% | +0.1% | +0.8% |

Population: underrepresented minority students only

Applications for admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 37.9 | +1.2% | +3.1% | -0.7% | -0.7% | -5.4% |
| Private Nonrelig. | 5.252 | -0.2% | +0.6% | -0.5% | -0.2% | +5.7% |
| Religious | 14.206 | -1.1% | +1.7% | +0.1% | +0.7% | +6.8% |
| Non-TX Public | 11.669 | +1.4% | +2.6% | -0.2% | -0.1% | +2.6% |
| Highly Selective | 3.486 | -1.6% | -1.7% | -0.6% | -0.4% | +14.1% |
| Baylor U. | 4.914 | +1.4% | +2.8% | -0.3% | -0.0% | -2.6% |
| U. Houston | 7.173 | +3.4% | +4.5% | -0.4% | -0.5% | -3.2% |
| U. North Texas | 5.719 | +1.9% | +2.7% | -0.1% | -0.3% | -5.5% |
| S.F. Austin State U. | 6.53 | +4.4% | +4.9% | -0.1% | -0.3% | -9.4% |
| SW Texas State U. | 8.135 | -0.2% | +2.1% | -0.2% | -0.5% | -4.7% |
| Texas A & M | 7.139 | +3.7% | +1.6% | -1.4% | -1.4% | -0.4% |
| U. Texas | 19.43 | +6.4% | -1.3% | +2.9% | +4.0% | +0.7% |
| Texas Tech U. | 7.286 | +1.8% | +3.3% | -0.4% | -0.7% | -2.7% |
| Total | 138.839 | +2.0% | +2.1% | +0.0% | +0.2% | -1.3% |

Population: underrepresented minority students only

Benchmark model-simulated outcomes vs. counterfactuals:

TTT: remove Texas Top Ten.

LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.

LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.

Info: automatic financial aid application and perfect signal of $q$, all students.

AA: race-based points system at flagship universities.

Table 12: Poor (>60% Free/Reduced Lunch) High Schools: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 16.368 | +3.1% | +5.2% | -2.9% | -3.4% | -6.8% |
| Private Nonrelig. | 0.901 | +4.0% | +5.6% | -4.7% | -3.5% | +22.1% |
| Religious | 2.999 | +7.6% | +11.0% | -2.4% | -0.7% | +16.1% |
| Non-TX Public | 4.231 | +5.7% | +6.7% | -1.4% | -1.5% | +16.3% |
| Highly Selective | 0.369 | -1.3% | -0.9% | -5.8% | -5.8% | +111.4% |
| Baylor U. | 0.655 | +8.9% | +11.6% | -4.9% | -2.2% | -1.2% |
| U. Houston | 1.599 | +6.0% | +8.0% | -4.2% | -5.9% | -3.3% |
| U. North Texas | 0.776 | +5.0% | +6.8% | -2.1% | -4.1% | -10.4% |
| S.F. Austin State U. | 0.903 | +12.3% | +13.9% | -1.4% | -3.1% | -18.4% |
| SW Texas State U. | 1.697 | +2.7% | +6.3% | -3.1% | -6.2% | -5.6% |
| Texas A & M | 2.374 | -11.5% | -13.5% | -11.2% | -11.7% | +6.9% |
| U. Texas | 11.817 | -20.4% | -26.5% | +12.7% | +16.5% | +10.2% |
| Texas Tech U. | 1.467 | +0.2% | +2.7% | -3.8% | -6.6% | -3.2% |
| Total | 46.157 | -2.9% | -3.1% | +0.7% | +1.3% | +3.5% |

Population: students from poor (>60% poverty) high schools only

Offers of admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 34.867 | +4.1% | +5.8% | -2.2% | -2.4% | -7.0% |
| Private Nonrelig. | 3.95 | +1.7% | +2.3% | -1.8% | -1.1% | +13.6% |
| Religious | 9.131 | +6.3% | +8.4% | -1.4% | -0.1% | +11.9% |
| Non-TX Public | 10.557 | +5.5% | +6.2% | -0.9% | -0.9% | +12.0% |
| Highly Selective | 1.169 | -1.2% | -1.2% | -2.3% | -2.2% | +65.1% |
| Baylor U. | 3.832 | +4.8% | +5.9% | -1.4% | -0.3% | -0.3% |
| U. Houston | 6.243 | +5.4% | +6.2% | -1.5% | -2.1% | -3.4% |
| U. North Texas | 4.669 | +2.1% | +2.7% | -0.6% | -1.1% | -4.6% |
| S.F. Austin State U. | 5.228 | +8.1% | +8.5% | -0.4% | -0.9% | -11.1% |
| SW Texas State U. | 6.502 | +1.9% | +3.5% | -1.4% | -2.5% | -3.5% |
| Texas A & M | 6.513 | -8.3% | -10.7% | -5.8% | -5.9% | +4.3% |
| U. Texas | 18.649 | -16.4% | -22.4% | +9.9% | +12.8% | +8.6% |
| Texas Tech U. | 5.759 | +0.3% | +1.4% | -1.5% | -2.5% | -1.8% |
| Total | 117.067 | +0.2% | +0.1% | +0.0% | +0.4% | +1.5% |

Population: students from poor (>60% poverty) high schools only

Applications for admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 39.031 | +5.6% | +7.2% | -1.9% | -2.1% | -7.3% |
| Private Nonrelig. | 5.17 | +1.3% | +1.9% | -1.5% | -0.8% | +5.9% |
| Religious | 10.818 | +6.3% | +8.3% | -1.2% | +0.1% | +5.1% |
| Non-TX Public | 12.368 | +5.6% | +6.2% | -0.8% | -0.8% | +4.7% |
| Highly Selective | 3.817 | -2.6% | -2.6% | -1.2% | -1.1% | +18.0% |
| Baylor U. | 4.736 | +4.5% | +5.4% | -1.2% | +0.1% | -3.3% |
| U. Houston | 6.991 | +7.2% | +7.9% | -1.3% | -1.8% | -6.0% |
| U. North Texas | 5.308 | +4.9% | +5.4% | -0.6% | -0.9% | -7.5% |
| S.F. Austin State U. | 5.909 | +9.4% | +9.8% | -0.3% | -0.7% | -11.9% |
| SW Texas State U. | 7.358 | +4.6% | +6.1% | -1.2% | -2.2% | -7.3% |
| Texas A & M | 7.793 | -2.2% | -3.8% | -4.9% | -4.8% | +0.4% |
| U. Texas | 21.068 | -8.5% | -13.6% | +9.9% | +13.0% | +4.0% |
| Texas Tech U. | 6.564 | +3.5% | +4.6% | -1.3% | -2.3% | -5.8% |
| Total | 136.931 | +2.7% | +2.7% | +0.2% | +0.6% | -1.8% |

Population: students from poor (>60% poverty) high schools only
Benchmark model-simulated outcomes vs. counterfactuals:
TTT: remove Texas Top Ten.
LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.
LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.
Info: automatic financial aid application and perfect signal of $q$, all students.
AA: race-based points system at flagship universities.

# Table 13: Affluent High Schools: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 13.165 | -3.1% | -3.6% | +0.3% | +0.5% | -0.5% |
| Private Nonrelig. | 1.8 | -1.7% | -2.3% | +0.4% | +0.6% | +15.3% |
| Religious | 9.205 | -3.0% | -3.6% | +0.5% | +0.7% | +9.1% |
| Non-TX Public | 5.476 | -4.1% | -5.0% | +0.6% | +0.9% | +3.7% |
| Highly Selective | 0.67 | -0.1% | -0.2% | +0.1% | +0.1% | +44.1% |
| Baylor U. | 1.263 | -2.1% | -2.5% | +0.3% | -0.1% | +0.6% |
| U. Houston | 1.709 | -3.0% | -3.5% | +0.6% | +0.9% | +1.5% |
| U. North Texas | 2.399 | -2.5% | -3.0% | +0.3% | +0.5% | -2.3% |
| S.F. Austin State U. | 1.504 | -2.2% | -2.7% | +0.2% | +0.3% | -6.6% |
| SW Texas State U. | 1.739 | -4.0% | -4.7% | +0.5% | +0.6% | -1.9% |
| Texas A & M | 7.897 | +6.2% | +6.6% | +0.5% | +0.5% | -2.5% |
| U. Texas | 6.02 | +12.7% | +16.6% | -3.9% | -5.0% | -7.1% |
| Texas Tech U. | 2.823 | -1.2% | -1.9% | +0.5% | +0.7% | +0.1% |
| Total | 55.668 | +0.1% | +0.1% | -0.0% | -0.0% | +1.4% |

Population: students from affluent (<15% poverty) high schools only

Offers of admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 27.806 | -1.9% | -2.3% | +0.2% | +0.3% | -1.5% |
| Private Nonrelig. | 5.677 | -0.5% | -0.8% | +0.2% | +0.3% | +8.4% |
| Religious | 19.899 | -1.9% | -2.4% | +0.4% | +0.5% | +6.5% |
| Non-TX Public | 13.475 | -2.2% | -2.8% | +0.4% | +0.5% | +1.8% |
| Highly Selective | 1.348 | -0.0% | -0.1% | +0.0% | +0.0% | +38.0% |
| Baylor U. | 5.268 | -0.1% | -0.2% | +0.0% | -0.3% | -2.0% |
| U. Houston | 6.374 | -0.2% | -0.5% | +0.2% | +0.4% | -0.5% |
| U. North Texas | 7.733 | -0.6% | -0.9% | +0.1% | +0.2% | -2.2% |
| S.F. Austin State U. | 6.349 | -0.2% | -0.4% | +0.1% | +0.1% | -4.8% |
| SW Texas State U. | 6.403 | -0.9% | -1.3% | +0.2% | +0.2% | -2.1% |
| Texas A & M | 13.996 | +7.2% | +7.6% | +0.4% | +0.3% | -3.3% |
| U. Texas | 10.942 | +14.7% | +18.3% | -3.8% | -4.9% | -7.2% |
| Texas Tech U. | 7.42 | +0.6% | +0.2% | +0.2% | +0.3% | -0.4% |
| Total | 132.69 | +1.0% | +1.0% | -0.1% | -0.1% | +0.1% |

Population: students from affluent (<15% poverty) high schools only

Applications for admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 29.322 | -1.9% | -2.2% | +0.2% | +0.3% | -1.3% |
| Private Nonrelig. | 6.465 | -0.5% | -0.8% | +0.2% | +0.3% | +6.9% |
| Religious | 21.171 | -1.9% | -2.4% | +0.3% | +0.5% | +5.7% |
| Non-TX Public | 14.371 | -2.2% | -2.8% | +0.4% | +0.5% | +1.1% |
| Highly Selective | 4.193 | -0.2% | -0.2% | +0.0% | +0.0% | +13.0% |
| Baylor U. | 5.752 | -0.1% | -0.3% | +0.1% | -0.1% | -0.8% |
| U. Houston | 6.68 | -0.2% | -0.4% | +0.2% | +0.4% | -0.9% |
| U. North Texas | 8.137 | -0.6% | -0.9% | +0.1% | +0.2% | -2.6% |
| S.F. Austin State U. | 6.652 | -0.2% | -0.4% | +0.1% | +0.1% | -4.8% |
| SW Texas State U. | 6.782 | -0.9% | -1.2% | +0.2% | +0.2% | -2.5% |
| Texas A & M | 15.766 | +6.2% | +6.5% | +0.4% | +0.4% | -3.3% |
| U. Texas | 12.789 | +12.5% | +15.3% | -3.1% | -4.0% | -6.5% |
| Texas Tech U. | 7.872 | +0.4% | +0.1% | +0.2% | +0.3% | -1.1% |
| Total | 145.953 | +0.8% | +0.8% | -0.0% | -0.1% | -0.2% |

Population: students from affluent (<15% poverty) high schools only
Benchmark model-simulated outcomes vs. counterfactuals:
TTT: remove Texas Top Ten.
LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.
LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.
Info: automatic financial aid application and perfect signal of $q$, all students.
AA: race-based points system at flagship universities.

Table 14: Parents Without College Degrees: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 14.493 | -1.2% | -0.4% | -0.4% | -0.4% | -3.7% |
| Private Nonrelig. | 1.394 | -1.2% | -1.1% | -0.2% | +0.1% | +15.3% |
| Religious | 5.612 | -2.9% | -2.5% | +0.5% | +1.0% | +12.2% |
| Non-TX Public | 4.064 | -0.5% | -0.5% | +0.1% | +0.3% | +7.3% |
| Highly Selective | 0.313 | -0.8% | -0.7% | -1.2% | -1.3% | +75.9% |
| Baylor U. | 0.934 | -1.0% | -0.4% | -0.3% | -0.2% | -0.4% |
| U. Houston | 1.787 | -0.6% | -0.3% | -0.3% | -0.3% | +0.9% |
| U. North Texas | 1.303 | -1.3% | -1.1% | +0.1% | -0.1% | -4.4% |
| S.F. Austin State U. | 1.362 | +0.9% | +1.0% | +0.0% | -0.2% | -10.1% |
| SW Texas State U. | 2.187 | -4.9% | -3.9% | +0.3% | -0.0% | -1.5% |
| Texas A & M | 4.98 | +1.3% | +1.1% | -0.5% | -0.5% | +1.9% |
| U. Texas | 8.225 | +1.2% | -1.2% | +1.5% | +2.0% | +3.3% |
| Texas Tech U. | 2.404 | -1.0% | -0.5% | -0.1% | -0.4% | +0.9% |
| Total | 49.06 | -0.7% | -0.8% | +0.1% | +0.3% | +2.2% |

Population: students without a parent w/ college degree

Offers of admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 31.002 | +0.2% | +0.7% | -0.3% | -0.3% | -4.5% |
| Private Nonrelig. | 4.821 | -0.3% | -0.3% | -0.1% | +0.1% | +9.4% |
| Religious | 13.89 | -1.1% | -0.7% | +0.3% | +0.7% | +8.6% |
| Non-TX Public | 10.56 | +0.6% | +0.6% | +0.1% | +0.2% | +4.4% |
| Highly Selective | 0.879 | -0.5% | -0.6% | -0.6% | -0.5% | +49.1% |
| Baylor U. | 4.518 | +1.0% | +1.4% | -0.2% | -0.2% | -2.1% |
| U. Houston | 6.625 | +1.7% | +1.8% | -0.1% | -0.1% | -1.2% |
| U. North Texas | 5.698 | +0.5% | +0.5% | -0.0% | -0.1% | -3.2% |
| S.F. Austin State U. | 6.115 | +2.3% | +2.3% | -0.0% | -0.1% | -7.4% |
| SW Texas State U. | 7.233 | -1.1% | -0.6% | +0.0% | -0.1% | -2.3% |
| Texas A & M | 10.0 | +2.6% | +2.1% | -0.4% | -0.4% | +0.5% |
| U. Texas | 13.722 | +4.1% | +2.1% | +0.4% | +0.6% | +1.8% |
| Texas Tech U. | 7.026 | +0.7% | +1.0% | -0.1% | -0.3% | -0.0% |
| Total | 122.088 | +0.9% | +0.9% | -0.1% | +0.0% | +0.4% |

Population: students without a parent w/ college degree

Applications for admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 33.726 | +0.8% | +1.3% | -0.3% | -0.3% | -4.4% |
| Private Nonrelig. | 5.873 | -0.3% | -0.3% | -0.1% | +0.1% | +5.7% |
| Religious | 15.46 | -0.9% | -0.5% | +0.3% | +0.6% | +5.8% |
| Non-TX Public | 11.786 | +0.7% | +0.8% | +0.0% | +0.2% | +1.5% |
| Highly Selective | 3.425 | -1.0% | -1.1% | -0.2% | -0.2% | +12.6% |
| Baylor U. | 5.227 | +1.0% | +1.3% | -0.1% | -0.1% | -2.3% |
| U. Houston | 7.148 | +2.2% | +2.4% | -0.1% | -0.0% | -2.5% |
| U. North Texas | 6.216 | +1.3% | +1.3% | -0.0% | -0.0% | -4.4% |
| S.F. Austin State U. | 6.608 | +2.7% | +2.8% | -0.0% | -0.1% | -7.7% |
| SW Texas State U. | 7.903 | -0.1% | +0.4% | +0.1% | -0.1% | -4.0% |
| Texas A & M | 11.707 | +3.4% | +3.0% | -0.3% | -0.2% | -1.0% |
| U. Texas | 16.131 | +6.5% | +4.9% | +0.7% | +1.1% | -0.9% |
| Texas Tech U. | 7.701 | +1.5% | +1.8% | -0.1% | -0.2% | -2.1% |
| Total | 138.913 | +1.6% | +1.6% | +0.0% | +0.1% | -1.0% |

Population: students without a parent w/ college degree
Benchmark model-simulated outcomes vs. counterfactuals:
TTT: remove Texas Top Ten.
LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.
LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.
Info: automatic financial aid application and perfect signal of $q$, all students.
AA: race-based points system at flagship universities.

Table 15: Top-Decile Students: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 8.254 | +25.2% | +25.9% | -2.3% | -2.7% | -2.2% |
| Private Nonrelig. | 2.166 | +9.8% | +9.7% | -0.7% | -0.6% | +8.7% |
| Religious | 5.85 | +22.0% | +21.9% | -0.5% | -0.5% | +5.9% |
| Non-TX Public | 4.287 | +18.7% | +18.5% | -0.5% | -0.5% | +4.6% |
| Highly Selective | 1.112 | +0.1% | +0.1% | -0.6% | -0.6% | +53.4% |
| Baylor U. | 0.896 | +24.9% | +24.9% | -1.2% | -1.3% | +4.9% |
| U. Houston | 0.977 | +30.8% | +31.0% | -2.7% | -3.4% | -3.7% |
| U. North Texas | 1.065 | +17.6% | +17.4% | -0.7% | -1.1% | -3.3% |
| S.F. Austin State U. | 0.757 | +33.9% | +33.9% | -0.9% | -1.3% | -4.0% |
| SW Texas State U. | 1.372 | +30.1% | +30.8% | -1.6% | -2.5% | -3.3% |
| Texas A & M | 10.191 | -17.8% | -18.0% | -1.0% | -1.1% | -1.1% |
| U. Texas | 17.401 | -32.3% | -32.6% | +3.2% | +4.0% | -1.8% |
| Texas Tech U. | 2.495 | +9.2% | +9.2% | -0.9% | -1.3% | -5.3% |
| Total | 56.821 | -2.6% | -2.6% | +0.2% | +0.3% | +0.9% |

Population: students in top decile of HS class

Offers of admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 19.639 | +21.0% | +21.5% | -1.6% | -1.9% | -1.8% |
| Private Nonrelig. | 6.622 | +6.8% | +6.7% | -0.4% | -0.3% | +5.0% |
| Religious | 14.634 | +17.4% | +17.4% | -0.4% | -0.4% | +4.5% |
| Non-TX Public | 11.177 | +14.8% | +14.6% | -0.4% | -0.3% | +3.1% |
| Highly Selective | 2.498 | -0.4% | -0.4% | -0.3% | -0.3% | +41.9% |
| Baylor U. | 4.824 | +12.5% | +12.6% | -0.4% | -0.4% | +1.5% |
| U. Houston | 5.089 | +15.6% | +15.6% | -0.9% | -1.1% | -1.8% |
| U. North Texas | 5.354 | +9.6% | +9.5% | -0.3% | -0.5% | -1.7% |
| S.F. Austin State U. | 4.728 | +16.4% | +16.4% | -0.3% | -0.4% | -1.9% |
| SW Texas State U. | 5.96 | +15.0% | +15.2% | -0.7% | -1.1% | -1.8% |
| Texas A & M | 18.511 | -14.8% | -15.0% | -0.8% | -0.9% | -1.0% |
| U. Texas | 27.79 | -27.9% | -28.1% | +2.5% | +3.2% | -1.6% |
| Texas Tech U. | 7.333 | +6.8% | +6.9% | -0.5% | -0.7% | -3.4% |
| Total | 134.158 | +1.8% | +1.8% | -0.1% | -0.0% | +0.6% |

Population: students in top decile of HS class

Applications for admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 19.655 | +23.7% | +24.2% | -1.6% | -1.9% | -1.8% |
| Private Nonrelig. | 7.07 | +7.0% | +6.8% | -0.4% | -0.3% | +3.8% |
| Religious | 14.998 | +18.3% | +18.3% | -0.4% | -0.4% | +3.7% |
| Non-TX Public | 11.5 | +15.5% | +15.4% | -0.4% | -0.3% | +2.0% |
| Highly Selective | 5.571 | -1.7% | -1.8% | -0.2% | -0.2% | +17.8% |
| Baylor U. | 5.018 | +13.0% | +13.0% | -0.4% | -0.4% | +1.8% |
| U. Houston | 5.091 | +17.8% | +17.9% | -0.9% | -1.1% | -1.8% |
| U. North Texas | 5.356 | +12.0% | +11.9% | -0.3% | -0.5% | -1.8% |
| S.F. Austin State U. | 4.73 | +18.3% | +18.3% | -0.3% | -0.4% | -1.9% |
| SW Texas State U. | 5.964 | +18.1% | +18.4% | -0.7% | -1.1% | -1.8% |
| Texas A & M | 18.536 | -9.8% | -10.0% | -0.8% | -0.9% | -1.0% |
| U. Texas | 27.823 | -22.0% | -22.2% | +2.5% | +3.2% | -1.6% |
| Texas Tech U. | 7.338 | +9.6% | +9.7% | -0.5% | -0.7% | -3.4% |
| Total | 138.651 | +4.7% | +4.7% | -0.1% | -0.0% | +0.4% |

Population: students in top decile of HS class
Benchmark model-simulated outcomes vs. counterfactuals:
TTT: remove Texas Top Ten.
LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.
LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.
Info: automatic financial aid application and perfect signal of $q$, all students.
AA: race-based points system at flagship universities.

Table 16: Minorities from Affluent High Schools: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 15.751 | -6.6% | -4.7% | +0.5% | +0.7% | -0.2% |
| Private Nonrelig. | 1.24 | -7.6% | -5.2% | +0.9% | +1.2% | +18.7% |
| Religious | 9.06 | -8.9% | -6.2% | +1.0% | +1.3% | +12.2% |
| Non-TX Public | 5.346 | -11.0% | -7.8% | +1.2% | +1.6% | +3.7% |
| Highly Selective | 0.488 | -1.0% | -0.8% | +0.3% | +0.4% | +48.7% |
| Baylor U. | 1.2 | -8.1% | -5.1% | +0.7% | +0.4% | -0.1% |
| U. Houston | 2.379 | -6.8% | -4.2% | +0.9% | +1.3% | +4.9% |
| U. North Texas | 2.164 | -6.8% | -4.9% | +0.7% | +0.9% | -3.0% |
| S.F. Austin State U. | 1.783 | -5.0% | -3.5% | +0.4% | +0.5% | -8.0% |
| SW Texas State U. | 1.951 | -9.1% | -6.3% | +0.8% | +1.1% | -1.1% |
| Texas A & M | 2.751 | +13.2% | +9.2% | +1.2% | +1.4% | -2.7% |
| U. Texas | 7.24 | +44.2% | +30.3% | -5.4% | -7.0% | -10.0% |
| Texas Tech U. | 2.729 | -6.2% | -3.2% | +0.9% | +1.2% | +2.1% |
| Total | 54.082 | +0.4% | +0.2% | -0.0% | -0.0% | +1.6% |

Population: underrepresented minority students from affluent high schools

Offers of admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 31.892 | -4.8% | -3.3% | +0.4% | +0.5% | -1.5% |
| Private Nonrelig. | 4.46 | -3.3% | -2.0% | +0.4% | +0.5% | +9.0% |
| Religious | 19.15 | -6.5% | -4.3% | +0.7% | +0.9% | +8.8% |
| Non-TX Public | 12.885 | -7.0% | -4.8% | +0.7% | +0.9% | +1.7% |
| Highly Selective | 0.929 | -0.4% | -0.4% | +0.1% | +0.2% | +43.9% |
| Baylor U. | 4.833 | -2.9% | -1.3% | +0.1% | -0.2% | -3.0% |
| U. Houston | 7.412 | -2.5% | -1.1% | +0.4% | +0.6% | +1.9% |
| U. North Texas | 6.986 | -2.8% | -1.8% | +0.2% | +0.3% | -2.5% |
| S.F. Austin State U. | 6.803 | -1.7% | -0.9% | +0.1% | +0.1% | -5.9% |
| SW Texas State U. | 6.554 | -3.7% | -2.2% | +0.3% | +0.4% | -1.8% |
| Texas A & M | 6.616 | +14.1% | +10.4% | +0.7% | +0.8% | -4.2% |
| U. Texas | 11.871 | +42.4% | +30.2% | -5.2% | -6.8% | -10.0% |
| Texas Tech U. | 6.965 | -2.1% | -0.3% | +0.4% | +0.5% | +0.9% |
| Total | 127.355 | +0.9% | +0.9% | -0.1% | -0.1% | +0.1% |

Population: underrepresented minority students from affluent high schools

Applications for admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 36.02 | -4.3% | -3.0% | +0.3% | +0.4% | -1.5% |
| Private Nonrelig. | 5.388 | -3.1% | -1.9% | +0.3% | +0.5% | +7.1% |
| Religious | 20.867 | -6.2% | -4.2% | +0.6% | +0.8% | +7.6% |
| Non-TX Public | 14.173 | -6.7% | -4.5% | +0.7% | +0.9% | +0.8% |
| Highly Selective | 3.703 | -0.3% | -0.4% | +0.1% | +0.1% | +12.3% |
| Baylor U. | 5.53 | -2.6% | -1.3% | +0.2% | -0.1% | -2.0% |
| U. Houston | 8.1 | -2.2% | -0.9% | +0.4% | +0.6% | +1.4% |
| U. North Texas | 7.717 | -2.6% | -1.6% | +0.2% | +0.3% | -3.1% |
| S.F. Austin State U. | 7.593 | -1.6% | -0.9% | +0.1% | +0.1% | -6.1% |
| SW Texas State U. | 7.254 | -3.4% | -2.0% | +0.3% | +0.4% | -2.5% |
| Texas A & M | 8.093 | +9.6% | +7.3% | +0.6% | +0.7% | -3.3% |
| U. Texas | 14.47 | +33.6% | +24.4% | -4.1% | -5.4% | -9.4% |
| Texas Tech U. | 7.711 | -1.9% | -0.3% | +0.3% | +0.5% | -0.2% |
| Total | 146.619 | +0.4% | +0.6% | -0.1% | -0.1% | -0.3% |

Population: underrepresented minority students from affluent high schools
Benchmark model-simulated outcomes vs. counterfactuals:
TTT: remove Texas Top Ten.
LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.
LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.
Info: automatic financial aid application and perfect signal of $q$, all students.
AA: race-based points system at flagship universities.

Table 17: Top-Decile Minority Students: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 10.641 | +29.9% | +34.3% | -5.9% | -7.2% | -4.2% |
| Private Nonrelig. | 1.221 | +14.3% | +16.6% | -3.9% | -3.3% | +13.4% |
| Religious | 3.754 | +35.4% | +41.6% | -2.4% | -2.7% | +11.9% |
| Non-TX Public | 3.917 | +20.6% | +22.7% | -1.9% | -1.6% | +12.9% |
| Highly Selective | 0.669 | -0.0% | +0.3% | -3.1% | -3.0% | +75.7% |
| Baylor U. | 0.616 | +38.7% | +44.6% | -5.0% | -4.9% | +7.5% |
| U. Houston | 1.031 | +36.3% | +41.3% | -8.0% | -10.0% | -4.0% |
| U. North Texas | 0.701 | +27.3% | +31.2% | -3.1% | -5.6% | -6.5% |
| S.F. Austin State U. | 0.561 | +59.5% | +64.2% | -3.9% | -5.6% | -5.7% |
| SW Texas State U. | 1.495 | +34.2% | +42.0% | -5.0% | -7.5% | -3.9% |
| Texas A & M | 3.157 | -21.5% | -22.9% | -7.7% | -8.9% | -1.7% |
| U. Texas | 25.038 | -37.9% | -42.8% | +6.9% | +8.8% | -1.6% |
| Texas Tech U. | 1.815 | +9.3% | +13.2% | -3.8% | -5.4% | -6.5% |
| Total | 54.619 | -5.2% | -5.5% | +0.6% | +1.0% | +0.9% |

Population: underrepresented minority students in top decile of HS class

Offers of admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 24.448 | +25.9% | +29.2% | -4.4% | -5.3% | -3.5% |
| Private Nonrelig. | 4.921 | +6.8% | +7.9% | -1.7% | -1.4% | +7.4% |
| Religious | 10.932 | +25.1% | +29.1% | -1.6% | -1.7% | +8.5% |
| Non-TX Public | 10.321 | +16.8% | +18.3% | -1.2% | -1.0% | +9.0% |
| Highly Selective | 1.849 | -1.2% | -1.2% | -1.4% | -1.2% | +48.6% |
| Baylor U. | 4.19 | +15.2% | +17.3% | -1.4% | -1.3% | +2.1% |
| U. Houston | 5.334 | +18.2% | +20.0% | -2.7% | -3.3% | -2.2% |
| U. North Texas | 4.752 | +9.6% | +10.9% | -1.0% | -1.7% | -2.9% |
| S.F. Austin State U. | 4.436 | +23.4% | +24.6% | -1.1% | -1.5% | -2.6% |
| SW Texas State U. | 6.441 | +15.5% | +18.8% | -2.2% | -3.2% | -2.4% |
| Texas A & M | 9.113 | -18.6% | -20.2% | -4.1% | -4.6% | -1.6% |
| U. Texas | 37.553 | -34.7% | -39.4% | +5.8% | +7.4% | -1.6% |
| Texas Tech U. | 6.571 | +4.5% | +6.5% | -1.8% | -2.5% | -4.6% |
| Total | 130.86 | +0.6% | +0.8% | -0.2% | -0.1% | +0.6% |

Population: underrepresented minority students in top decile of HS class

Applications for admission per 100 test-taking Texas high school seniors

| **College** | **Benchmark** | **AA** | **NoTTT** | **LOS** | **LOS+** | **Info** |
|---|---|---|---|---|---|---|
| TX Public | 24.497 | +31.9% | +35.3% | -4.4% | -5.3% | -3.5% |
| Private Nonrelig. | 5.572 | +6.7% | +7.8% | -1.6% | -1.3% | +4.7% |
| Religious | 11.562 | +26.8% | +30.8% | -1.6% | -1.8% | +6.3% |
| Non-TX Public | 11.002 | +18.0% | +19.5% | -1.2% | -1.0% | +6.0% |
| Highly Selective | 4.708 | -3.8% | -3.9% | -0.8% | -0.7% | +18.3% |
| Baylor U. | 4.563 | +15.7% | +17.7% | -1.4% | -1.1% | +1.9% |
| U. Houston | 5.34 | +23.5% | +25.4% | -2.7% | -3.3% | -2.2% |
| U. North Texas | 4.759 | +15.8% | +17.1% | -1.0% | -1.7% | -2.9% |
| S.F. Austin State U. | 4.441 | +28.6% | +29.8% | -1.1% | -1.5% | -2.6% |
| SW Texas State U. | 6.45 | +22.2% | +25.7% | -2.2% | -3.2% | -2.5% |
| Texas A & M | 9.134 | -8.8% | -9.6% | -4.1% | -4.6% | -1.6% |
| U. Texas | 37.6 | -27.5% | -31.6% | +5.8% | +7.4% | -1.7% |
| Texas Tech U. | 6.583 | +10.7% | +12.7% | -1.8% | -2.5% | -4.6% |
| Total | 136.21 | +5.9% | +6.3% | -0.2% | -0.1% | +0.1% |

Population: underrepresented minority students in top decile of HS class
Benchmark model-simulated outcomes vs. counterfactuals:
TTT: remove Texas Top Ten.
LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.
LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.
Info: automatic financial aid application and perfect signal of $q$, all students.
AA: race-based points system at flagship universities.

Table 18: Minority Students from Poor High Schools: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 16.898 | +2.0% | +4.7% | -2.8% | -3.4% | -6.7% |
| Private Nonrelig. | 0.8 | +3.1% | +5.6% | -5.0% | -3.7% | +22.9% |
| Religious | 2.982 | +4.6% | +9.2% | -2.2% | -0.5% | +16.6% |
| Non-TX Public | 4.159 | +4.9% | +6.3% | -1.4% | -1.4% | +16.9% |
| Highly Selective | 0.337 | -1.6% | -1.0% | -6.1% | -6.0% | +113.3% |
| Baylor U. | 0.579 | +8.9% | +13.1% | -4.3% | -1.8% | -0.8% |
| U. Houston | 1.546 | +5.0% | +7.8% | -4.2% | -5.9% | -3.3% |
| U. North Texas | 0.756 | +4.3% | +6.9% | -1.9% | -4.0% | -10.7% |
| S.F. Austin State U. | 0.885 | +11.5% | +13.7% | -1.4% | -3.1% | -18.5% |
| SW Texas State U. | 1.678 | +0.6% | +5.3% | -3.1% | -6.3% | -5.6% |
| Texas A & M | 1.732 | -9.4% | -12.8% | -10.5% | -11.7% | +6.3% |
| U. Texas | 11.645 | -17.8% | -26.0% | +12.0% | +16.0% | +11.5% |
| Texas Tech U. | 1.431 | -0.5% | +2.9% | -3.7% | -6.4% | -2.9% |
| Total | 45.428 | -2.8% | -3.0% | +0.7% | +1.3% | +3.6% |

Population: minority students from poor (>60% poverty) high schools

Offers of admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 35.772 | +3.2% | +5.3% | -2.2% | -2.5% | -6.9% |
| Private Nonrelig. | 3.748 | +1.2% | +2.2% | -1.8% | -1.1% | +13.7% |
| Religious | 9.046 | +4.4% | +7.3% | -1.3% | +0.0% | +12.4% |
| Non-TX Public | 10.373 | +4.8% | +5.8% | -0.9% | -0.8% | +12.5% |
| Highly Selective | 1.101 | -1.3% | -1.3% | -2.4% | -2.2% | +64.6% |
| Baylor U. | 3.655 | +4.5% | +5.9% | -1.1% | -0.1% | +0.0% |
| U. Houston | 6.123 | +4.9% | +6.0% | -1.5% | -2.0% | -3.2% |
| U. North Texas | 4.589 | +1.8% | +2.6% | -0.6% | -1.1% | -4.5% |
| S.F. Austin State U. | 5.168 | +7.8% | +8.3% | -0.4% | -0.9% | -11.1% |
| SW Texas State U. | 6.437 | +0.9% | +3.0% | -1.4% | -2.6% | -3.3% |
| Texas A & M | 5.527 | -6.4% | -10.0% | -5.0% | -5.2% | +4.1% |
| U. Texas | 18.333 | -13.9% | -21.9% | +9.3% | +12.4% | +9.7% |
| Texas Tech U. | 5.646 | -0.0% | +1.5% | -1.5% | -2.4% | -1.4% |
| Total | 115.518 | +0.1% | +0.0% | +0.0% | +0.4% | +1.6% |

Population: minority students from poor (>60% poverty) high schools

Applications for admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 40.233 | +4.7% | +6.7% | -1.9% | -2.1% | -7.3% |
| Private Nonrelig. | 4.97 | +0.9% | +1.7% | -1.5% | -0.8% | +5.6% |
| Religious | 10.797 | +4.6% | +7.3% | -1.1% | +0.2% | +5.3% |
| Non-TX Public | 12.222 | +4.9% | +5.8% | -0.8% | -0.7% | +4.9% |
| Highly Selective | 3.724 | -2.5% | -2.6% | -1.2% | -1.0% | +17.3% |
| Baylor U. | 4.566 | +4.2% | +5.5% | -0.9% | +0.2% | -3.2% |
| U. Houston | 6.898 | +6.6% | +7.6% | -1.3% | -1.7% | -6.0% |
| U. North Texas | 5.253 | +4.5% | +5.3% | -0.5% | -0.9% | -7.5% |
| S.F. Austin State U. | 5.882 | +9.0% | +9.5% | -0.3% | -0.7% | -11.9% |
| SW Texas State U. | 7.337 | +3.6% | +5.6% | -1.2% | -2.3% | -7.4% |
| Texas A & M | 6.765 | -0.7% | -2.8% | -4.1% | -4.1% | +0.1% |
| U. Texas | 20.858 | -6.3% | -13.0% | +9.3% | +12.6% | +4.7% |
| Texas Tech U. | 6.48 | +3.2% | +4.6% | -1.3% | -2.2% | -5.7% |
| Total | 135.987 | +2.5% | +2.6% | +0.2% | +0.6% | -1.8% |

Population: minority students from poor (>60% poverty) high schools
Benchmark model-simulated outcomes vs. counterfactuals:
TTT: remove Texas Top Ten.
LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.
LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.
Info: automatic financial aid application and perfect signal of $q$, all students.
AA: race-based points system at flagship universities.

## Table 19: Non-URM students: Enrollment, Admissions, Applications

Matriculating students per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 12.051 | -0.3% | -1.3% | +0.3% | +0.4% | -2.3% |
| Private Nonrelig. | 2.129 | +0.1% | -0.6% | +0.3% | +0.4% | +13.5% |
| Religious | 7.527 | -0.8% | -2.1% | +0.6% | +0.8% | +10.0% |
| Non-TX Public | 5.142 | -0.2% | -1.3% | +0.4% | +0.6% | +3.8% |
| Highly Selective | 0.578 | -0.2% | -0.3% | -0.1% | -0.1% | +55.5% |
| Baylor U. | 1.152 | +0.3% | -0.7% | +0.2% | -0.0% | +0.3% |
| U. Houston | 1.678 | -0.0% | -1.2% | +0.4% | +0.7% | -0.0% |
| U. North Texas | 1.674 | -0.6% | -1.5% | +0.3% | +0.4% | -3.5% |
| S.F. Austin State U. | 1.471 | +0.9% | +0.1% | +0.2% | +0.3% | -7.9% |
| SW Texas State U. | 2.144 | -2.5% | -4.1% | +0.7% | +0.9% | -1.7% |
| Texas A & M | 8.214 | -0.0% | +0.3% | +0.3% | +0.3% | -0.3% |
| U. Texas | 7.549 | -0.0% | +5.3% | -2.2% | -3.0% | -2.9% |
| Texas Tech U. | 3.146 | +0.5% | -0.4% | +0.3% | +0.4% | -0.3% |
| Total | 54.455 | -0.3% | -0.2% | -0.0% | +0.0% | +1.5% |

Population: all non-URM students

Offers of admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 26.394 | +0.6% | -0.1% | +0.2% | +0.3% | -3.3% |
| Private Nonrelig. | 6.246 | +0.6% | +0.1% | +0.1% | +0.2% | +8.3% |
| Religious | 17.364 | +0.1% | -0.8% | +0.4% | +0.6% | +6.9% |
| Non-TX Public | 12.716 | +0.6% | -0.1% | +0.2% | +0.3% | +1.7% |
| Highly Selective | 1.296 | -0.2% | -0.2% | -0.1% | -0.1% | +43.7% |
| Baylor U. | 5.145 | +1.4% | +1.1% | +0.0% | -0.2% | -2.0% |
| U. Houston | 6.464 | +1.8% | +1.3% | +0.2% | +0.3% | -1.8% |
| U. North Texas | 6.501 | +0.8% | +0.4% | +0.1% | +0.1% | -3.0% |
| S.F. Austin State U. | 6.346 | +1.9% | +1.6% | +0.1% | +0.1% | -6.1% |
| SW Texas State U. | 7.202 | +0.2% | -0.6% | +0.3% | +0.3% | -2.5% |
| Texas A & M | 14.686 | +1.6% | +2.0% | +0.2% | +0.2% | -1.3% |
| U. Texas | 13.216 | +3.2% | +8.0% | -2.4% | -3.2% | -3.4% |
| Texas Tech U. | 8.173 | +1.6% | +1.1% | +0.1% | +0.1% | -0.9% |
| Total | 131.747 | +1.1% | +1.1% | -0.1% | -0.1% | -0.0% |

Population: all non-URM students

Applications for admission per 100 test-taking Texas high school seniors

| College | Benchmark | AA | NoTTT | LOS | LOS+ | Info |
|---|---|---|---|---|---|---|
| TX Public | 27.779 | +0.8% | +0.1% | +0.2% | +0.2% | -2.9% |
| Private Nonrelig. | 7.147 | +0.5% | +0.1% | +0.1% | +0.2% | +6.2% |
| Religious | 18.598 | +0.1% | -0.8% | +0.4% | +0.5% | +5.6% |
| Non-TX Public | 13.637 | +0.7% | -0.0% | +0.2% | +0.3% | +0.6% |
| Highly Selective | 4.055 | -0.5% | -0.5% | -0.0% | -0.0% | +14.2% |
| Baylor U. | 5.644 | +1.4% | +1.0% | +0.0% | -0.1% | -1.3% |
| U. Houston | 6.762 | +1.9% | +1.4% | +0.2% | +0.3% | -2.3% |
| U. North Texas | 6.848 | +1.1% | +0.7% | +0.1% | +0.1% | -3.5% |
| S.F. Austin State U. | 6.634 | +2.0% | +1.7% | +0.1% | +0.1% | -6.1% |
| SW Texas State U. | 7.617 | +0.6% | -0.2% | +0.2% | +0.3% | -3.2% |
| Texas A & M | 16.393 | +2.3% | +2.5% | +0.2% | +0.3% | -2.0% |
| U. Texas | 15.12 | +4.4% | +8.3% | -1.9% | -2.6% | -4.0% |
| Texas Tech U. | 8.655 | +1.8% | +1.4% | +0.1% | +0.1% | -1.8% |
| Total | 144.889 | +1.4% | +1.3% | -0.0% | -0.0% | -0.6% |

Population: all non-URM students
Benchmark model-simulated outcomes vs. counterfactuals:
TTT: remove Texas Top Ten.
LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.
LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.
Info: automatic financial aid application and perfect signal of $q$, all students.
AA: race-based points system at flagship universities.

### A.2.3 Grades and persistence

Table 20: Predicted College GPA at Flagship Universities

Mean GPA at flagship universities: all matriculating students

| College | GPA (benchmark) | NoTTT | LOS | LOS+ | Info | AA |
|---|---|---|---|---|---|---|
| Texas A & M | 3.064 | 3.059 | 3.065 | 3.065 | 3.047 | 3.058 |
| U. Texas | 2.812 | 2.792 | 2.806 | 2.802 | 2.783 | 2.781 |

underrepresented minority students

| College | GPA (benchmark) | NoTTT | LOS | LOS+ | Info | AA |
|---|---|---|---|---|---|---|
| Texas A & M | 2.916 | 2.903 | 2.921 | 2.922 | 2.895 | 2.9 |
| U. Texas | 2.693 | 2.647 | 2.686 | 2.677 | 2.658 | 2.638 |

Population: all non-URM students

| College | GPA (benchmark) | NoTTT | LOS | LOS+ | Info | AA |
|---|---|---|---|---|---|---|
| Texas A & M | 3.078 | 3.073 | 3.078 | 3.078 | 3.061 | 3.072 |
| U. Texas | 2.876 | 2.858 | 2.875 | 2.874 | 2.856 | 2.858 |

students from affluent (<15% poverty) high schools only

| College | GPA (benchmark) | NoTTT | LOS | LOS+ | Info | AA |
|---|---|---|---|---|---|---|
| Texas A & M | 3.148 | 3.142 | 3.148 | 3.148 | 3.132 | 3.142 |
| U. Texas | 2.989 | 2.974 | 2.991 | 2.992 | 2.974 | 2.973 |

Population: students from poor (>60% poverty) high schools only

| College | GPA (benchmark) | NoTTT | LOS | LOS+ | Info | AA |
|---|---|---|---|---|---|---|
| Texas A & M | 2.866 | 2.829 | 2.874 | 2.873 | 2.843 | 2.828 |
| U. Texas | 2.626 | 2.553 | 2.618 | 2.606 | 2.59 | 2.546 |

students in top decile of HS class

| College | GPA (benchmark) | NoTTT | LOS | LOS+ | Info | AA |
|---|---|---|---|---|---|---|
| Texas A & M | 3.102 | 3.094 | 3.104 | 3.104 | 3.092 | 3.094 |
| U. Texas | 2.854 | 2.846 | 2.846 | 2.843 | 2.84 | 2.84 |

Population: underrepresented minority students outside of top decile of HS class

| College | GPA (benchmark) | NoTTT | LOS | LOS+ | Info | AA |
|---|---|---|---|---|---|---|
| Texas A & M | 2.851 | 2.859 | 2.854 | 2.853 | 2.826 | 2.856 |
| U. Texas | 2.571 | 2.589 | 2.557 | 2.54 | 2.52 | 2.58 |

underrepresented minority students in top decile of HS class

| College | GPA (benchmark) | NoTTT | LOS | LOS+ | Info | AA |
|---|---|---|---|---|---|---|
| Texas A & M | 2.993 | 2.98 | 3.007 | 3.013 | 2.985 | 2.979 |
| U. Texas | 2.75 | 2.722 | 2.741 | 2.735 | 2.738 | 2.718 |

Benchmark model-simulated outcomes vs. counterfactuals:

TTT: remove Texas Top Ten.

LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.

LOS+: expand LOS and automatic financial aid apps, all schools with >60% poverty.

Info: automatic financial aid application and perfect signal of $q$, all students.

AA: race-based points system at flagship universities.

Table 21: Per-capita financial aid amounts, benchmark and counterfactuals

| **College** | **avg. aid** | **(no TTT)** | **(LOS)** | **(LOS+)** | **(Info)** | **(AA)** |
|---|---|---|---|---|---|---|
| TX Public | 8341.826 | 8343.309 | 8344.416 | 8345.053 | 8313.355 | 8347.501 |
| Private Nonrelig. | 22429.479 | 22457.069 | 22442.959 | 22445.235 | 22519.586 | 22459.081 |
| Religious | 14766.001 | 14791.953 | 14763.623 | 14766.691 | 14863.74 | 14805.045 |
| Non-TX Public | 10766.889 | 10748.352 | 10770.288 | 10777.2 | 10786.218 | 10757.09 |
| Highly Selective | 28162.47 | 28160.024 | 28179.588 | 28187.677 | 28166.382 | 28161.275 |
| Baylor U. | 17329.87 | 17332.692 | 17336.024 | 17330.501 | 17319.186 | 17341.343 |
| U. Houston | 7604.748 | 7623.699 | 7611.932 | 7615.183 | 7573.803 | 7628.911 |
| U. North Texas | 8711.911 | 8710.908 | 8712.345 | 8713.943 | 8650.08 | 8714.605 |
| S.F. Austin State U. | 4612.895 | 4614.643 | 4612.438 | 4615.932 | 4598.378 | 4617.96 |
| SW Texas State U. | 6886.117 | 6906.127 | 6885.156 | 6891.906 | 6854.994 | 6922.7 |
| Texas A & M | 10976.281 | 10974.904 | 10978.665 | 10979.624 | 10929.192 | 10972.609 |
| U. Texas | 10785.325 | 10765.197 | 10850.123 | 10848.891 | 10735.545 | 10749.462 |
| Texas Tech U. | 7344.602 | 7344.985 | 7348.081 | 7352.813 | 7293.465 | 7355.098 |

Aid expenditure per matriculating student in 2002 dollars.

Benchmark model-simulated outcomes vs. counterfactuals:

TTT: remove Texas Top Ten.

LOS: expand Longhorn Scholarship to cover all schools with >60% poverty.

LOS+: LOS and automatic financial aid apps, all schools with >60% poverty.

Info: automatic financial aid application and perfect signal of $q$.

AA: race-based points system at flagship universities.

### A.2.4 Financial Aid

Table 22: SAT score quantiles, benchmark vs. no Texas Top Ten

| **college** | **10th** | **(-TTT)** | **25th** | **(-TTT)** | **75th** | **(-TTT)** | **90th** | **(-TTT)** |
|---|---|---|---|---|---|---|---|---|
| TX Public | 0.519 | 0.519 | 0.569 | 0.569 | 0.719 | 0.719 | 0.781 | 0.788 |
| Private Nonrelig. | 0.569 | 0.569 | 0.631 | 0.638 | 0.775 | 0.775 | 0.825 | 0.825 |
| Religious | 0.569 | 0.569 | 0.625 | 0.625 | 0.769 | 0.769 | 0.825 | 0.825 |
| Non-TX Public | 0.55 | 0.55 | 0.619 | 0.619 | 0.75 | 0.756 | 0.813 | 0.813 |
| Highly Selective | 0.625 | 0.625 | 0.694 | 0.694 | 0.85 | 0.85 | 0.913 | 0.913 |
| Baylor U. | 0.55 | 0.556 | 0.619 | 0.619 | 0.763 | 0.763 | 0.819 | 0.819 |
| U. Houston | 0.531 | 0.531 | 0.588 | 0.594 | 0.725 | 0.731 | 0.788 | 0.794 |
| U. North Texas | 0.544 | 0.544 | 0.619 | 0.619 | 0.756 | 0.756 | 0.813 | 0.819 |
| S.F. Austin State U. | 0.519 | 0.519 | 0.575 | 0.581 | 0.719 | 0.725 | 0.788 | 0.788 |
| SW Texas State U. | 0.544 | 0.544 | 0.6 | 0.606 | 0.738 | 0.738 | 0.8 | 0.8 |
| Texas A & M | 0.594 | 0.594 | 0.656 | 0.65 | 0.788 | 0.788 | 0.844 | 0.844 |
| U. Texas | 0.569 | 0.569 | 0.644 | 0.638 | 0.788 | 0.781 | 0.838 | 0.838 |
| Texas Tech U. | 0.544 | 0.544 | 0.619 | 0.619 | 0.75 | 0.75 | 0.806 | 0.806 |

### A.2.5 SAT scores

Table 23: SAT score quantiles, benchmark vs. no LOS

| **college** | **10th** | **(LOS)** | **25th** | **(LOS)** | **75th** | **(LOS)** | **90th** | **(LOS)** |
|---|---|---|---|---|---|---|---|---|
| TX Public | 0.519 | 0.519 | 0.569 | 0.569 | 0.719 | 0.719 | 0.781 | 0.781 |
| Private Nonrelig. | 0.569 | 0.569 | 0.631 | 0.631 | 0.775 | 0.775 | 0.825 | 0.825 |
| Religious | 0.569 | 0.569 | 0.625 | 0.625 | 0.769 | 0.769 | 0.825 | 0.825 |
| Non-TX Public | 0.55 | 0.55 | 0.619 | 0.619 | 0.75 | 0.75 | 0.813 | 0.813 |
| Highly Selective | 0.625 | 0.625 | 0.694 | 0.694 | 0.85 | 0.85 | 0.913 | 0.913 |
| Baylor U. | 0.55 | 0.55 | 0.619 | 0.619 | 0.763 | 0.763 | 0.819 | 0.819 |
| U. Houston | 0.531 | 0.531 | 0.588 | 0.588 | 0.725 | 0.725 | 0.788 | 0.788 |
| U. North Texas | 0.544 | 0.544 | 0.619 | 0.619 | 0.756 | 0.756 | 0.813 | 0.813 |
| S.F. Austin State U. | 0.519 | 0.519 | 0.575 | 0.575 | 0.719 | 0.725 | 0.788 | 0.788 |
| SW Texas State U. | 0.544 | 0.544 | 0.6 | 0.6 | 0.738 | 0.738 | 0.8 | 0.8 |
| Texas A & M | 0.594 | 0.594 | 0.656 | 0.656 | 0.788 | 0.788 | 0.844 | 0.844 |
| U. Texas | 0.569 | 0.569 | 0.644 | 0.644 | 0.788 | 0.788 | 0.838 | 0.838 |
| Texas Tech U. | 0.544 | 0.544 | 0.619 | 0.619 | 0.75 | 0.75 | 0.806 | 0.806 |

### A.2.6 Short-run effects

Table 24: Effects of policy experiments, cutoffs fixed

Matriculation per 100 students holding admissions rules fixed

| **college** | **benchmark** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|---|
| TX Public | 13.182 | -0.6% | -0.2% | -0.8% | -0.1% | -5.2% | -3.1% |
| Private Nonrelig. | 1.839 | -0.4% | +0.0% | -0.3% | +0.2% | +11.5% | +14.2% |
| Religious | 6.806 | -0.2% | +0.5% | -0.2% | +0.9% | +6.2% | +11.0% |
| Non-TX Public | 4.826 | -0.2% | +0.3% | -0.3% | +0.4% | +2.4% | +5.3% |
| Highly Selective | 0.507 | -0.6% | -0.5% | -0.7% | -0.5% | +60.7% | +61.1% |
| Baylor U. | 1.051 | -0.5% | -0.0% | -0.2% | -0.1% | +7.1% | +0.2% |
| U. Houston | 1.693 | -0.7% | -0.0% | -1.0% | +0.0% | -9.1% | +0.1% |
| U. North Texas | 1.499 | -0.2% | +0.2% | -0.4% | +0.1% | -6.3% | -4.0% |
| S.F. Austin State U. | 1.41 | -0.2% | +0.1% | -0.3% | +0.0% | -10.4% | -9.0% |
| SW Texas State U. | 2.171 | -0.5% | +0.5% | -0.9% | +0.4% | -6.4% | -1.7% |
| Texas A & M | 6.512 | -0.6% | -0.0% | -0.7% | +0.0% | +7.4% | +0.0% |
| U. Texas | 8.418 | +3.0% | -0.0% | +4.0% | -0.0% | +9.6% | +0.0% |
| Texas Tech U. | 2.851 | -0.3% | +0.1% | -0.6% | +0.0% | -5.6% | -0.0% |
| Total | 52.763 | +0.1% | +0.1% | +0.2% | +0.1% | +2.0% | +1.8% |

Population: all matriculating students

Percentage change in matricualtion relative to benchmark:

(1): Expand Longhorn Opportunity Scholarship, cutoffs fixed.

(2): LOS, cutoffs adjust.

(3): Expand LOS and complete financial aid applications, cutoffs fixed.

(4): Expand LOS and complete financial aid applications, cutoffs adjust.

(5): automatic financial aid application and perfect signal of $q$, cutoffs fixed.

(6): automatic financial aid application and perfect signal of $q$, cutoffs adjust.

Table 25: Effects of policy experiments on Black and Hispanic students, cutoffs fixed

Matriculation per 100 students holding admissions rules fixed

| **college** | **benchmark** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|---|
| TX Public | 16.171 | -1.6% | -1.0% | -2.0% | -1.2% | -6.3% | -4.7% |
| Private Nonrelig. | 1.073 | -1.9% | -1.3% | -1.5% | -0.7% | +14.5% | +17.7% |
| Religious | 4.901 | -0.9% | +0.3% | -0.6% | +1.0% | +9.7% | +15.2% |
| Non-TX Public | 3.992 | -0.8% | -0.3% | -0.8% | -0.1% | +8.5% | +10.5% |
| Highly Selective | 0.318 | -3.0% | -2.8% | -3.0% | -2.7% | +87.3% | +87.9% |
| Baylor U. | 0.783 | -1.6% | -0.9% | -0.7% | -0.4% | +8.5% | -0.1% |
| U. Houston | 1.732 | -1.9% | -1.1% | -2.8% | -1.5% | -9.6% | +0.2% |
| U. North Texas | 1.036 | -0.8% | -0.2% | -1.5% | -0.8% | -8.4% | -6.2% |
| S.F. Austin State U. | 1.246 | -0.5% | -0.2% | -1.1% | -0.7% | -13.4% | -12.6% |
| SW Texas State U. | 2.24 | -1.4% | -0.2% | -2.6% | -1.0% | -6.1% | -1.7% |
| Texas A & M | 2.01 | -4.3% | -3.3% | -4.9% | -3.6% | +10.3% | +3.8% |
| U. Texas | 10.716 | +6.8% | +4.1% | +9.1% | +5.5% | +14.4% | +5.3% |
| Texas Tech U. | 2.073 | -1.3% | -0.8% | -2.2% | -1.4% | -5.4% | +1.1% |
| Total | 48.289 | +0.3% | +0.3% | +0.6% | +0.5% | +2.9% | +2.7% |

Population: underrepresented minority students

Percentage change in matricualtion relative to benchmark:

(1): Expand Longhorn Opportunity Scholarship, cutoffs fixed.

(2): LOS, cutoffs adjust.

(3): Expand LOS and complete financial aid applications, cutoffs fixed.

(4): Expand LOS and complete financial aid applications, cutoffs adjust.

(5): automatic financial aid application and perfect signal of $q$, cutoffs fixed.

(6): automatic financial aid application and perfect signal of $q$, cutoffs adjust.

Table 26: Effects of policy experiments on students from poor high schools, cutoffs fixed

| Matriculation per 100 students holding admissions rules fixed | | | | | | | |
|---|---|---|---|---|---|---|---|
| **college** | **benchmark** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| TX Public | 16.368 | -3.4% | -2.9% | -4.1% | -3.4% | -8.0% | -6.8% |
| Private Nonrelig. | 0.901 | -5.3% | -4.7% | -4.3% | -3.5% | +18.4% | +22.1% |
| Religious | 2.999 | -3.5% | -2.4% | -2.3% | -0.7% | +11.0% | +16.1% |
| Non-TX Public | 4.231 | -1.7% | -1.4% | -2.0% | -1.5% | +15.1% | +16.3% |
| Highly Selective | 0.369 | -6.0% | -5.8% | -6.2% | -5.8% | +111.0% | +111.4% |
| Baylor U. | 0.655 | -5.7% | -4.9% | -2.7% | -2.2% | +6.4% | -1.2% |
| U. Houston | 1.599 | -4.9% | -4.2% | -7.0% | -5.9% | -11.3% | -3.3% |
| U. North Texas | 0.776 | -2.7% | -2.1% | -4.9% | -4.1% | -12.7% | -10.4% |
| S.F. Austin State U. | 0.903 | -1.7% | -1.4% | -3.5% | -3.1% | -19.2% | -18.4% |
| SW Texas State U. | 1.697 | -4.1% | -3.1% | -7.5% | -6.2% | -8.9% | -5.6% |
| Texas A & M | 2.374 | -11.9% | -11.2% | -12.6% | -11.7% | +10.3% | +6.9% |
| U. Texas | 11.817 | +14.6% | +12.7% | +19.1% | +16.5% | +16.0% | +10.2% |
| Texas Tech U. | 1.467 | -4.4% | -3.8% | -7.4% | -6.6% | -9.1% | -3.2% |
| Total | 46.157 | +0.8% | +0.7% | +1.4% | +1.3% | +3.6% | +3.5% |

Population: Population: students from poor (>60% poverty) high schools only

Percentage change in matricualtion relative to benchmark:

(1): Expand Longhorn Opportunity Scholarship, cutoffs fixed.

(2): LOS, cutoffs adjust.

(3): Expand LOS and complete financial aid applications, cutoffs fixed.

(4): Expand LOS and complete financial aid applications, cutoffs adjust.

(5): automatic financial aid application and perfect signal of $q$, cutoffs fixed.

(6): automatic financial aid application and perfect signal of $q$, cutoffs adjust.

# B Data Appendix

In order to construct the final dataset, I constructed aggregate colleges. I keep each student in the THEOP survey who took a college entrance exam.

## B.1 Aggregate colleges

In this section I provide lists of the colleges and universities that make up each aggregate college. The data use agreement requires me to aggregate each college that has fewer than ten applicants in the data.

| Institution | Sum | |
|---|---|---|
| | apply | admit |
| ANGELO STATE UNIVERSITY | 148 | 119 |
| Institutions with ten or fewer apps | 10 | 9 |
| LAMAR UNIVERSITY-BEAUMONT | 80 | 61 |
| MIDWESTERN STATE UNIVERSITY | 30 | 24 |
| PRAIRIE VIEW A & M UNIVERSITY | 95 | 49 |
| SAM HOUSTON STATE UNIVERSITY | 187 | 143 |
| SUL ROSS STATE UNIVERSITY | 27 | 15 |
| TARLETON STATE UNIVERSITY | 71 | 49 |
| TEXAS A & M INTERNATIONAL UNIVERSITY | 56 | 37 |
| TEXAS A & M UNIVERSITY-CORPUS CHRISTI | 55 | 43 |
| TEXAS A & M UNIVERSITY-GALVESTON | 26 | 21 |
| TEXAS A & M UNIVERSITY-KINGSVILLE | 77 | 61 |
| TEXAS A&M UNIVERSITY-COMMERCE | 47 | 30 |
| TEXAS SOUTHERN UNIVERSITY | 125 | 79 |
| TEXAS WOMAN'S UNIVERSITY | 38 | 27 |
| THE UNIVERSITY OF TEXAS AT ARLINGTON | 170 | 120 |
| THE UNIVERSITY OF TEXAS AT BROWNSVILLE | 62 | 40 |
| THE UNIVERSITY OF TEXAS AT DALLAS | 86 | 61 |
| THE UNIVERSITY OF TEXAS AT EL PASO | 275 | 183 |
| THE UNIVERSITY OF TEXAS AT SAN ANTONIO | 166 | 121 |
| THE UNIVERSITY OF TEXAS AT TYLER | 27 | 17 |
| THE UNIVERSITY OF TEXAS OF THE PERMIAN BASIN | 30 | 22 |
| THE UNIVERSITY OF TEXAS-PAN AMERICAN | 194 | 165 |
| UNIVERSITY OF HOUSTON-DOWNTOWN | 37 | 18 |
| WEST TEXAS A & M UNIVERSITY | 42 | 37 |
| Total | 2,161 | 1,551 |

Colleges comprising OTHER TX PUBLIC 4-YEAR

| Institution | Sum | |
|---|---|---|
| | apply | admit |
| EMBRY-RIDDLE AERONAUTICAL UNIVERSITY | 12 | 10 |
| Institutions with ten or fewer apps | 235 | 190 |
| NEW YORK UNIVERSITY | 29 | 21 |
| NORTHWOOD UNIVERSITY | 21 | 17 |
| TULANE UNIVERSITY OF LOUISIANA | 17 | 16 |
| UNIVERSITY OF SOUTHERN CALIFORNIA | 23 | 22 |
| VANDERBILT UNIVERSITY | 12 | 11 |
| Total | 349 | 287 |

Colleges comprising PRIVATE NONRELIGIOUS

| Institution | Sum | |
|---|---|---|
| | apply | admit |
| ABILENE CHRISTIAN UNIVERSITY | 60 | 53 |
| AUSTIN COLLEGE | 16 | 15 |
| BRIGHAM YOUNG UNIVERSITY | 28 | 24 |
| DILLARD UNIVERSITY | 18 | 14 |
| EAST TEXAS BAPTIST UNIVERSITY | 29 | 21 |
| HARDIN-SIMMONS UNIVERSITY | 21 | 19 |
| HOUSTON BAPTIST UNIVERSITY | 41 | 29 |
| HOWARD PAYNE UNIVERSITY | 27 | 19 |
| Institutions with 15 or fewer apps | 383 | 310 |
| LUBBOCK CHRISTIAN UNIVERSITY | 17 | 14 |
| MCMURRY UNIVERSITY | 19 | 17 |
| OUR LADY OF THE LAKE UNIVERSITY-SAN ANTONIO | 53 | 42 |
| SAINT EDWARDS UNIVERSITY | 35 | 29 |
| SOUTHERN METHODIST UNIVERSITY | 58 | 50 |
| SOUTHWESTERN UNIVERSITY | 33 | 32 |
| ST MARYS UNIVERSITY | 59 | 47 |
| TEXAS CHRISTIAN UNIVERSITY | 126 | 106 |
| TRINITY UNIVERSITY | 40 | 39 |
| UNIVERSITY OF MARY HARDIN BAYLOR | 19 | 13 |
| UNIVERSITY OF SAINT THOMAS | 28 | 23 |
| UNIVERSITY OF THE INCARNATE WORD | 25 | 23 |
| XAVIER UNIVERSITY OF LOUISIANA | 20 | 16 |
| Total | 1,155 | 955 |

Colleges comprising RELIGIOUS

| Institution | Sum | |
|---|---|---|
| | apply | admit |
| ARIZONA STATE UNIVERSITY-MAIN CAMPUS | 30 | 27 |
| COLORADO STATE UNIVERSITY | 14 | 12 |
| FLORIDA AGRICULTURAL AND MECHANICAL UNIVERSITY | 11 | 10 |
| FLORIDA STATE UNIVERSITY | 14 | 12 |
| GRAMBLING STATE UNIVERSITY | 11 | 6 |
| Institutions with ten or fewer apps | 421 | 346 |
| KANSAS STATE UNIVERSITY OF AGRICULTURE AND APP SCI | 11 | 9 |
| LOUISIANA ST UNIV & AGRL & MECH & HEBERT LAWS CTR | 64 | 51 |
| NEW MEXICO STATE UNIVERSITY-MAIN CAMPUS | 102 | 76 |
| OKLAHOMA STATE UNIVERSITY-MAIN CAMPUS | 45 | 42 |
| PURDUE UNIVERSITY-MAIN CAMPUS | 12 | 12 |
| SOUTHERN UNIVERSITY-NEW ORLEANS | 10 | 3 |
| THE UNIVERSITY OF ALABAMA | 13 | 12 |
| UNITED STATES AIR FORCE ACADEMY | 13 | 12 |
| UNITED STATES NAVAL ACADEMY | 11 | 8 |
| UNIVERSITY OF CALIFORNIA-BERKELEY | 16 | 14 |
| UNIVERSITY OF COLORADO AT BOULDER | 15 | 15 |
| UNIVERSITY OF GEORGIA | 12 | 10 |
| UNIVERSITY OF MISSISSIPPI MAIN CAMPUS | 11 | 10 |
| UNIVERSITY OF NEW MEXICO-MAIN CAMPUS | 17 | 9 |
| UNIVERSITY OF OKLAHOMA NORMAN CAMPUS | 36 | 32 |
| Total | 889 | 728 |

Colleges comprising NON-TX PUBLIC

| Institution | Sum | |
|---|---|---|
| | apply | admit |
| HARVARD UNIVERSITY | 16 | 12 |
| Institutions with ten or fewer apps | 55 | 41 |
| MASSACHUSETTS INSTITUTE OF TECHNOLOGY | 12 | 11 |
| NORTHWESTERN UNIVERSITY | 13 | 12 |
| PRINCETON UNIVERSITY | 14 | 10 |
| RICE UNIVERSITY | 52 | 44 |
| STANFORD UNIVERSITY | 19 | 17 |
| WASHINGTON UNIVERSITY | 19 | 17 |
| YALE UNIVERSITY | 11 | 7 |
| Total | 211 | 171 |

Colleges comprising SELECTIVE PRIVATE

## B.2 Calculating EFC

**Matching THEOP and CPS datasets** In order to draw incomes from the CPS, I recode parents' education in the THEOP survey to match the CPS dataset. I then draw incomes for each student in THEOP from the distribution of income given parents' occupation and the education of the most-educated parent.

1. THEOP senior survey

   - Mother's education: q71
   - Father's education: q67
   - ```
     label list q71
     q71:
     1 No Schooling
     2 Elementary School
     3 Some High School
     4 High School Graduate
     5 Some College
     6 Two-Year College
     7 Four-Year College
     8 Master's Degree
     9 Professional Degree
     ```

2. 2002 March CPS

   - Education of household head
   - ```
     label list EDUC_HEAD
     EDUC_HEAD:
     0 NIU or no schooling
     1 niu
     2 None or preschool
     10 Grades 1, 2, 3, or 4
     11 Grade 1
     12 Grade 2
     13 Grade 3
     14 Grade 4
     20 Grades 5 or 6
     21 Grade 5
     22 Grade 6
     ```

```
30 Grades 7 or 8
31 Grade 7
32 Grade 8
40 Grade 9
50 Grade 10
60 Grade 11
70 Grade 12
71 12th grade, no diploma
72 12th grade, diploma unclear
73 High school diploma or equivalent
80 1 year of college
81 Some college but no degree
90 2 years of college
91 Associate's degree, occupational/vocational program
92 Associate's degree, academic program
100 3 years of college
110 4 years of college
111 Bachelor's degree
120 5+ years of college
121 5 years of college
122 6+ years of college
123 Master's degree
124 Professional school degree
125 Doctorate degree
999 Missing/Unknown
```

3. Matching procedure:

   - EDUC_HEAD $\in \{0, 1\}$: $Ed = 1$
   - EDUC_HEAD $\in \{10, ..., 32\}$: $Ed = 2$
   - EDUC_HEAD $\in \{40, ..., 71\} \mapsto Ed = 3$.
     - Note that in the 2002 March CPS, TX subsample there are no household heads with unclear graduation status EDUC_HEAD=72.

     EDUC_HEAD $\in \{73\} \mapsto Ed = 4$.
   - EDUC_HEAD $\in \{81\} \mapsto Ed = 5$.
   - EDUC_HEAD $\in \{91, 92\} \mapsto Ed = 6$.

- EDUC_HEAD $\in \{111\} \mapsto Ed = 7$.
- EDUC_HEAD $\in \{123\} \mapsto Ed = 8$.
- EDUC_HEAD $\in \{124\} \mapsto Ed = 9$.

4. Administrative data: UT Austin codes parents' education similarly to the THEOP survey.

# C Estimation Appendix

## C.1 Calculating the objective

Consider the optimization problem

$$\max_{\theta} \frac{1}{N} \sum_{i=1}^{N} \log lik_i(\theta) + [g_{aid}(\theta), g_{outcome}(\theta)] * W_{aid,outcome} * [g_{aid}(\theta), g_{outcome}(\theta)]^T , \tag{1}$$

where

$$g_{aid}(\theta) = \frac{1}{N} \sum_i g_{aid,i}(\theta)$$

and

$$g_{outcome}(\theta) = \frac{1}{N} \sum_i g_{outcome,i}(\theta).$$

Suppose that the objective in 1 is maximized at $\theta_0$. Then the FOC of objective 1 is given by

$$\frac{1}{N} \sum_i \nabla_\theta \log lik_i(\theta_0) + 2 * [g_{aid}(\theta_0), g_{outcome}(\theta_0)] * W_{aid,outcome} * [\nabla_\theta g_{aid}(\theta_0), \nabla_\theta g_{outcome}(\theta_0)]^T = 0. \tag{FOC1}$$

Define the matrix $W$ by

$$\begin{aligned} W &= \begin{pmatrix} \frac{1}{2} \left[\frac{1}{N} \sum_i \left((\nabla_\theta \log lik_i(\theta_0))^T * (\nabla_\theta \log lik_i(\theta_0))\right)\right]^{-1} & 0 \\ 0 & W_{aid,outcome} \end{pmatrix} \\ &= \begin{pmatrix} \frac{1}{2} \cdot \mathcal{I}_{\theta_0}^{-1} & 0 \\ 0 & W_{aid,outcome} \end{pmatrix} \\ &= \begin{pmatrix} -\frac{1}{2} \left[\frac{1}{N} \sum_i \frac{\partial^2}{\partial\theta\partial\theta'} loglik_i(\theta_0)\right]^{-1} & 0 \\ 0 & W_{aid,outcome} \end{pmatrix}, \end{aligned}$$

where $\mathcal{I}_{\theta_0}$ is the Fisher information matrix evaluated at $\theta_0$. Define $loglik(\theta) = \sum_i \log lik_i(\theta)$. Then $FOC1$ is also the first-order condition of the following GMM objective function:

$$\min_\theta [\frac{1}{N}\nabla_\theta \log lik(\theta), g_{aid}(\theta), g_{outcome}(\theta)] * W * [\frac{1}{N}\nabla_\theta \log lik(\theta), g_{aid}(\theta), g_{outcome}(\theta)]^T, \qquad (2)$$

Hence the solution to 1 will also satisfy 2. The advantage of 1 for my purposes is that it is possible to use gradient-based methods without needing to calculate second derivatives of $\log lik(\theta)$. Therefore, 1 is a relatively computationally inexpensive way to optimize the GMM objective 2.

The weight matrix is not known in advance; however it is a fixed function of the parameters $\theta_0$ that optimize the penalized-likelihood objective.

### C.2 Standard errors

Define

$$G = \frac{1}{N}\sum_i \begin{pmatrix} \mathcal{I}^{(i)}_{\theta_0} \\ \nabla_\theta g^{(i)}_{aid}(\theta_0) \\ \nabla_\theta g^{(i)}_{outcome}(\theta_0) \end{pmatrix}$$

and

$$\Omega = \frac{1}{N}\sum_i [\nabla_\theta \log lik_i(\theta), g_{aid}(\theta), g_{outcome}(\theta)][\nabla_\theta \log lik_i(\theta), g_{aid}(\theta), g_{outcome}(\theta)]^T$$

Then

$$WG = \begin{pmatrix} \frac{1}{2} Id \\ W_{aid,outc} * \nabla_\theta g_{aid,outcome}(\theta_0) \end{pmatrix}$$

And

$$\sqrt{n}\,(\theta_0 - \theta_{true}) \sim \mathcal{N}(0, (GWG)^{-1}(WG)'\Omega(WG)(GWG)^{-1}).$$

This variance-covariance matrix ignores the fact that the "observed" outcome distribution is estimated using administrative data. The administrative datasets are much larger than the survey, containing the universe of students matriculating at each of the flagship universities. One can extend the variance-covariance formula to account for the error from this second dataset, however, using the methods of Ichimura and Martinez-Sanchis (2008).

## D Computational Details

### D.1 Computing the value of application sets via the inclusion-exclusion principle

Computing the value of an application set $A \subset \mathcal{A}$ requires integrating over all possible outcomes $B \subseteq A$, as the value depends on the probabilities and utilities of each admissions set $B$ that is possible given application to $A$.

In principle, and dropping $i$ subscripts, computing $V(A)$ for all $A$ requires computing $|\mathcal{A}|$ utility terms $\{U(B)\}_{B\in\mathcal{A}}$, and $\mathcal{O}(|\mathcal{A}|^2)$ multivariate normal CDF evaluations $\{P(B|A)\}_{B\subseteq A, A\in\mathcal{A}}$. With over 800 portfolios, it would be expensive to compute all of these probabilities directly for each draw for each individual at each trial parameter value. In what follows, I show that one needs only evaluate $|\mathcal{A}|$ multivariate normal CDFs and perform some matrix multiplication.

Define

$$P_B = \int_q \prod_{j\in B} \Phi(q_i + z'_{ij}\gamma_j - \underline{\pi}_j) dF(q|s)$$

as the probability of admission to every school in $B$ given application set $B$ and a realization of the applicant's information $q^s$. Let $X_B$ be the event that $i$ is admitted to all schools in $B$. Let $X_{A;B}$ denote the event that $i$ is admitted to all schools in $B$ and rejected from all schools in $A\backslash B$, and $P_{A;B}$ the probability of this event. If $B \not\subseteq A$ then let $X_{A;B}$ be empty and $P_{A;B} = 0$. Let $\mathbb{P}$ be the probability measure associated with $i$'s characteristics and signal $s$, so that $P_{A;B} = \mathbb{P}(X_{A;B})$.

**Proposition.** *(inclusion-exclusion formula) Given the above definitions, the following result holds:*

$$P_{A;B} = \sum_{B':B\subseteq B'\subseteq A} P_{B'} \cdot (-1)^{|A|-|B'|} \text{ for all sets } A, B \in \mathcal{A} \text{ with } B \subseteq A.$$

*Proof.*

$$\begin{aligned}
P_{A;B} &= \mathbb{P}\left(X_B \backslash \left(\cup_{j\in A\backslash B}\left(X_{B\cup\{j\}}\right)\right)\right) \\
&= \mathbb{P}(X_B) - \mathbb{P}\left(\cup_{j\in A\backslash B}\left(X_{B\cup\{j\}}\right)\right) \\
&= P_B - \sum_{j\in B\backslash A} \mathbb{P}(X_{B\cup\{j\}}) + \sum_{j_1,j_2\in B\backslash A} \mathbb{P}(X_{B\cup\{j_1\}} \cap X_{B\cup\{j_2\}}) - \ldots + \mathbb{P}(\cap_{j\in A\backslash B} X_{B\cup\{j\}}) \\
&= P_B - \sum_{B':B\subseteq B'\subseteq A} P_{B'} \cdot (-1)^{|A|-|B'|+1}.
\end{aligned}$$

The second line follows because $X_{B\cup\{j\}} \subseteq X_B$ and the third line is the standard inclusion-exclusion formula. $\square$

List all the portfolios $A_0, A_1, \ldots, A_{|\mathcal{A}|}$ in some order, and define the matrix $T$ by

$$T_{kl} = 1_{A_k\subseteq A_l} \prod_{j\in A_k} \binom{A_{lj}}{A_{kj}},$$

where $A_{lj}$ is the number of applications to $j$ in portfolio $A_l$. Similarly, define the matrix $S$ by

$$S_{kl} = (-1)^{|A_l|-|A_k|}.$$

It follows that $P_{A_k;A_l} = \sum_{A_k\subseteq A_r\subseteq A_l} T_{kr} P_r$

**Corollary.** *Let $P$ be the diagonal matrix with kth entry $P_{A_k}$. The vector $V = \{V_A\}_{A\in\mathcal{A}}$ is given by*

$$V = T * Diag(P) * S * U.$$

Computing only the admissions probabilities $P_B$ rather than all $P_{A;B}$ vastly simplifies computation. As an example, if $\mathcal{A} = \{\{1\},\{2\},\{1,2\}\}$ we have the following calculation:

$$\begin{pmatrix} V_{\{1\}} \\ V_{\{2\}} \\ V_{\{1,2\}} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix} * \begin{pmatrix} P_{\{1\}} & 0 & 0 \\ 0 & P_{\{2\}} & 0 \\ 0 & 0 & P_{\{1,2\}} \end{pmatrix} * \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ -1 & -1 & 1 \end{pmatrix} * \begin{pmatrix} U_{\{1\}} \\ U_{\{2\}} \\ U_{\{1,2\}} \end{pmatrix}.$$

By using the inclusion-exclusion principle, we avoid having to compute $P_{\{1,2\};\{1\}}$ or $P_{\{1,2\};\{2\}}$ by integrating over multivariate normal densities.

## D.2 Discretization

To make computation possible, we use discrete approximations for $q$ and $s$. We discretize the signal distribution,

$$s \in S$$

where $S$ is a discrete grid with $nS = 6$ points of support. Moreover, we fix

$$q \in Q = \{-10, ..., 10\}$$

with $nQ = 128$ points of support. Hence

$$\hat{\ell}_i(\theta) = \sum_{s\in S} \Phi(s)\hat{\ell}_i(\theta, s).$$

We draw $M$ simulation draws $\omega_{i,m}$ for each individual $i$, which contain random coefficients, income $y_{im}$ and EFC $efc_{im}$. Our objective then becomes

$$\hat{l}_i(\theta) = \log \sum_{q^s\in Q^S} \sum_{m=1}^{M} \left(\hat{\ell}_i^{Ap}(\theta, \omega_i, q^s)\hat{\ell}_i^{Ad|Ap}(\theta, q^s)\ell_i^{F|Ap,Ad}(\theta, m)\ell_i^{C|Ad}(\theta, m)\ell_i^{Outcome|C}(\theta, m)\right)\Phi(q^s)$$

## D.3 Simulation of financial-aid awareness

We observe financial-aid application or failure to apply for aid only at schools to which $i$ submits an application. In order to compute the likelihood that $i$ chooses his observed application portfolio, however, we need to calculate the value of all application portfolios he could have chosen. Therefore calculating the likelihood requires integrating over financial-aid awareness at colleges to which $i$ did not apply.

In order to obtain an estimator that is smooth in $\theta$, we draw financial-aid awareness for student $i$ using an importance sampling procedure. Before searching over parameter values, we draw a vector of outcomes $aware_{ijm} \in \{0,1\}$ once for each simulation draw, for all colleges $j$ to which $i$ did not submit an application. We estimate weights on each vector for each parameter vector $\theta$. These weights are then smooth functions of $\theta$.

Initially, for each individual $i$ and simulation draw $m$, we draw a vector of financial-aid awareness outcomes for the schools to which $i$ did not apply, using starting values for the financial-aid parameters:

$$Aware_{ijm} = 1(h_{ijm} > Pr_{0ij}), \text{ for } j \notin A_i$$
$$Aware^{obs}_{ijm} \text{ for } j \in A_i,$$

where $h_{ijm}$ is an independent uniform random draw, and

$$Pr_{0ijm} = Pr_0(\text{i aware of aid at j}|y_m) = (X^{aware}_{im})' \, \beta^{aware}_0$$

where $X^{aware}_{im} = (d^f_j, X^S, y_i)$ is the vector of observables that shift awareness of financial aid.

Let $P^{aware}_{0i}$ denote the probability of the vector of financial aid awareness draws under $\{Pr_{0ijm}\}_{j\in\mathcal{J}}$:

$$P^{aware}_{0im} = \prod_{j\in\mathcal{J}\backslash A_i} \left[ (Pr_{0ijm})^{aware_{ijm}} \, (1 - Pr_{0ijm})^{1-aware_{ijm}} \right].$$

Now, for each trial parameter value $\theta$ we calculate the probability of financial-aid awareness,

$$P^{aware}_{im}(\theta) = \prod_{j\in\mathcal{J}} \left[ (Pr_{ij}(\theta))^{aware_{ijm}} \, (1 - Pr_{0ij}(\theta))^{1-aware_{ijm}} \right].$$

Note that the probability of the financial aid awareness draw under parameters $\theta$ includes the probability of $aware_{ijm}$ for $j \in A_i$.

The likelihood of financial aid awareness is then approximated by

$$\hat{\ell}^{F^{aware}|A,B}_i(\theta, m) \approx \frac{p^{aware}_{im}(\theta)}{p^{aware}_{0im}},$$

and the likelihood of financial aid awareness and outcomes is

$$\frac{p^{aware}_{im}(\theta)}{p^{aware}_{0im}} \cdot \prod_{j\in B^{finaid}_i} Pr(B^{finaid}_{ij};\theta) \prod_{j\in B_i\backslash B^{finaid}_i} \left(1 - Pr(B^{finaid}_{ij};\theta)\right)$$

In estimation, I obtain a starting guess for financial-aid awareness parameters via probits on observed data and draw financial-aid awareness according to these parameters. I then run the estimation procedure and use the estimated values of $\beta^{aware}$ as new initial parameters for constructing $p^{aware}_{0im}$.

## D.4 Smoothing application choice probabilities

We use logit smoothing to approximate $\arg\max_A V_i(A)$ in simulating choice probabilities. We do so for computational reasons: this smoothing allows the use of derivative-based optimization methods. Given a draw $\omega_i^m$ of unobservables and values $V_{i,m}(A)$ for all allowed application sets $A$, the probability that $i$ applies to $A$ with draws $\omega_i^m$ is

$$Pr(Apply_i = A|\omega_i^m) = \frac{\exp(\Lambda V_{i,m}(A))}{\sum_{A'} \exp(\Lambda V_{i,m}(A'))}.$$

In the empirical application we set $\Lambda$ to a large value ($\Lambda = 10$ implies a variance that is very small relative to the variance of the preference errors $\epsilon_{ij}^A$ which are normalized to 1; as $\lambda^A \to \infty$ the logit-smoothed approximation approaches probability 1 on the application set $A$ that maximizes $V_{i,m}(A)$ ).

While I interpret $\Lambda$ as a smoothing parameter, the procedure is also consistent with the existence of additive portfolio-level shocks $\tilde{\epsilon}_{iA}$ with independent extreme-value distributions. Under this interpretation, individuals choose the set $A$ that maximizes $V_i(A) + \tilde{\epsilon}_{iA}$. The value of $\Lambda$ that I choose makes these shocks small relative to the college-level shocks $\epsilon_{ij}^A$.

## D.5 Implementation

The estimation procedure and counterfactual simulations are coded in the Julia programming language.[73] I use the IPopt interior-point solver to obtain parameter estimates. I provide analytic first derivatives to the solver.

# E Additional Results

## E.1 Existence of Equilibrium

Suppose there is a continuum of students with type $\omega \in \Omega \subseteq R^N$ and measure $F(\omega)$ with density $f$ with respect to Lebesgue measure. (In the model, an individual is defined by his observables $z_i$, his preference terms and random coefficients, and his caliber and signal $(q, s)$.) Each cutoff vector $\underline{\pi}$ induces a joint distribution of application portfolios $A \in \mathcal{A}$ and types $\omega$. In particular, for almost all $\omega$ there is a unique portfolio $A(\underline{\pi}, \omega) \in \mathcal{A}$ that is optimal.

To prove existence, we need to show that there is a cutoff $\underline{\pi}$ such that $A_i$ is a best response to $\underline{\pi}$ for all $i$, and$\underline{\pi}$ maximizes quality subject to capacity constraints given applications $A(\underline{\pi}, \omega)_{\omega\in\Omega}$.[74][75]

[73] http://www.julialang.org

[74] In this proof I ignore financial aid. A similar argument would apply with financial aid present.

[75] The "partial uniqueness" argument in the paper shows that, holding applications fixed, there is a unique market-clearing $\underline{\pi}$.

Let $\tilde{A}(\underline{\pi})$ denote the joint distribution of $(A \in \mathcal{A}, \omega \in \Omega)$ induced by students' best responses to $\underline{\pi}$. Because $\omega$ admits a density and the indirect utility $U(\mathcal{A}; \underline{\pi})$ is continuous in $\underline{\pi}$, the share of applicants to each portfolio $A \in \mathcal{A}$ changes continuously in $\underline{\pi}$. Moreover, the share of students with admission set $B$ given application set $A$ changes continuously in $\underline{\pi}$, for all $A, B \in \mathcal{A}$. Conditional on admission set $B$, application set $A$, and $j$'s information about $\omega$, the probability from of attending $j \in B$ is continuous in $\underline{\pi}$. As a result the best-response cutoff function $h(\underline{\pi}) \equiv \underline{\pi}^*(\tilde{A}(\underline{\pi})) : R^J \to R^J$ is continuous in $\underline{\pi}$.

We now show that $h(\cdot)$ is bounded, i.e. we can restrict attention to the map $h(\cdot)$ on a box in $R^J$. For each $j$, taking the distribution of applications $A$ that has every student apply to $\{j\}$ with probability 1 gives an upper bound $\underline{\pi}_j^{high} \leq \underline{\pi}^*(E(A))$. There exists a cutoff $\underline{\pi}_j^{low}$ such that $j$ strictly prefers empty seats to students with caliber less than $\underline{\pi}_j^{low}$.

From Brouwer's fixed point theorem, $h$ has a fixed point $\underline{\pi}^*$. $\underline{\pi}^*$ is a set of market-clearing cutoffs given applications $\tilde{A}(\underline{\pi})$, and applications $\tilde{A}$ are optimal given $\underline{\pi}^*$.

## E.2 Model Fit

### E.2.1 Model fit: shares, SATs, and aid

In this section, I compare model-predicted numbers of applications, offers of admissions, and enrollment at each college to the numbers obtained in the raw survey. The total population of public high school students is normalized to 100, so that the enrollment columns represent the percentage of public high school seniors who have taken the SAT or ACT that enroll at each of the listed colleges. Using the survey's population weights, we compare the weighted actual number of applications, offers and matriculations in the survey to the weighted values obtained from the model at the estimated parameters.

The model captures the patterns of applications found in the data. In particular, regional Texas public four-year colleges receive the most applications, followed by religious institutions and then state flagship schools. Relative to the survey data we match applications, offers and enrollment closely at the state flagship universities. I underestimate enrollment slightly at the regional state universities. While the model matches the number of applications to Texas Tech, and overpredicts the number of offers, it underestimates enrollment at Texas Tech.

I also provide the same table considering only underrepresented minority (Black and/or Hispanic) students. I did not use race anywhere in the model of preferences or admissions chances; there is nothing in the estimation strategy that forces the number of applications here to match the survey. Nonetheless I closely match the actual data. In particular, in the data, 10 out of every 100 black and Hispanic exam-taking seniors matriculates at UT Austin. In the model the figure is 10.7 out of 100. I match the key pattern that while minority students are about as likely as the population average to attend the University of Texas at Austin, they are much more likely than

| College | apps (data) | (model) | offers (data) | (model) | enroll. (data) | (model) |
|---|---|---|---|---|---|---|
| TX Public | 29.064 | 30.556 | 24.252 | 28.486 | 16.787 | 13.182 |
| Private Nonrelig. | 6.959 | 6.627 | 5.404 | 5.659 | 2.34 | 1.839 |
| Religious | 21.831 | 17.393 | 18.504 | 16.008 | 9.884 | 6.806 |
| Non-TX Public | 15.818 | 13.097 | 12.5 | 12.017 | 4.049 | 4.826 |
| Highly Selective | 4.128 | 3.899 | 1.211 | 1.194 | 0.326 | 0.507 |
| Baylor U. | 4.707 | 5.444 | 4.315 | 4.855 | 1.984 | 1.051 |
| U. Houston | 3.499 | 6.875 | 2.403 | 6.469 | 0.038 | 1.693 |
| U. North Texas | 6.056 | 6.539 | 4.973 | 6.115 | 2.931 | 1.499 |
| S.F. Austin State U. | 3.879 | 6.605 | 3.336 | 6.213 | 1.43 | 1.41 |
| SW Texas State U. | 7.203 | 7.759 | 5.593 | 7.223 | 3.251 | 2.171 |
| Texas A & M | 14.658 | 13.854 | 11.158 | 12.246 | 8.433 | 6.512 |
| U. Texas | 16.451 | 16.303 | 13.589 | 14.191 | 10.976 | 8.418 |
| Texas Tech U. | 7.845 | 8.28 | 6.958 | 7.707 | 4.072 | 2.851 |

Table 27: Applications, Offers, Enrollment per 100 students

| College | apps (data) | (model) | offers (data) | (model) | enroll. (data) | (model) |
|---|---|---|---|---|---|---|
| TX Public | 54.675 | 37.9 | 44.193 | 34.019 | 26.496 | 16.171 |
| Private Nonrelig. | 8.262 | 5.252 | 5.231 | 4.106 | 2.267 | 1.073 |
| Religious | 23.444 | 14.206 | 17.709 | 12.423 | 7.501 | 4.901 |
| Non-TX Public | 13.683 | 11.669 | 10.517 | 10.17 | 2.98 | 3.992 |
| Highly Selective | 5.509 | 3.486 | 1.013 | 0.924 | 0.57 | 0.318 |
| Baylor U. | 3.875 | 4.914 | 3.352 | 4.09 | 1.941 | 0.783 |
| U. Houston | 4.813 | 7.173 | 2.798 | 6.482 | 0.0 | 1.732 |
| U. North Texas | 4.807 | 5.719 | 3.441 | 5.093 | 1.857 | 1.036 |
| S.F. Austin State U. | 3.207 | 6.53 | 2.218 | 5.861 | 0.427 | 1.246 |
| SW Texas State U. | 7.453 | 8.135 | 5.676 | 7.279 | 1.379 | 2.24 |
| Texas A & M | 7.59 | 7.139 | 6.078 | 5.794 | 1.771 | 2.01 |
| U. Texas | 15.06 | 19.43 | 12.168 | 16.77 | 10.09 | 10.716 |
| Texas Tech U. | 4.185 | 7.286 | 3.354 | 6.473 | 2.872 | 2.073 |

Table 28: Applications, Offers, Enrollment per 100 students, Black and Hispanic only

| College | apps (data) | (model) | offers (data) | (model) | enroll. (data) | (model) |
|---|---|---|---|---|---|---|
| TX Public | 37.979 | 33.726 | 31.416 | 31.002 | 20.729 | 14.493 |
| Private Nonrelig. | 4.278 | 5.873 | 2.833 | 4.821 | 1.683 | 1.394 |
| Religious | 21.072 | 15.46 | 16.956 | 13.89 | 8.012 | 5.612 |
| Non-TX Public | 9.083 | 11.786 | 6.85 | 10.56 | 2.05 | 4.064 |
| Highly Selective | 2.919 | 3.425 | 0.531 | 0.879 | 0.311 | 0.313 |
| Baylor U. | 3.885 | 5.227 | 3.226 | 4.518 | 1.441 | 0.934 |
| U. Houston | 4.252 | 7.148 | 2.662 | 6.625 | 0.044 | 1.787 |
| U. North Texas | 5.57 | 6.216 | 4.795 | 5.698 | 2.626 | 1.303 |
| S.F. Austin State U. | 3.732 | 6.608 | 3.086 | 6.115 | 0.783 | 1.362 |
| SW Texas State U. | 8.157 | 7.903 | 6.51 | 7.233 | 2.319 | 2.187 |
| Texas A & M | 10.737 | 11.707 | 7.59 | 10.0 | 5.439 | 4.98 |
| U. Texas | 12.274 | 16.131 | 9.628 | 13.722 | 8.511 | 8.225 |
| Texas Tech U. | 4.862 | 7.701 | 4.225 | 7.026 | 2.723 | 2.404 |

Table 29: Applications, Offers, Enrollment per 100 students, parents do not have college degree

| College | Avg. Aid (IPEDS) | Avg. Aid (model) |
|---|---|---|
| TX Public | 8215.86 | 8341.83 |
| Private Nonrelig. | 19591.83 | 22429.48 |
| Religious | 14625.34 | 14766.0 |
| Non-TX Public | 9321.26 | 10766.89 |
| Highly Selective | 26535.58 | 28162.47 |
| Baylor U. | 17753.8 | 17329.87 |
| U. Houston | 9037.8 | 7604.75 |
| U. North Texas | 8388.0 | 8711.91 |
| S.F. Austin State U. | 4014.0 | 4612.9 |
| SW Texas State U. | 7504.8 | 6886.12 |
| Texas A & M | 10984.4 | 10976.28 |
| U. Texas | 10960.0 | 10785.33 |
| Texas Tech U. | 6979.4 | 7344.6 |

Table 30: Average financial aid (dollars grant equivalent per enrolled first-time freshman), IPEDS vs. model

white students to enroll at non-flagship public university campuses, and much less likely to apply to and attend Texas A&M.

Considering students whose parents did not graduate college, I obtain similar results. Such students are relatively likely to attend non-flagship campuses in both the model and the data. I match the number of offers closely, although I underpredict the enrollment share at these campuses.

I also compare average financial aid grants for entering freshmen, in 2003 dollars, as reported in IPEDS and as predicted by the model. The estimation procedure uses a moment that requires that IPEDS match the average aid amount among surveyed students who were observed to attend each college. Because the model does not predict exactly the pattern of matriculation observed in the data, the numbers do not match perfectly; nonetheless the fit is quite close, to \$10 at UT-Austin and \$200 per student at Texas A&M.[76]

In figure 31 I show how the model-predicted SAT quantiles match those in the data. The model fits the state flagship schools well. The numbers diverge more for selective private schools, but Texas public high school students who attend these schools may have different characteristics from the general population of matriculating students, who may come from private schools and from other regions of the country.

[76]The average financial aid offer in IPEDS is calculated as the sum of average federal, state and institutional aid grants plus (.6)*average loans.

| College | 25th (model) | (data) | 75th (model) | (data) |
|---|---|---|---|---|
| TX Public | 0.569 | 0.532 | 0.719 | 0.672 |
| Private Nonrelig. | 0.631 | 0.678 | 0.775 | 0.808 |
| Religious | 0.625 | 0.614 | 0.769 | 0.751 |
| Non-TX Public | 0.619 | 0.636 | 0.75 | 0.777 |
| Highly Selective | 0.694 | 0.837 | 0.85 | 0.951 |
| Baylor U. | 0.619 | 0.669 | 0.763 | 0.8 |
| U. Houston | 0.588 | 0.575 | 0.725 | 0.719 |
| U. North Texas | 0.619 | 0.6 | 0.756 | 0.75 |
| S.F. Austin State U. | 0.575 | 0.538 | 0.719 | 0.675 |
| SW Texas State U. | 0.6 | 0.588 | 0.738 | 0.706 |
| Texas A & M | 0.656 | 0.669 | 0.788 | 0.806 |
| U. Texas | 0.644 | 0.681 | 0.788 | 0.831 |
| Texas Tech U. | 0.619 | 0.625 | 0.75 | 0.75 |

Table 31: SAT quantiles, model vs. IPEDS

### E.2.2 Matriculation effects of Texas Top Ten eligibility

Niu and Tienda estimate probit regressions of attendance at Texas A&M and/or UT Austin on control variables, class rank, and a discontinuity at the tenth percentile. They then estimate marginal effects of qualifying for Texas Top Ten, relative to not qualifying in the 2002 college market.[77]

Niu and Tienda generally find positive point estimates but wide standard errors leading to insignificant results. On the full sample, depending on specification, the point estimate is either a three percentage point increase in the probability of attending a flagship university for the average student near the tenth percentile of class rank, or a nine percentage point increase. That is, they find that the marginal effect of top-decile rank on Pr(attend flagship) is 0.03 with standard error 0.034 using a second-order polynomial, and they find a marginal effect of 0.09 (0.042) using a fourth-order polynomial in rank. In neither case is the result significant. Niu and Tienda find highly significant, larger positive effects for some subcategories, including at predominantly minority schools, and schools with average poverty rates.

[77] They estimate models of the form

$$\text{Flagship Enrollment} = \alpha_0 + \alpha_1 * rank + \ldots + \alpha_k * rank^k + \gamma * 1(\text{Top } 10\%) + \beta Z + \epsilon$$

and report marginal effects at the average characteristics $Z$.

My estimation procedure gives similar numbers. To evaluate the effects of threshold crossing, I first estimate the model-predicted probability of matriculation for top-decile students. I then "turn off" automatic admissions for these students, but keep the cutoffs $\underline{\pi}$ as they are. I estimate the effect at the average observable characteristics for a top-decile student. Under the Texas Top Ten benchmark, this average student has a 17.4% chance of attending UT Austin and a 10.3% chance of attending Texas A&M, resulting in a total flagship attendance probability of 27.7%. After disabling automatic admissions, this student has a 7.4% chance of attending Texas A&M and a 9.1% chance of attending UT Austin, for a total flagship attendance probability of 16.5%. The marginal effect of Texas Top Ten eligibility on flagship attendance is therefore 11.2 percentage points. This estimate is above the point estimates that Niu and Tienda find for the average student, but well within their confidence intervals. Figure 4 suggests one reason why Tienda and Niu did not find significant effects among white people at majority-majority schools: crossing the cutoff may have little effect on admissions chances for such students if they are already very likely to be admitted.

## E.3 Peer Effects

Recall

$$\delta_{jt} = \overline{\beta}^{\overline{SAT}} \overline{SAT}_{jt} + \overline{\beta}^{SFratio} SFratio_{jt} + \xi_{jt}$$

If $Cov(\xi_j + \overline{\beta}^{SFratio} SFratio_j, \overline{SAT}_j) \geq 0$ then the OLS estimates will overstate $\overline{\beta}^{\overline{SAT}}$. At the same time, we can assume that $\overline{\beta}^{\overline{SAT}} \geq 0$, i.e. that higher-scoring peers are preferred on average, holding one's rank among peers fixed.[78]

With instruments, the econometrician could obtain unbiased point estimates; potential instruments must correlate with SAT scores but be excluded from other terms that enter the mean utility $\delta$. Potential instruments include rival schools' investment decisions or student-faculty ratios.[79]

[78] We regress $\delta_{jt}$ on $\overline{SAT}_{jt}$, for now ignoring estimation error in $\delta_{jt}$. Under our assumptions, the OLS estimator $\hat{\overline{\beta}}^{\overline{SAT}}$ from the regression of $\delta_{jt}$ on $\overline{SAT}_{jt}$ would give an upper bound. With $\overline{SAT}_{jt}$ rescaled so that a perfect score is 1.0, we estimate an OLS point estimate of 9.71, with standard error 1.57. (We include a constant term as well). This value implies that if the SAT score index at UT Austin (currently 0.756, or 1210 out of 1600) fell to the level of non-flagship public universities (0.602, or 963.6 out of 1600), the gap in mean utilities between UT Austin and non-flagship colleges would decrease but not disappear; UT Austin's mean utility $\delta$ would decrease to -0.023, below Texas A&M, Texas Tech, private colleges, out-of-state institutions and Christian colleges, but above the aggregate in-state public university.

[79] Football records of rival universities would be valid instruments if they affect only own-school preferences. If Texas A&M had a particularly successful season, it might cause students to apply to Texas A&M rather than UT, without affecting the utility that students get from attending UT.

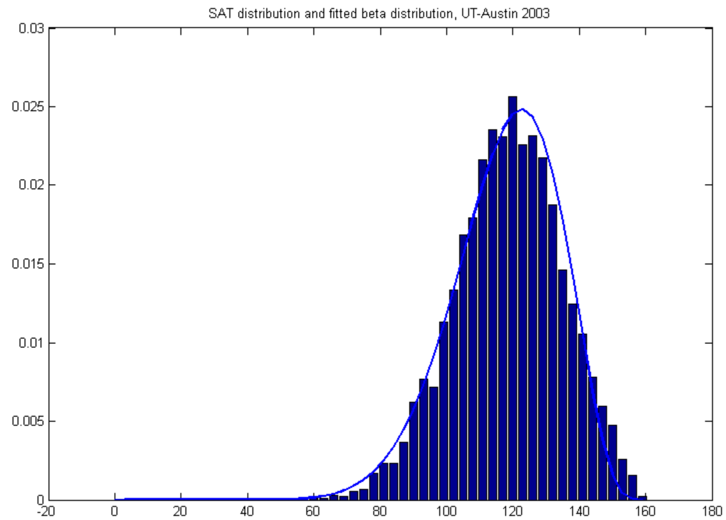


Figure 3: A fitted beta distribution: UT Austin, 2003, SAT/10.

## E.4 Additional Descriptive analysis

Table 32: Descriptive analysis of financial aid

| | Applications for financial aid |
|---|---|
| Mean income of household head's occupation | -0.0306* |
| | (0.0149) |
| SAT w/ ACT->SAT via nat'l xwalk | 3.046*** |
| | (0.502) |
| Fraction of students ever economically disadvantaged | 2.890*** |
| | (0.299) |
| Participates in Longhorn Opportunity Scholars Program | -0.983*** |
| | (0.279) |
| Participates in Century Scholars Program | 0.0217 |
| | (0.316) |
| Number of parents or guardians | -0.455*** |
| | (0.117) |
| TX Public | 0.0879 |
| | (0.161) |
| Private Nonreligious | 0.502* |
| | (0.222) |
| Religious | 0.548*** |
| | (0.166) |
| Non-TX Public | -0.134 |
| | (0.171) |
| Highly Selective | -0.123 |
| | (0.253) |
| Baylor | 0.793*** |
| | (0.230) |
| U. Houston | -0.0555 |
| | (0.209) |
| U. North Texas | -0.176 |
| | (0.221) |
| S.F. Austin State U. | -0.0550 |
| | (0.223) |
| SW Texas State U. | -0.146 |
| | (0.204) |
| Texas A&M | 0.0753 |
| | (0.164) |
| U. Texas | -0.111 |
| | (0.165) |
| o.Texas Tech | 0 |
| | (.) |
| lnsig2u | 1.100*** |
| | (0.120) |
| $\sigma_u$ | 1.733*** |
| | (0.104) |
| $\rho$ | 0.750*** |
| (N) | 4915 |

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001
SAT and HS poverty rescaled to [0,1]
College and parental education fixed effects included

Table 33: Descriptive analysis of admissions

| | Admissions | Admissions |
|---|---|---|
| classrank | -0.0259*** | -0.0248*** |
| | (0.00225) | (0.00226) |
| SAT w/ ACT->SAT via nat'l xwalk | 3.604*** | 3.335*** |
| | (0.358) | (0.376) |
| HS mean SAT | 0.0167*** | 0.0169*** |
| | (0.00377) | (0.00430) |
| TX Public | -1.977*** | -2.268*** |
| | (0.376) | (0.498) |
| Private Nonreligious | -3.187*** | -3.773*** |
| | (0.420) | (0.580) |
| Religious | -2.097*** | -2.518*** |
| | (0.394) | (0.533) |
| Non-TX Public | -2.216*** | -2.666*** |
| | (0.399) | (0.540) |
| Highly Selective | -5.172*** | -5.905*** |
| | (0.453) | (0.632) |
| Baylor | -1.654*** | -2.187*** |
| | (0.429) | (0.576) |
| U. Houston | -2.574*** | -2.917*** |
| | (0.401) | (0.525) |
| U. North Texas | -2.419*** | -2.739*** |
| | (0.409) | (0.531) |
| S.F. Austin State U. | -1.852*** | -2.184*** |
| | (0.413) | (0.533) |
| SW Texas State U. | -2.616*** | -3.068*** |
| | (0.408) | (0.548) |
| Texas A&M | -3.216*** | -3.684*** |
| | (0.407) | (0.549) |
| U. Texas | -2.650*** | -3.232*** |
| | (0.402) | (0.569) |
| Texas Tech | -1.995*** | -2.342*** |
| | (0.411) | (0.533) |
| mean Barrons | | 1.111*** |
| | | (0.315) |
| Barrons x HS pov. | | 0.137 |
| | | (0.317) |
| lnsig2u | 0.163 | 0.164 |
| | (0.122) | (0.120) |
| $\sigma_u$ | 1.085*** | 1.085*** |
| | (0.0664) | (0.0653) |
| $\rho$ | 0.541*** | 0.541*** |
| (N) | 5949 | 5949 |

Standard errors in parentheses

Table 34: GPA at state flagship schools

| | Semester GPA (UTA) | Semester GPA (TAMU) |
|---|---|---|
| SAT | 1.003*** | 1.201*** |
| | (0.0983) | (0.0899) |
| HS mean SAT | 4.221*** | 2.703*** |
| | (0.246) | (0.233) |
| classrank | -2.609*** | -1.962*** |
| | (0.0789) | (0.0690) |
| HS percent ever economically disadvantaged | -0.203*** | -0.314*** |
| | (0.0570) | (0.0534) |
| HS in LOS Program | 0.217*** | 0.111 |
| | (0.0434) | (0.0606) |
| HS in Century Scholars Program | 0.00337 | -0.109* |
| | (0.0511) | (0.0550) |
| Male | -0.187*** | -0.156*** |
| | (0.0150) | (0.0142) |
| 1st semester | 0.167*** | -0.134*** |
| | (0.0111) | (0.00931) |
| 2nd semester | 0.0878*** | -0.0903*** |
| | (0.0111) | (0.00938) |
| 3rd semester | 0.0100 | -0.121*** |
| | (0.0112) | (0.00956) |
| 4th semester | 0.0463*** | -0.0500*** |
| | (0.0113) | (0.00964) |
| Parents' education: less than HS | -0.135* | |
| | (0.0618) | |
| some HS | -0.0304 | |
| | (0.0570) | |
| HS graduate | -0.125*** | |
| | (0.0320) | |
| Some college, or two-year degree | -0.111*** | |
| | (0.0227) | |
| Four-year college degree | -0.0541** | |
| | (0.0167) | |
| Constant | -0.0820 | 0.788*** |
| | (0.161) | (0.150) |
| $\sigma_u$ | 0.472 | 0.434 |
| $\sigma_e$ | 0.561 | 0.594 |
| $\rho$ | 0.415 | 0.348 |
| (N) | 27997 | 40921 |

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 35: Dropout rates at state flagship schools

| | Dropout (UTA) | Dropout (TAMU) |
|---|---|---|
| Semester gpa | -0.218*** | -0.107* |
| | (0.0304) | (0.0451) |
| Cumulative gpa | -0.627*** | -0.810*** |
| | (0.0427) | (0.0579) |
| SAT | 0.649** | 0.785*** |
| | (0.220) | (0.238) |
| HS mean SAT | -0.573 | -0.462 |
| | (0.574) | (0.628) |
| classrank | -0.375* | 0.530** |
| | (0.176) | (0.167) |
| HS percent ever economically disadvantaged | -0.140 | 0.0835 |
| | (0.125) | (0.138) |
| HS in LOS Program | -0.0381 | 0.186 |
| | (0.0897) | (0.132) |
| HS in Century Scholars Program | -0.0559 | -0.0935 |
| | (0.110) | (0.127) |
| 1st semester | -0.897*** | -0.340*** |
| | (0.0539) | (0.0575) |
| 2nd semester | -0.346*** | 0.242*** |
| | (0.0416) | (0.0490) |
| 3rd semester | -0.542*** | -0.166** |
| | (0.0459) | (0.0569) |
| Parents' education: less than HS | 0.145 | |
| | (0.126) | |
| some HS | 0.178 | |
| | (0.116) | |
| HS graduate | 0.101 | |
| | (0.0672) | |
| Some college, or two-year degree | 0.0670 | |
| | (0.0498) | |
| Four-year college degree | -0.0410 | |
| | (0.0405) | |
| Constant | 0.982** | 0.269 |
| | (0.365) | (0.403) |

Standard errors in parentheses

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 36: Fraction of admissions and matriculations from in-state applicants, UT Austin

| year | admitted (total) | enrolled (total) | % admitted (in-state) | (TX public) | % enrolled (in-state) | (TX public) |
|---|---|---|---|---|---|---|
| 1991 | 10403 | 5818 | 85.0 | 71.8 | 90.4 | 84.1 |
| 1992 | 9726 | 5613 | 85.0 | 71.5 | 90.9 | 84.2 |
| 1993 | 10085 | 5861 | 86.0 | 72.3 | 91.6 | 84.3 |
| 1994 | 10278 | 6156 | 84.0 | 74.3 | 89.6 | 81.7 |
| 1995 | 10506 | 6346 | 84.3 | 74.3 | 90.9 | 82.8 |
| 1996 | 11041 | 6381 | 81.7 | 71.7 | 90.1 | 81.7 |
| 1997 | 11352 | 7138 | 82.2 | 72.8 | 89.9 | 82.2 |
| 1998 | 10693 | 6833 | 84.9 | 75.7 | 92.0 | 83.2 |
| 1999 | 10990 | 7288 | 89.1 | 79.4 | 93.5 | 84.6 |
| 2000 | 13061 | 8118 | 87.5 | 77.8 | 93.1 | 84.7 |
| 2001 | 12564 | 7243 | 85.0 | 76.7 | 91.1 | 83.8 |
| 2002 | 14138 | 7868 | 86.3 | 77.7 | 90.9 | 83.6 |
| 2003 | 10820 | 6493 | 87.1 | 80.0 | 92.9 | 86.9 |

Figure 4: Admission chances for 12th-percentile student at affluent high school with average SAT scores, $s$=1

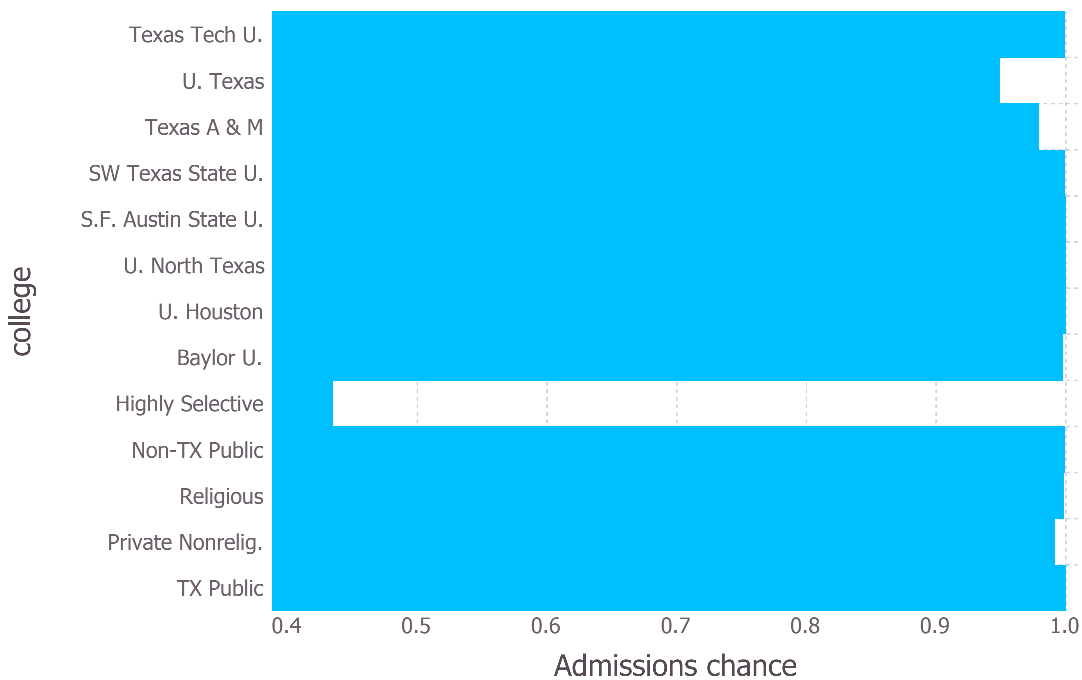

Table 37: Total applications, admissions and enrollment at UT Austin by year

Applications, Admissions and Matriculation at UT Austin by year

| | apply | admit | enroll | apply (URM) | admit (URM) | enroll (URM) |
|---|---|---|---|---|---|---|
| 1992 | 9624 | 7233 | 4732 | 2123 | 1607 | 962 |
| 1993 | 10048 | 7608 | 4946 | 2308 | 1791 | 1087 |
| 1994 | 9936 | 7660 | 5029 | 2284 | 1669 | 977 |
| 1995 | 10385 | 7832 | 5254 | 2291 | 1661 | 1020 |
| 1996 | 11501 | 7924 | 5212 | 2454 | 1630 | 972 |
| 1997 | 10065 | 8282 | 5869 | 1977 | 1463 | 991 |
| 1998 | 11332 | 8100 | 5685 | 2341 | 1489 | 1009 |
| 1999 | 12420 | 8735 | 6165 | 2884 | 1764 | 1199 |
| 2000 | 12711 | 10169 | 6876 | 2701 | 2090 | 1336 |
| 2001 | 11818 | 9642 | 6070 | 2647 | 2046 | 1168 |
| 2002 | 13422 | 10990 | 6583 | 3054 | 2397 | 1296 |
| 2003 | 14922 | 8658 | 5641 | 3592 | 2005 | 1281 |

Population: Texas public high school graduates only

Table 38: Black/Hispanic/Native American applications, admissions, and enrollment at UT Austin

| | share, app | share, admit | share, enroll | pct diff., app. | pct diff., admit | pct diff., enroll |
|---|---|---|---|---|---|---|
| 1992 | 22.06 | 22.22 | 20.33 | -3.05 | 1.87 | 3.26 |
| 1993 | 22.97 | 23.54 | 21.98 | .95 | 7.93 | 11.63 |
| 1994 | 22.99 | 21.79 | 19.43 | 1.03 | -.1 | -1.32 |
| 1995 | 22.06 | 21.21 | 19.41 | -3.05 | -2.76 | -1.39 |
| 1996 | 21.34 | 20.57 | 18.65 | -6.22 | -5.69 | -5.27 |
| 1997 | 19.64 | 17.66 | 16.89 | -13.67 | -19.01 | -14.23 |
| 1998 | 20.66 | 18.38 | 17.75 | -9.21 | -15.72 | -9.85 |
| 1999 | 23.22 | 20.19 | 19.45 | 2.05 | -7.41 | -1.21 |
| 2000 | 21.25 | 20.55 | 19.43 | -6.61 | -5.77 | -1.31 |
| 2001 | 22.4 | 21.22 | 19.24 | -1.56 | -2.71 | -2.26 |
| 2002 | 22.75 | 21.81 | 19.69 | 0 | 0 | 0 |
| 2003 | 24.07 | 23.16 | 22.71 | 5.79 | 6.18 | 15.35 |

underrepresented minority students as share of TX public high school students at UT Austin
columns 4-7: percentage differences relative to 2002

Table 39: Top-decile students' applications, admissions, and enrollment at UT Austin

| | share, app | share, admit | share, enroll | pct diff., app. | pct diff., admit | pct diff., enroll |
|---|---|---|---|---|---|---|
| 1992 | 41.58 | 54.17 | 45.22 | -7.67 | -1.41 | -21.49 |
| 1993 | 41.25 | 53.17 | 44.9 | -8.41 | -3.23 | -22.04 |
| 1994 | 41.16 | 52.01 | 43.39 | -8.6 | -5.33 | -24.68 |
| 1995 | 42.11 | 53.91 | 44.94 | -6.5 | -1.88 | -21.99 |
| 1996 | 39.31 | 54.32 | 42.73 | -12.72 | -1.14 | -25.82 |
| 1997 | 37.92 | 45.13 | 37.77 | -15.8 | -17.85 | -34.42 |
| 1998 | 37.81 | 51.38 | 42.23 | -16.04 | -6.48 | -26.68 |
| 1999 | 40.63 | 54.1 | 46.1 | -9.79 | -1.52 | -19.97 |
| 2000 | 42 | 52.42 | 47.09 | -6.74 | -4.58 | -18.25 |
| 2001 | 45.63 | 55.82 | 54.37 | 1.3 | 1.6 | -5.62 |
| 2002 | 45.04 | 54.94 | 57.6 | 0 | 0 | 0 |
| 2003 | 45.71 | 78.34 | 73.37 | 1.49 | 42.6 | 27.38 |

topten students as share of TX public high school students at UT Austin
columns 4-7: percentage differences relative to 2002

Table 40: Top-decile minority students' applications, admissions, and enrollment at UT Austin

| | share, app | share, admit | share, enroll | pct diff., app. | pct diff., admit | pct diff., enroll |
|---|---|---|---|---|---|---|
| 1992 | 9.72 | 12.54 | 9.26 | -8.75 | -3.49 | -28.06 |
| 1993 | 9.76 | 12.62 | 9.93 | -8.3 | -2.89 | -22.84 |
| 1994 | 8.85 | 10.78 | 7.68 | -16.91 | -17.01 | -40.35 |
| 1995 | 8.81 | 11.02 | 7.99 | -17.24 | -15.2 | -37.87 |
| 1996 | 8.23 | 10.95 | 7.46 | -22.66 | -15.7 | -41.99 |
| 1997 | 7.34 | 8.63 | 6.54 | -31.04 | -33.56 | -49.15 |
| 1998 | 7.8 | 10.43 | 7.85 | -26.73 | -19.71 | -39.03 |
| 1999 | 10.34 | 13.02 | 10.85 | -2.9 | .18 | -15.66 |
| 2000 | 10.01 | 12.49 | 10.7 | -5.93 | -3.88 | -16.81 |
| 2001 | 10.31 | 12.59 | 11.43 | -3.12 | -3.1 | -11.14 |
| 2002 | 10.65 | 12.99 | 12.87 | 0 | 0 | 0 |
| 2003 | 11.45 | 19.64 | 18.38 | 7.51 | 51.11 | 42.88 |

minority students in top 10% of HS class as share of TX public high school students at UT Austin
columns 4-7: percentage differences relative to 2002